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Efficiency and Anomalies in Stock Markets

Edited by

Wing-Keung Wong

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About the Editor

Professor Wing-Keung Wong obtained his Ph.D. from the University of Wisconsin-Madison, the USA with a major in Business Statistics (Statistics and Finance) and obtained his Bachelor degree from the Chinese University of Hong Kong, Hong Kong, with a major in Mathematics and a double minor in Economics and Statistics. Currently, he is a Chair Professor at the Department of Finance, Asia University. He was a Full Professor at the Department of Economics, Hong Kong Baptist University, and Deputy Director at Risk Management Institute, National University of Singapore.

He appears in "Who's Who in the World". He is ranked top 1% by SSRN and in the list of top Taiwan economists and Asian economists and top economists by RePEc. He has published more than three hundred papers including papers published in some top journals. He has more than 11100 citations in Google Scholar, and more than 9600 citations in Researchgate. His h-index is 59, and i10-index is 225 by Google Scholar citation.

He has been providing consultancy to several Government departments and corporations, giving lectures and seminars to several universities, serving as editor, guest leading editor, advisor, associate editor for some international journals, and appointed as an external examiner.

Preface to "Efficiency and Anomalies in Stock Markets"

The Efficient Market Hypothesis believes that it is impossible for an investor to outperform the market because all available information is already built into stock prices. However, some anomalies could persist in stock markets, while some other anomalies could appear, disappear, and re-appear again without any warning. To explore new theories with applications in this direction, this Special Issue on "Efficiency and Anomalies in Stock Markets", edited by Wing-Keung Wong, is devoted to advancements in developing theories on market efficiency and anomalies in stock markets, as well as applications in market efficiency and financial anomalies in 2019. We invite investigators to submit manuscripts of original innovative research in theory, practice, and applications in the areas of market efficiency and anomalies in stock markets to be considered for publication in *Economies*. We are open to interesting and imaginative ideas that fit within the spirit and scope of the call for papers that should have a quantitative orientation.

Wing-Keung Wong
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Editorial

Editorial Statement and Research Ideas for Efficiency and Anomalies in Stock Markets

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Abstract: The Efficient Market Hypothesis states that it is impossible for an investor to outperform the market because all available information is already built into stock prices. However, some anomalies could persist in stock markets while some other anomalies could appear, disappear and re-appear again without any warning. To explore new theories with applications in this direction, in this editorial, we suggest ideas to authors on what types of papers we will accept for publication in the areas of on Efficiency and Anomalies in Stock Markets. We will discuss some papers published in the special issue of Efficiency and Anomalies in Stock Markets.

Keywords: market efficiency; anomaly; stock market; finance; applications

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The Efficient Market Hypothesis believes that it is impossible for an investor to outperform the market because all available information is already built into stock prices. However, some anomalies could persist in stock markets while some other anomalies could appear, disappear and re-appear again without any warning. To explore new theories with applications in this direction, the special issue on Efficiency and Anomalies in Stock Markets edited by Wing-Keung Wong is devoted to advancements in the theory development on market efficiency and anomalies in stock markets as well as applications in market efficiency and financial anomalies in 2019. We invite investigators to submit manuscripts of original innovative research in theory, practice and applications in the areas of market efficiency and anomalies in stock markets to be considered for publication in *Economies*. We are open to interesting and imaginative ideas that fit within the spirit and scope of the call for papers that should have a quantitative orientation.

The special issue of Efficiency and Anomalies in Stock Markets has published 10 papers including (Guo et al. 2017; Ali et al. 2018; Ahn et al. 2018; Chiang 2019; Ehigiamusoe and Lean 2019; Jena et al. 2019; Lam et al. 2019; Zhang and Li 2019; Chang et al. 2019; Woo et al. 2019; Wong 2020).

Among them, (Woo et al. 2019) review the theory and literature on market efficiency and market anomalies. (Chiang 2019) examines the efficient market hypothesis for 15 international equity markets, and (Guo et al. 2017) develop the theory to test for market efficiency and check whether there is any expected arbitrage opportunity and anomaly in the market. market. (Ehigiamusoe and Lean 2019) examine the moderating effects of the real exchange rate and its volatility on the finance-growth nexus and determine the marginal effects of financial development on economic growth at various levels of the real exchange rates and its volatility, (Zhang and Li 2019) explore the fitting of Autoregressive (AR) and Threshold AR (TAR) models with a non-Gaussian error structure and propose to use a Gamma random error to cater for the non-negativity of the realized volatility, and (Ahn et al. 2018) examine the effects of low-frequency liquidity, high-frequency spread measures and price impact measures. On the other hand, (Lam et al. 2019) examine whether there is any value premium in the Chinese stock market by using the conventional buy-and-hold approach to buy long the portfolio with the highest BM ratio and sell short the one with the lowest BM ratio, (Ali et al. 2018) use three methods to construct factors and identify pitfalls that arise in the application of Fama-French's three-factor model and examine the ability of the three factors to predict the future growth of economy, (Jena et al. 2019) examine the efficacy of the Put–Call Ratio (PCR) measured in terms of volume and open interest in predicting market return at different time scale, and (Chang et al. 2019) study the effect of financial constraints on short-term performance.

We first discuss more detail about the work by (Woo et al. 2019; Chiang 2019; Guo et al. 2017). (Woo et al. 2019) review the theory and literature on market efficiency and market anomalies. They first review market efficiency, define clearly the concept of market efficiency and efficient-market hypothesis (EMH), and discuss some efforts that challenge EMH. Thereafter, they review different market anomalies and review different theories of Behavioral Finance that could be used to explain market anomalies. Their review is useful to academics for their studies in EMH, anomalies, and Behavioral Finance, useful to investors for their decisions on their investment, and useful to policy makers in reviewing their policies in stock markets. (Chiang 2019) examines the efficient market hypothesis by applying monthly data for 15 international equity markets. He finds that the null for the absence of autocorrelations of stock returns is rejected except Canada and the U.S, the independence of market volatility correlations is rejected. However, the existence of correlations between stock returns and lagged news measured by lagged economic policy uncertainty is not rejected for all markets, implying that a change of lagged EPUs positively predicts conditional variance. In addition, (Guo et al. 2017) study the relationship between stochastic dominance and the Omega ratio. They find that second-order stochastic dominance (SD) and/or second-order risk-seeking SD (RSD) alone for any two prospects is not sufficient to imply Omega ratio dominance insofar that the Omega ratio of one asset is always greater than that of the other one. They extend the theory of risk measures by proving that the preference of second-order SD implies the preference of the corresponding Omega ratios only when the return threshold is less than the mean of the higher return asset. They also find that the preference of the second-order RSD implies the preference of the corresponding Omega ratios only when the return threshold is larger than the mean of the smaller return asset and observe that first-order SD does imply Omega ratio dominance. Applying their theory to examine the relationship between property size and property investment in the Hong Kong real estate market, they conclude that the Hong Kong real estate market is not efficient and there are expected arbitrage opportunities and anomalies in the Hong Kong real estate market.

We turn to discuss the work by (Ehigiamusoe and Lean 2019; Zhang and Li 2019; Ahn et al. 2018) on volatility and liquidity. (Ehigiamusoe and Lean 2019) examine the moderating effects of the real exchange rate and its volatility on the finance-growth nexus in the West African region and determine the marginal effects of financial development on economic growth at various levels of the real exchange rates and its volatility. They find that financial development has a long-term positive impact on economic growth, but this impact is weakened by real exchange rate and its volatility. They also find that the marginal effects of financial development on economic growth vary with the levels of the real exchange rate and its volatility: the higher the real exchange rate and its volatility, the less finance spurs growth. Their findings imply that the development of the financial sector would not provide the desirable economic benefits except it is accompanied by a reduction and stability in the real exchange rates. Motivated by the problem of finding a possible probabilistic model for the realized volatility, (Zhang and Li 2019) explore the fitting of Autoregressive (AR) and Threshold AR (TAR) models with a non-Gaussian error structure. They propose to use a Gamma random error to cater for the non-negativity of the realized volatility, apply the maximum likelihood estimation and employ a non-gradient numerical Nelder–Mead method for optimization and a penalty method, introduced for the non-negative constraint imposed by the Gamma distribution, in their analysis. In their simulation, they show that their proposed fitting method fits the true AR or TAR model with insignificant bias and mean square error (MSE). They also test the AR and TAR models with Gamma random error on empirical realized volatility data of 30 stocks and find that one third of the cases are fitted quite well, implying that the models have potential as a supplement for current Gaussian random error models with proper adaptation. On the other hand, (Ahn et al. 2018) conduct a comprehensive analysis on 1183 stocks from 21 emerging markets to examine the low-frequency liquidity proxies that best measure liquidity in emerging markets and compare several low-frequency liquidity proxies with high-frequency spread measures and price impact measures. They find that the Lesmond, Ogden, and Trzcinka measure is the most effective spread proxy in most of the emerging markets. In addition, the Amihud measure is the most effective one among the price impact proxies.

Lastly, we discuss the work done by (Lam et al. 2019; Ali et al. 2018; Jena et al. 2019; Chang et al. 2019) on value premium, the application of Fama-French's three-factor model, the efficacy of the Put–Call Ratio, and the effect of financial constraints on short-term performance. (Lam et al. 2019) examine whether there is any value premium in the Chinese stock market by using a conventional buy-and-hold approach to buy long the portfolio with the highest BM ratio and sell short the one with the lowest BM ratio. They propose a new strategy by combining the value premium effect and technical analysis. To trade the objective portfolio or risk-free asset according to the moving average timing signals, they find excess return from such a zero-cost trading strategy. They perform various robustness tests and find that the excess returns remain significantly positive after adjusting for risks (on three factor models) and transaction costs and find that the combined trading strategy can generate significant positive risk-adjusted returns after the transaction costs. (Ali et al. 2018) use three methods to construct factors and identify pitfalls that arise in the application of Fama-French's three-factor model to the Pakistani stock returns and examine the ability of the three factors to predict the future growth of Pakistan's economy. They find that the special features in Pakistan significantly affect both size and value factors and influence the explanatory power of the three-factor model. They find that size and book-to-market factors exist in the Pakistani stock market and two mimic portfolios SMB and HML generate a return of 9.15% and 12.27% per annum, respectively. They observe that including both SMB and HML factors into the model will increase the explanatory power of the model. They also find that except for value factor, the model's factors predict future gross domestic product (GDP) growth of Pakistan and remain robust. (Jena et al. 2019) examine the efficacy of the Put–Call Ratio (PCR) measured in terms of volume and open interest in predicting market return at different time scale. They find that volume PCR is an efficient predictor of the market return in a short period of 2.5 days and open interest PCR in a long period of 12 days. Their findings suggest that traders and portfolio investors should use the appropriate PCR depending upon the time horizon of their trade and investment. In addition, (Chang et al. 2019) hypothesize that when companies have investment plans, they are expected to have higher future cash flows and they will become increasingly more valuable regardless of the fact that they raise funds through the issue of convertible bonds (due to financial constraints), positively affecting the performance of companies. Their findings show that financial constraints have no effect on short-term performance but have a significantly positive impact on the long-term performance of companies after their issuance of convertible bonds.

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Article

Stochastic Dominance and Omega Ratio: Measures to Examine Market Efficiency, Arbitrage Opportunity, and Anomaly

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Abstract: Both stochastic dominance and Omegaratio can be used to examine whether the market is efficient, whether there is any arbitrage opportunity in the market and whether there is any anomaly in the market. In this paper, we first study the relationship between stochastic dominance and the Omega ratio. We find that second-order stochastic dominance (SD) and/or second-order risk-seeking SD (RSD) alone for any two prospects is not sufficient to imply Omega ratio dominance insofar that the Omega ratio of one asset is always greater than that of the other one. We extend the theory of risk measures by proving that the preference of second-order SD implies the preference of the corresponding Omega ratios only when the return threshold is less than the mean of the higher return asset. On the other hand, the preference of the second-order RSD implies the preference of the corresponding Omega ratios only when the return threshold is larger than the mean of the smaller return asset. Nonetheless, first-order SD does imply Omega ratio dominance. Thereafter, we apply the theory developed in this paper to examine the relationship between property size and property investment in the Hong Kong real estate market. We conclude that the Hong Kong real estate market is not efficient and there are expected arbitrage opportunities and anomalies in the Hong Kong real estate market. Our findings are useful for investors and policy makers in real estate.

Keywords: stochastic dominance; Omega ratio; risk averters; risk seekers; utility maximization; market efficiency; anomaly

JEL Classification: C0, D81, G10

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1. Introduction

It is well known that the standard deviation is not a good measure of risk because it penalizes upside deviation, as well as downside deviation. Additionally, it is also poor at measuring risk with asymmetric payoff profiles. The poor performance of the standard deviation will lead to poor performance of the Sharpe ratio, which establishes a relationship between the ratio of return versus volatility (Kapsos et al. (2014); Guastaroba et al. (2016)). A number of studies developed some theories that propose to circumvent the limitations. For example, Homm and Pigorsch (2012) develop an economic performance measure based on Aumann and Serrano's (2008) index of riskiness. They prove that the proposed economic performance measure is consistent with first- and second-order stochastic dominance (SD). Keating and Shadwick (2002) propose to use the Omega ratio, the probability weighted ratio of gains versus losses to a prospect or the ratio of upside returns (good) relative to downside returns (bad), to replace the Sharpe ratio to measure the risk return performance of a prospect. Thus, the Omega ratio considers all moments, while the Sharpe ratio considers only the first two moments of the return distribution in the construction. According to Caporin et al. (2016), Bellini et al. (2017) and the references provided therein, the Omega ratios are strongly related to expectiles, which are a type of inverse of the Omega ratio and present interesting properties as risk measures. Guastaroba et al. (2016) discuss the advantages of using the Omega ratio further. Thus, the Omega ratio has been commonly used by academics and practitioners as noted by Kapsos et al. (2014) and the references therein.

It is well known that the SD theory can be used to examine whether the market is efficient, whether there is any arbitrage opportunity in the market, and whether there is any anomaly in the market (Sriboonchitta et al. (2009); Levy (2015)), and thus, academics are interested in checking whether there is any relationship between any risk measure with SD. The work from Darsinos and Satchell (2004) and others can be used to establish the relationship between the second-order SD (SSD) and the Omega ratio. By using two counterexamples, we first demonstrate that SSD and/or second-order risk-seeking SD (SRSD) alone for any two prospects is not sufficient to imply Omega ratio dominance (OD) and that the Omega ratio of one asset is always greater than that of the other one. We then extend the work of Darsinos and Satchell (2004) and others by proving that the preference of SSD (for risk averters) implies the preference of the corresponding Omega ratios are selected only when the return threshold is less than the mean of the higher return asset. On the other hand, the preference of SRSD (for risk seekers) implies the preference of the corresponding Omega ratios only when the return threshold is larger than the mean of the smaller return asset. Lastly, we develop the relationship between the first-order SD (FSD) and the Omega ratio in such a way that the preference of FSD for any investor with increasing utility functions does imply the preference of the corresponding Omega ratios for any return threshold.

Qiao and Wong (2015) apply SD tests to examine the relationship between property size and property investment in the Hong Kong real estate market. They do not find any FSD relationship in their study. Tsang et al. (2016) extend their work to reexamine the relationship between property size and property investment in the same market. They suggest to analyze both rental and total yields and find the FSD relationship of rental yield in adjacent pairings of different housing classes in Hong Kong. Based on their analysis on both rental and total yields, they conclude that investing in a smaller house is better than a bigger house. We note that analyzing both rental and total yields is not sufficient to draw such a conclusion. To circumvent the limitation, we extend their work by applying the Omega ratio to examine the relationship between property size and property investment in the Hong Kong real estate market. In addition to analyzing the rental yield, we recommend analyzing the price yields of different houses. We find that a smaller house dominates a bigger house in terms of rental yield, and there is no dominance between smaller and bigger houses in price yield. Our findings lead us to conclude that regardless of whether the buyers are risk averse or risk seeking, they will not only achieve higher expected utility, but also obtain higher expected wealth when buying smaller properties. This implies that the Hong Kong real estate market is not efficient, and there are expected arbitrage opportunities and anomalies in the Hong Kong real estate market. Our findings are useful for real estate investors in their investment decision making and useful to policy makers in real estate for their policy making to make the real estate market become efficient.

The rest of this paper is organized as follows: Section 2 presents the formal definitions of the SD rules and Omega ratios. We then show our main results about the consistency of Omega ratios with respect to the SD in Section 3. In Section 4, we discuss how to apply the theory developed in this paper to examine whether the market is efficient, whether there is any arbitrage opportunity in the market and whether there is any anomaly in the market. An illustration of the Hong Kong housing market is included in Section 5. The final section offers our conclusion.

2. Definitions of Stochastic Dominance and Omega Ratios

We first define cumulative distribution functions (CDFs) for X and Y:

$$F_Z^{(1)}(\eta) = F_Z(\eta) = P(Z \le \eta) \text{ , for } \; Z = X, Y \,. \tag{1}$$

We define the second-order integral of Z, $F_Z^{(2)}$,

$$F_Z^{(2)}(\eta) = \int_{-\infty}^{\eta} F_Z^{(1)}(\xi) d\xi \;\text{ for }\; Z = X, Y \,; \tag{2}$$

and define the second-order reverse integral, $F_Z^{(2)R}$, of Z

$$F_Z^{(2)R}(\eta) = \int_{\eta}^{\infty} (1 - F_Z^{(1)}(\xi)) d\xi \;\text{ for }\; Z = X, Y \,. \tag{3}$$

If Z is the return, then $F_Z^{(1)}(\eta)$ is the CDF of the return up to η and $F_Z^{(2)}(\eta)$ is the second-order integral of Z up to η, that is the probability of the CDF of the return up to η, and $F_Z^{(2)R}(\eta)$ is the second-order reverse integral of Z up to η, that is the reverse integration of the reverse CDF of the return up to η. We call $F_Z^{(i)}$ the i-th-order integral of Z, which will be used to define the SD theory for risk averters (see, for example, Quirk and Saposnik (1962)). On the other hand, we call $F_Z^{(i)R}$ the i-th-order reversed integral, which will be used to define the SD theory for risk seekers (see, for example, Hammond (1974)). Risk averters typically have a preference for assets with a lower probability of loss, while risk seekers have a preference for assets with a higher probability of gain. When choosing between two assets X or Y, risk averters will compare their corresponding i-th order SD integrals $F_X^{(i)}$ and $F_Y^{(i)R}$ and choose X if $F_X^{(i)}$ is smaller, since it has a lower probability of loss. On the other hand, risk seekers will compare their corresponding i-th order RSD integrals $F_X^{(i)R}$ and $F_Y^{(i)R}$ and choose X if $F_X^{(i)R}$ is larger since it has a higher probability of gain.

Following the definition of stochastic dominance (Hanoch and Levy (1969)), prospect X first-order stochastically dominates prospect Y:

$$\text{if and only if } \;\; F_X^{(1)}(\eta) \le F_Y^{(1)}(\eta) \;\;\text{ for any }\;\; \eta \in R, \tag{4}$$

which is denoted by $X \succeq_{FSD} Y$; prospect X second-order stochastically dominates prospect Y:

$$\text{if and only if } \;\; F_X^{(2)}(\eta) \le F_Y^{(2)}(\eta) \;\;\text{ for any }\;\; \eta \in R, \tag{5}$$

which is denoted by $X \succeq_{SSD} Y$. Here, FSD and SSD denote first- and second-order stochastic dominance, respectively.

Next, we follow Levy (2015) to define risk-seeking stochastic dominance (RSD)[1] for risk seekers. Prospect X stochastically dominates prospect Y in the sense of second-order risk seeking:

$$\text{if and only if } \;\; F_X^{(2)R}(\eta) \ge F_Y^{(2)R}(\eta) \;\;\text{ for any }\;\; \eta \in R, \tag{6}$$

which is denoted by $X \succeq_{SRSD} Y$. Here, SRSD denotes second-order RSD.

[1] Levy (2015) denotes it as RSSD, while we denote it as RSD.

Quirk and Saposnik (1962), Hanoch and Levy (1969), Levy (2015) and Guo and Wong (2016) have studied various properties of stochastic dominance (for risk averters), while Hammond (1974), Meyer (1977), Stoyan and Daley (1983), Li and Wong (1999), Wong and Li (1999), Wong (2007), Levy (2015) and Guo and Wong (2016) have developed additional properties of risk-seeking stochastic dominance for risk seekers. One important property for SD is that SSD and SRSD are equivalent to the expected-utility maximization for (second-order) risk-averse and risk-seeking investors, respectively, while FSD is equivalent to the expected-utility/wealth maximization for any investor with increasing utility functions.

We turn to define $\Omega_X(\eta)$ as follows:

$$\Omega_X(\eta) = \frac{\int_\eta^\infty (1 - F_X(\xi))d\xi}{\int_{-\infty}^\eta F_X(\xi)d\xi}. \tag{7}$$

Here, η is called the return threshold. For any investor, returns below (above) her/his return threshold are considered as losses (gains). Thus, the Omega ratio is the probability weighted ratio of gains to losses relative to a return threshold.

According to Darsinos and Satchell (2004), we can also rewrite $\Omega_X(\eta)$ as follows:

$$\Omega_X(\eta) = \frac{F_X^{(2)R}(\eta)}{F_X^{(2)}(\eta)} = \frac{F_X^{(2)}(\eta) - (\eta - \mu_X)}{F_X^{(2)}(\eta)} = 1 + \frac{\mu_X - \eta}{F_X^{(2)}(\eta)}. \tag{8}$$

We state the following Omega ratio dominance (OD) rule by using the Omega ratio:

Definition 1. *For any two prospects X and Y with Omega ratios, $\Omega_X(\eta)$ and $\Omega_Y(\eta)$, respectively, X is said to dominate Y by the Omega ratio or X is said to Omega ratio dominate Y, denote by:*

$$X \succeq_{OD} Y \quad \textit{if} \quad \Omega_X(\eta) \geq \Omega_Y(\eta) \;\; \textit{for any } \eta \in R. \tag{9}$$

3. Consistency Results

We will use the term "theorem" to state new results obtained in this paper and "proposition" to state some well-known results. Some academics may believe that the SSD is consistent with the Omega ratio because they assert the following:

$$\text{if} \quad X \succeq_{SSD} Y\,, \quad \text{then} \quad \Omega_X(\eta) \geq \Omega_Y(\eta) \quad \text{for any} \quad \eta \in R\,, \tag{10}$$

where $\Omega_X(\eta)$ is the Omega ratio for X defined in (7) or (8). The above assertion is in Darsinos and Satchell (2004) and others. We first establish the following property to state that the argument in (10) may not be correct:

Property 1. *SSD alone is not sufficient to imply $\Omega_X(\eta) \geq \Omega_Y(\eta)$ for any η.*

Property 1 implies that the assertion made by Darsinos and Satchell (2004) and others may not be always correct. We construct the following example to support the argument stated in Property 1.

Example 1. *Consider two prospects X and Y having the following distributions:*

$$X = 10 \quad \textit{with prob. } 1, \quad \textit{and} \quad Y = \begin{cases} 1 & \textit{with prob. } 2/3 \\ 11 & \textit{with prob. } 1/3 \end{cases}. \tag{11}$$

Then, we get $\mu_X = 10$ *and* $\mu_Y = 13/3$ *and obtain the following:*

$$F_X^{(2)}(\eta) = \begin{cases} 0 & \text{if } \eta < 10 \\ \eta - 10 & \text{if } \eta \geq 10 \end{cases}, \quad F_Y^{(2)}(\eta) = \begin{cases} 0 & \text{if } \eta < 1 \\ 2(\eta-1)/3 & \text{if } 1 \leq \eta < 11 \\ \eta - 13/3 & \text{if } \eta \geq 11 \end{cases},$$

$$F_X^{(2)R}(\eta) = \begin{cases} 10 - \eta & \text{if } \eta < 10 \\ 0 & \text{if } \eta \geq 10 \end{cases}, \quad F_Y^{(2)R}(\eta) = \begin{cases} 13/3 - \eta & \text{if } \eta < 1 \\ (11-\eta)/3 & \text{if } 1 \leq \eta < 11 \\ 0 & \text{if } \eta \geq 11 \end{cases}.$$

It follows that $F_X^{(2)}(\eta) \leq F_Y^{(2)}(\eta)$*, for all* $\eta \in R$*. That is,* $X \succeq_{SSD} Y$*. However, for any* $10 \leq \eta < 11$*, we have* $F_X^{(2)R}(\eta) \equiv 0 < F_Y^{(2)R}(\eta)$*. Recalling the definition of* $\Omega_X(\eta)$*, we can conclude that* $\Omega_X(\eta) \equiv 0 < \Omega_Y(\eta)$ *for any* $10 \leq \eta < 11$*, and thus, the statement "*$\Omega_X(\eta) \geq \Omega_Y(\eta)$ *for any* η*" does not hold.*

To complement Property 1, we establish the following property:

Property 2. *SRSD alone is not sufficient to imply* $\Omega_X(\eta) \geq \Omega_Y(\eta)$ *for any* η*.*

We construct the following example to support the argument stated in Property 2.

Example 2. *Consider two prospects* X *and* Y *as follows:*

$$X = \begin{cases} 2 & \textit{with prob. } 1/2 \\ 8 & \textit{with prob. } 1/2 \end{cases} \quad \textit{and} \quad Y = \begin{cases} 3 & \textit{with prob. } 2/3 \\ 6 & \textit{with prob. } 1/3 \end{cases}. \tag{12}$$

We have $\mu_X = 5$ *and* $\mu_Y = 4$ *and obtain the following:*

$$F_X^{(2)}(\eta) = \begin{cases} 0 & \text{if } \eta < 2 \\ (\eta-2)/2 & \text{if } 2 \leq \eta < 8, \\ \eta - 5 & \text{if } \eta \geq 8 \end{cases} \quad F_Y^{(2)}(\eta) = \begin{cases} 0 & \text{if } \eta < 3 \\ 2(\eta-3)/3 & \text{if } 3 \leq \eta < 6, \\ \eta - 4 & \text{if } \eta \geq 6 \end{cases}$$

$$F_X^{(2)R}(\eta) = \begin{cases} 5 - \eta & \text{if } \eta < 2 \\ 4 - \eta/2 & \text{if } 2 \leq \eta < 8, \\ 0 & \text{if } \eta \geq 8 \end{cases} \quad F_Y^{(2)R}(\eta) = \begin{cases} 4 - \eta & \text{if } \eta < 3 \\ 2 - \eta/3 & \text{if } 3 \leq \eta < 6. \\ 0 & \text{if } \eta \geq 6 \end{cases}$$

It follows that $F_X^{(2)R}(\eta) \geq F_Y^{(2)R}(\eta)$*, for all* $\eta \in R$*. This concludes that* $X \succeq_{SRSD} Y$*. However, for* $\eta = 3.3$*, we can get:*

$$\Omega_X(\eta) = \frac{F_X^{(2)R}(\eta)}{F_X^{(2)}(\eta)} = \frac{4 - \eta/2}{(\eta-2)/2} = \frac{8-\eta}{\eta-2} = 3.615.$$

$$\Omega_Y(\eta) = \frac{F_Y^{(2)R}(\eta)}{F_Y^{(2)}(\eta)} = \frac{2 - \eta/3}{2(\eta-3)/3} = \frac{6-\eta}{2\eta-6} = 4.5.$$

That is, $\Omega_X(\eta) < \Omega_Y(\eta)$*. In fact, for any* $3 < \eta < 7 - \sqrt{13}$*, we have* $\Omega_X(\eta) < \Omega_Y(\eta)$*, and thus, the statement "*$\Omega_X(\eta) \geq \Omega_Y(\eta)$ *for any* η*" does not hold.*

Properties 1 and 2 tell us that SSD and SRSD alone are not sufficient to imply $\Omega_X(\eta) \geq \Omega_Y(\eta)$ for any η. Then, one may ask: what is the relationship between $\Omega_X(\eta)$ and $\Omega_Y(\eta)$ when there is SSD or SRSD? Guo et al. (2016) and Balder and Schweizer (2017) provide an answer. In this paper, we restate their result to extend the work by Darsinos and Satchell (2004) and others by first deriving the relationship between SSD (for risk averters) and the Omega ratio:

Proposition 1. *For any two returns X and Y with means μ_X and μ_Y and Omega ratios $\Omega_X(\eta)$ and $\Omega_Y(\eta)$, respectively, if $X \succeq_{SSD} Y$, then $\Omega_X(\eta) \geq \Omega_Y(\eta)$ for any $\eta \leq \mu_X$.*

Now, it is clear that Proposition 1 extends the results of Darsinos and Satchell (2004) by restricting the range of the return threshold. We note that Balder and Schweizer (2017) obtain a similar result of Proposition 1. However, we have independently derived Proposition 1 and reported the results in Guo et al. (2016). Moreover, our proof is different from Balder and Schweizer (2017).

In addition, we also study the relationship of second-order risk-seeking stochastic dominance and the corresponding Omega ratios. A dual result as stated in Theorem 1 is obtained. Finally, the relationship between first-order stochastic dominance and the Omega ratios is established in Corollary 2. Some simple examples (Examples 1 and 2) are presented to show that SSD or SRSD alone are not sufficient to imply $\Omega_X(\eta) \geq \Omega_Y(\eta)$ for any η.

Here, we provide a short proof[2] as follows: although it is true that if $X \succeq_{SSD} Y$, then $\mu_X - \eta \geq \mu_Y - \eta$ for any η. However, the sign of $\mu_X - \eta$ and $\mu_Y - \eta$ can be negative. To be precise, for $\eta > \mu_X \geq \mu_Y$, $0 > \mu_X - \eta \geq \mu_Y - \eta$. In this situation, we can get:

$$\frac{\mu_X - \eta}{F_X^{(2)}(\eta)} \leq \frac{\mu_X - \eta}{F_Y^{(2)}(\eta)}.$$

Furthermore, we note that:

$$\frac{\mu_Y - \eta}{F_Y^{(2)}(\eta)} = \frac{\mu_Y - \mu_X}{F_Y^{(2)}(\eta)} + \frac{\mu_X - \eta}{F_Y^{(2)}(\eta)} \leq \frac{\mu_X - \eta}{F_Y^{(2)}(\eta)}.$$

Consequently, we cannot determine the sign of $\frac{\mu_X - \eta}{F_X^{(2)}(\eta)} - \frac{\mu_Y - \eta}{F_Y^{(2)}(\eta)}$. Thus, we cannot determine the sign of $\Omega_X(\eta) - \Omega_Y(\eta)$. However, for any $\eta \leq \mu_X$, we can have $\mu_X - \eta \geq 0$, and thus, we have:

$$\frac{\mu_X - \eta}{F_X^{(2)}(\eta)} \geq \frac{\mu_X - \eta}{F_Y^{(2)}(\eta)} \geq \frac{\mu_Y - \eta}{F_Y^{(2)}(\eta)}.$$

This implies that $\Omega_X(\eta) \geq \Omega_Y(\eta)$, and thus, the assertion of Proposition 1 holds. □

In the proof of Proposition 1, one could conclude that if $X \succeq_{SSD} Y$, then $\Omega_X(\eta) \geq \Omega_Y(\eta)$ for any $\eta \leq \mu_X$. However, for $\eta > \mu_X$, we cannot determine which one is larger if we are using SSD. However, one could consider employing the SD (RSD) theory for risk seeking (refer to Equation (6)) in the study. By doing so, we establish the following theorem to state the relationship between the SRSD and Omega ratio:

Theorem 1. *For any two returns X and Y with means μ_X and μ_Y and Omega ratios $\Omega_X(\eta)$ and $\Omega_Y(\eta)$, respectively, if $X \succeq_{SRSD} Y$, then $\Omega_X(\eta) \geq \Omega_Y(\eta)$ for any $\eta \geq \mu_Y$.*

Here, we give a short proof as follows: assume that $X \succeq_{SRSD} Y$. This is equivalent to $F_X^{(2)R}(\eta) = \int_\eta^\infty (1 - F_X(\xi))d\xi \geq F_Y^{(2)R}(\eta)$. Recall that $F_X^{(2)R}(\eta) = F_X^{(2)}(\eta) - (\eta - \mu_X) \geq 0$. This yields the following equation:

$$\frac{1}{\Omega_X(\eta)} = \frac{F_X^{(2)}(\eta)}{F_X^{(2)R}(\eta)} = \frac{F_X^{(2)R}(\eta) + (\eta - \mu_X)}{F_X^{(2)R}(\eta)} = 1 + \frac{\eta - \mu_X}{F_X^{(2)R}(\eta)}.$$

[2] We note that our proof is different from that of Balder and Schweizer (2017).

Further, we note that $X \succeq_{SRSD} Y$ implies $\mu_X \geq \mu_Y$. Thus, for $\eta \geq \mu_Y$, we obtain:

$$\frac{\eta - \mu_X}{F_X^{(2)R}(\eta)} = \frac{\eta - \mu_Y}{F_X^{(2)R}(\eta)} + \frac{\mu_Y - \mu_X}{F_X^{(2)R}(\eta)} \leq \frac{\eta - \mu_Y}{F_X^{(2)R}(\eta)} \leq \frac{\eta - \mu_Y}{F_Y^{(2)R}(\eta)}.$$

In other words, we can get $\Omega_X(\eta) \geq \Omega_Y(\eta)$ for any $\eta \geq \mu_Y$, and thus, the assertion of Theorem 1 holds. □

We note that Darsinos and Satchell (2004) assert that SSD is consistent with the Omega ratio; that is, the relationship in Equation (10) holds. However, we find that the consistency of SSD and the Omega ratio holds only when we restrict the range of return threshold, as stated in our Proposition 1 and Theorem 1. From Proposition 1 and Theorem 1, one could then derive the following theorem to state the relationship between the FSD and Omega ratio:

Theorem 2. *If the SSD and SRSD hold, then the Omega ratio dominance also holds. In particular, this is the case when the FSD holds.*

We give a short proof as follows: if $X \succeq_{FSD} Y$, by using the hierarchy property (Levy (1992, 1998, 2015); Sriboonchitta et al. (2009)), we obtain both $X \succeq_{SSD} Y$ and $X \succeq_{SRSD} Y$. From Proposition 1 and Theorem 1, we have $\Omega_X(\eta) \geq \Omega_Y(\eta)$ for any $\eta \leq \mu_X$ and $\eta \geq \mu_Y$. Since $\mu_X \geq \mu_Y$, we have $\Omega_X(\eta) \geq \Omega_Y(\eta)$ for any $\eta \in R$, and thus, the assertion of Theorem 2 holds. □

4. Testing Market Efficiency, Arbitrage Opportunity and Anomaly

In this section, we will discuss how to apply the theory developed in this paper to examine whether the market is efficient, whether there is any arbitrage opportunity in the market and whether there is any anomaly in the market. To do so, we consider the following four pairs of hypotheses:

$$H_0^{SSD}: \ X \not\succ_{SSD} Y \quad \text{versus} \quad H_1^{SSD}: X \succ_{SSD} Y \tag{13}$$

$$H_0^{SRSD}: X \not\succ_{SRSD} Y \quad \text{versus} \quad H_1^{SRSD}: X \succ_{SRSD} Y \tag{14}$$

$$H_0^{FSD}: X \not\succ_{FSD} Y \quad \text{versus} \quad H_1^{FSD}: X \succ_{FSD} Y \tag{15}$$

$$H_0^{OD}: X \not\succ_{OD} Y \quad \text{versus} \quad H_1^{OD}: X \succ_{OD} Y \tag{16}$$

To test whether there is any SSD in two assets as stated in (13), we can apply Proposition 1 to test whether $\Omega_X(\eta) \geq \Omega_Y(\eta)$ for any $\eta \leq \mu_X$. If this is true, then we could have $X \succ_{SSD} Y$. Similarly, to test whether there is any SRSD in two assets as stated in (14), we can apply Theorem 1 to test whether $\Omega_X(\eta) \geq \Omega_Y(\eta)$ for any $\eta \geq \mu_Y$. If this is true, then we could have $X \succ_{SRSD} Y$. Last, to test whether there is any FSD in two assets as stated in (15), we can apply Theorem 2 and Definition 1 to test whether $X \succeq_{OD} Y$. If this is true, then we could have $X \succ_{FSD} Y$. Readers may ask: why should we test H_1^{SSD} in (13), H_1^{SRSD} in (14), H_1^{FSD} in (15), and H_1^{OD} in (16)? The answer is that we want to test whether there is any arbitrage opportunity in the market, whether there is any anomaly and whether the market is efficient. We first discuss testing arbitrage opportunity and anomaly, and, thereafter, discuss testing market efficiency and investor rationality in the next subsections.

4.1. Arbitrage Opportunity and Anomaly

It is well known from the market efficiency hypothesis that if one can get an abnormal return, then the market is considered inefficient, and there could exist arbitrage opportunity and anomaly. Thus, in order to test arbitrage opportunity and anomaly, one can apply Theorem 2 and Definition 1 to test H_1^{OD} in (16) and check whether $X \succeq_{OD} Y$. If $X \succeq_{OD} Y$, then applying Theorem 2, we can conclude that $X \succ_{FSD} Y$ could be true. Jarrow (1986) and Falk and Levy (1989) have claimed that if FSD exists, under certain conditions, arbitrage opportunities also exist, and investors will increase not only their expected utilities, but also their wealth if they shift from holding the dominated asset to the dominant one. One may consider it a financial anomaly.

However, Wong et al. (2008) have shown that if FSD exists statistically, arbitrage opportunities may not exist, but investors can increase their expected utilities, as well as their expected wealth, but not their wealth if they shift from holding the dominated asset to the dominant one. In this paper, we call this situation "expected arbitrage opportunity" or "arbitrage opportunity in expectation"; this means that if $X \succeq_{OD} Y$ appears many times and if investors could buy X and short sell Y each time, then on average, they could not only increase their expected utility, but also increase their expected wealth. In this situation, one may believe that there could be arbitrage opportunity and anomaly.

Falk and Levy (1989), Bernard and Seyhun (1997) and Larsen and Resnick (1999) comment that if there exists first-order dominance of a particular asset over another, but the dominance does not last for a long period, market efficiency and market rationality cannot be rejected. In general, the first-order dominance should not last for a long period of time because if the market is rational and efficient, then market forces will adjust the market so that there is no FSD. For example, if Property A dominates Property B at the FSD, then all investors would buy Property A and sell Property B. This will continue driving up the price of Property A relative to Property B, until the market price of Property A relative to Property B is high enough to make the marginal investor indifferent between Properties A and B. In this situation, we conclude that the market is still efficient and that investors are still rational. In the traditional theory of market efficiency, if one is able to earn an abnormal return for a considerable length of time, the market is considered inefficient. If new information is either quickly made public or anticipated, the opportunity to use the new information to earn an abnormal return is of very limited value. On the other hand, if the first-order dominance can hold for a long time and all investors can increase their expected wealth by switching their asset choice, we claim that the market is inefficient and that investors are irrational. However, sometimes FSD could still be held for a long period if investors do not realize such dominance exists or there are some reasons for the investors to buy the dominated asset. For example, investors could prefer to buy a bigger property for their status, even if the price is too high. If the FSD relationship among some assets still exists over a long period of time, then we could have arbitrage opportunity and anomaly, that market is inefficient and that investors are not rational.

4.2. Market Efficiency and Rationality

In last section, if H_1^{OD} in (16) such that $X \succeq_{OD} Y$ is not rejected over a long period of time, then we conclude that there could be arbitrage opportunity and anomaly, that the market is inefficient, and that investors are not rational. Nonetheless, if H_1^{OD} in (16) is rejected, should we conclude that the market is efficient and that investors are rational? Here, we would like to recommend academics and practitioners to further examine the higher order SD, say, for example, the second-order SD, before they conclude that the market is efficient.

Falk and Levy (1989) have argued that, given two assets, X and Y, if by switching from X to Y (or by selling X short and holding Y long), an investor can increase expected utility, the market is inefficient. SSD does not imply any arbitrage opportunity, but it does imply the preference of one asset over another by risk-averse investors. For example, if we apply Proposition 1 to test whether $\Omega_A(\eta) \geq \Omega_B(\eta)$ for any $\eta \leq \mu_A$ and find that it is true, then we could have $A \succ_{SSD} B$, and thus, Property A dominates Property B by SSD. In this situation, one would not make an expected profit by switching from Property B to Property A, but switching would allow risk-averse investors to increase their expected utility. In this situation, could we conclude that the property market is not efficient?

We suggest that this claim could be made if one believes that the market only contains risk-averse investors. However, it is well known that the market could have other types of investors (see, for example, Friedman and Savage (1948), Markowitz (1952), Thaler and Johnson (1990), Broll et al. (2010) and Egozcue et al. (2011) for more discussion). Under the assumption that the market could contain more than one type of investor, such as risk averters, as well as risk seekers, in this situations, academics could apply Theorem 1 to test whether $\Omega_B(\eta) \geq \Omega_A(\eta)$ for any $\eta \geq \mu_A$. If this is true, then we could have $B \succ_{SRSD} A$, and thus, Property A dominates Property B by SSD and Property B dominates Property A by SRSD. If this is the case, then risk averters could prefer to buy Property A, while risk seekers prefer to invest in Property B. Then, equilibrium could be reached in the sense that both Properties A and B can be sold well, and there is no upward or downward pressure on the price of both Properties A and B, while both risk averters and risk seekers could get what they want. Under these conditions, Qiao et al. (2012) argue that the market is still efficient and investors are still rational. On the other hand, if Property A dominates Property B by both SSD and SRSD, then one could conclude that the market is inefficient. However, if Property A dominates Property B by both SSD and SRSD, then Property A dominates Property B by FSD. We have discussed this case in the above.

5. Illustration

Investment in property is important in both consumption and investment decisions (Henderson and Ioannides (1987)). Ziering and McIntosh (2000) argue that housing size is important in determining the risk and return of housing and conclude that the largest class of housing provides investors with the highest return and the greatest volatility. However, Flavin and Nakagawa (2008) document that investing in larger houses does not reduce risk, while Kallberg et al. (1996) show that smaller property offers impactful diversification benefits for investment portfolios with high return aspirations. On the other hand, Cannon et al. (2006) explain housing returns by volatility, price level and stock-market risk, and Ghent and Owyang (2010) investigate supply and demand to explain movements in the housing market.

The housing market in Hong Kong plays a very important role in the Hong Kong economy (Haila (2000)), and Hong Kong is one of the most expensive housing markets in the world in terms of both prices and rents (Tsang et al. (2016)). Qiao and Wong (2015) apply SD tests to examine the relationship between property size and property investment in the Hong Kong real estate market. They do not find any FSD relationship in their study. Tsang et al. (2016) extend their work to reexamine the relationship between property size and property investment in the same market and find the FSD relationship in rental yield in any adjacent pairing of the five well-defined housing classes in Hong Kong. In empirical studies, very few studies could discover the existence of any FSD relationship, and it is very important to obtain the FSD relationship (if there is any) because this information is very helpful to investors. For example, the findings from Tsang et al. (2016) imply that by shifting investing from the largest class of housing to the smallest class of housing, investors could obtain higher expected utility, as well as higher expected wealth from rental income.

In this paper, we extend their work by applying the Omega ratio to examine the relationship between property size and property investment in the Hong Kong real estate market. We recommend that analysts apply the Omega ratio to examine whether there is any FSD relationship between any pair of variables being studied because it is easier to obtain the Omega ratio. The Omega ratio could serve as a complementary tool for the FSD test, and thus, we recommend that analysts use both the Omega ratio and FSD test in their analysis. The existence of dominance from both the Omega ratio and FSD test could assert the existence of the FSD relationship between the variables being examined. In addition, our illustration could also serve our purpose to demonstrate whether the theory developed in this paper holds true.

In order to readdress the issue studied by Tsang et al. (2016), we first use the same rental yield data used in Tsang et al. (2016) to compare monthly property-market rental yields in private domestic units of five different housing classes from January 1999–December 2013 in Hong Kong. The data are obtained from the Rating and Valuation Department of the Hong Kong SAR. The monthly rental yields for each class are calculated by dividing the average rent within the class by the average sale price for houses in the class for that month. Private domestic units are defined as independent dwellings with separate cooking facilities and bathrooms (and/or lavatories). They are sub-divided into five classes by reference to floor area: Class A salable area less than 40 m^2; Class B salable area of 40–69.9 m^2; Class C salable area of 70–99.9 m^2; Class D salable area of 100–159.9 m^2; and Class E salable area of 160 m^2 or above.

To analyze the rental yield and to illustrate Theorem 2, we set A = rental yield of Class A and E = rental yield of Class E and present the summary statistics of the rental yields for Classes A and E in Table 1.

Table 1. Summary statistics for X and Y.

Class	Mean	std	Skewness	Kurtosis	JBtest	*t*-test/F-test
A	0.0041	0.0008	−0.1957	1.9615	1	0.0000
E	0.0028	0.0008	0.4521	1.8709	1	0.7059

Note: A = the rental yield of Class A, E = the rental yield of Class E, and std = standard deviation. t- and F-tests report the p-values of the tests.

We first test the following hypotheses:

$$H_0^{\mu}: \ \mu_A = \mu_E \quad \text{versus} \quad H_1^{\mu}: \mu_A > \mu_E \tag{17}$$

for rental yield. The result of the t-test in Table 1 concludes that the mean rental yield of A is significantly higher than that of E. Thereafter, we test the following hypotheses:

$$H_0^{\sigma}: \ \sigma_A = \sigma_E \quad \text{versus} \quad H_1^{\sigma}: \sigma_A < \sigma_E \tag{18}$$

for rental yield. The result of the F-test in Table 1 does not reject that the variances of the rental yields of both A and E are the same. Applying the mean-variance rule for risk averters Markowitz (1952) that A is better than E if $\mu_A \geq \mu_E, \sigma_A \leq \sigma_E$ and there is at least one strictly inequality, we conclude that risk averters prefer Property A to Property E based on rental yield. On the other hand, if we apply the mean-variance rule for risk seekers (Wong (2006, 2007); Guo et al. (2017)) that A is better than E provided that $\mu_A \geq \mu_E, \sigma_A \geq \sigma_E$ and there is at least one strict inequality, we conclude that risk seekers prefer Property $A$to Property E based on rental yield under the condition that A and E belong to the same location-scale family or the same linear combination of location-scale families Wong (2006, 2007). Nonetheless, this conclusion cannot imply the existence of the first-order SD relationship between Properties A and E based on rental yield if A and E do not belong to the same location-scale family or the same linear combination of location-scale families. To circumvent the limitation, this paper recommends that academics and practitioners use the Omega ratio rule as discussed in this paper. Thus, we turn to applying the Omega ratio rule to analyze whether there is any first-order SD relationship between Properties A and E based on rental yield.

We note that for the existence of the Omega ratio, we need $Z < \eta$ with $Z = A, E$. To satisfy this condition, we choose $\eta > \max(\min(A), \min(E))$. In addition, the term $(\eta - Z)_+$ should not be too small. If not, the Omega ratios will be very large. Thus, in this illustration, we set $\eta \geq \max(\min(A), \min(E)) + 0.5\%$. Furthermore, for $\eta \geq \max(\max(A), \max(E))$, we have $(Z - \eta)_+ \equiv 0$. Thus, we set the upper-bound for η as $\max(\max(A), \max(E))$. We exhibit the plot in Figure 1.

From the figure, it is clear that $\Omega_A(\eta) \geq \Omega_E(\eta)$ for any $\eta \in R$. We skip displaying plots of other pairs of variables because all the plots draw the same conclusion. We find that Class A dominates Classes B, C, D and E, Class B dominates Classes C, D and E, Class C dominates Classes D and E and Class D dominates Class E, by using the Omega ratio rule. We summarize the results of the Omega ratio dominance in Table 2. The results in the table are read based on row versus column. For example, the cell in Row A and Column B tells us that Class A dominates Class B by the Omega ratio and is denoted by OD, while the cell in Row B and Column A means that Class B does not dominate Class A by the Omega ratio, as denoted by ND.

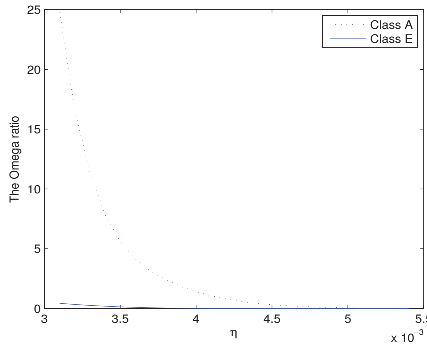

Figure 1. The plots of Omega ratios of rental yields of Class A and Class E. The dotted and solid line represent the results of Class A and Class E, respectively.

Table 2. Pairwise comparison between rental yields.

Class	A	B	C	D	E
A		OD	OD	OD	OD
B	ND		OD	OD	OD
C	ND	ND		OD	OD
D	ND	ND	ND		OD
E	ND	ND	ND	ND	

OD is Omega ratio dominance defined in Definition 1. ND means no Omega ratio dominance.

To check whether a smaller house (any house in the group with the smaller size) is better than a bigger house (any house in the group with the bigger size), only comparing their rental yields is not good enough. Tsang et al. (2016) suggest analyzing both rental and total yields. Based on their analysis on both rental and total yields, they conclude that investing in a smaller house is better than a bigger house. We note that analyzing both rental and total yields is not sufficient to draw such a conclusion. We explain the reasons as follows: Tsang et al. (2016) find that (a) the smaller house dominates the bigger house in terms of rental yield, and (c) there is no dominance between the smaller and bigger houses in total yield where total yield = rental yield + price yield. Under (a) and (c), it is possible that (b′) the bigger house dominates the smaller house in terms of the price yield, and thus, under (a), (b′) and (c), we cannot conclude that the smaller house is a better investment than the bigger house. To circumvent the limitation, in addition to analyzing the rental yield, we recommend analyzing the price yield as follows: We set A = price yield of Class A and E = price yield of Class E and present the summary statistics of the price yields for Classes A and E in Table 3.

Table 3. Summary statistics of the price yield for Classes A and E.

Class	**Mean**	**std**	**Skewness**	**Kurtosis**	**JB test**	***t*-test/F-test**
A	0.0054	0.0233	−0.2194	3.6554	0	0.5327
E	0.0056	0.0308	−0.1495	3.9346	1	0.0001

Note: A = the price yield of Class A and E = the price yield of Class E. t- and F-tests report the p-values of the tests.

We first test the null hypothesis H_0^μ that $\mu_A = \mu_E$ versus the alternative hypothesis H_1^μ that $\mu_A > \mu_E$ as shown in (17) for the price yield. The result of the t-test in Table 3 does not reject that the mean price yields for A and E are the same. Thereafter, we test the null hypothesis H_0^σ that $\sigma_A = \sigma_E$ versus the alternative hypothesis H_1^σ that $\sigma_A < \sigma_E$ as shown in (18) for the price yield. The result of the F-test in Table 3 concludes that the variance of the price yield of A is significantly smaller that that of E. Thus, applying the mean-variance rules, we can conclude that risk averters prefer to invest in A rather than E, but risk seekers are indifferent between A and E. Nonetheless, this conclusion cannot imply any first-order SD relationship between Properties A and E based on the price yield. In this paper, we recommend that academics and practitioners use the Omega ratio rule as discussed in this paper.

Continuing with our analysis in the rental yield, we find that when $\eta \geq 0.0054$, $\Omega_A(\eta)$ is smaller than $\Omega_E(\eta)$, while when $\eta < 0.0054$, $\Omega_A(\eta)$ is larger. Thus, there is no OD relationship between A and E. To illustrate our results empirically, we set $\eta \in [0.0054, \max(\max(A), \max(E))]$. The related results are exhibited in Figure 2. From this figure, it is clear that the Omega ratio of Class E is larger than that of Class A. For the Omega ratio dominance, different from the analysis for the rent yields, there is no dominance relationship between A and E in terms of the price yield by using the Omega ratio, and thus, we conclude that there is no FSD relationship between A and E in terms of the price yield.

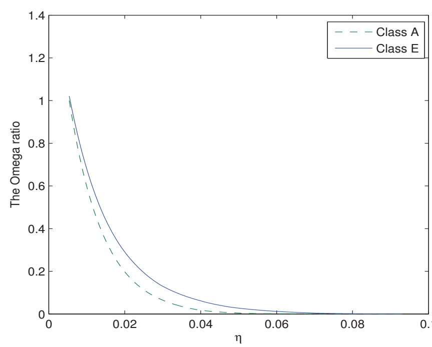

Figure 2. The plots of Omega ratios of the price yield of Class A and Class E. The dotted and solid line represent the results of Class A and Class E, respectively.

Tsang et al. (2016) find that Class A SSD dominates Class E in terms of total yield. We conduct the Omega ratio test analysis for this issue. Our findings are consistent with Tsang et al. (2016). Since using both rental yield and price yield could draw the conclusion that investing in the smaller house is better than the bigger house, we skip reporting the OD results for the total yield.

Recall that Tsang et al. (2016) have shown that (a) the smaller house dominates the bigger house in terms of rental yield and (c) there is no dominance between smaller and bigger houses in total yield. Under (a) and (c), it is possible that (b') the bigger house dominates the smaller house in terms of the price yield.

In this paper, we find that (a) the smaller house dominates the bigger house in terms of rental yield, and (b) there is no dominance between smaller and bigger houses in price yield. We note that total yield = rental yield + price yield. Findings (a) and (b) can get either (c) that the smaller house dominates the bigger house in terms of total yield or (c') there is no dominance between smaller and bigger houses in terms of the total yield. No matter under (a), (b) and (c) or under (a), (b) and (c') (actually, we find (c') in our paper), we conclude that regardless of whether the buyers are risk averse or risk seeking, they will not only achieve higher expected utility, but also obtain higher expected wealth when buying smaller properties. This implies that the Hong Kong real estate market is not efficient, and there are expected arbitrage opportunities and anomalies in the Hong Kong real estate market. Our findings are useful for real estate investors and policy makers in real estate for their policy making to make the real estate market become efficient.

Last, we note that though our paper finds that there exists "expected arbitrage opportunity" in the Hong Kong real estate market, however, it is very difficult, if not impossible, to short sell a property in Hong Kong. Thus, it is not easy to explore this "expected arbitrage opportunity". Nonetheless, if an investor would like to buy a big house to stay in Hong Kong and sell it a couple years later, then, she/he may consider buying a few smaller houses with the same amount of funds in total, rent out all the smaller houses she/he bought, rent a bigger house for her/him to stay and sell all the properties she/he bought as her/his plan a couple of years later. In this way, she/he will get positive net rental income each month (since the rental yield of the smaller house OD dominates that of the bigger house), while the price yield has no difference when she/he sells the big house or the small houses (since there is OD dominance between smaller and bigger houses in terms of price yield). Thus, when she/he sells all her/his properties, she/he still gets net profit by the rental rental if she/he chooses to buy small houses.

6. Concluding Remarks

This paper first develops the relationship between the first- and second-order SD with the Omega ratio dominance. We then illustrate the applicability of the theory developed in this paper to examine the relationship between property size and property investment in the Hong Kong real estate market and draw the conclusion that the Hong Kong real estate market is inefficient, and there are expected arbitrage opportunities and anomalies in the Hong Kong real estate market. Our findings are useful for real estate investors and policy makers in real estate for their policy making to make the real estate market become efficient.

We note that the stochastic dominance tests have been well developed by now. For example, one could apply the SD tests developed by Bai et al. (2015) to examine whether there is any FSD, SSD or SRSD relationship between any two prospects. Then, one could apply the theory developed in this paper to draw inference on the preference of the corresponding Omega ratios under different conditions and for different types of investors, including risk averters, risk seekers and investors with increasing utility functions. We note that recently, Hoang et al. (2015) hypothesized that the preference of the Omega ratios implies the preference of the corresponding assets for risk averters or risk seekers. We note that this is not so straight-forward, and this is another good direction of further study in this area (Guo and Wong (2017)). Another direction of related research is to extend Niu et al. (2016, 2017) and others to develop risk measures with a different order of stochastic dominance. This could further be used to examine whether the market is efficient and whether there is arbitrage opportunity in the market.

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Article

Size, Value and Business Cycle Variables. The Three-Factor Model and Future Economic Growth: Evidence from an Emerging Market

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Abstract: The paper empirically investigates three different methods to construct factors and identifies some pitfalls that arise in the application of Fama-French's three-factor model to the Pakistani stock returns. We find that the special features in Pakistan significantly affect size and value factors and also influence the explanatory power of the three-factor model. Additionally, the paper examines the ability of the three factors to predict the future growth of Pakistan's economy. Using monthly data of both financial and non-financial companies between 2002 and 2016, the article empirically investigates and finds that: (1) size and book-to-market factors exist in the Pakistani stock market, two mimic portfolios SMB and HML generate a return of 9.15% and 12.27% per annum, respectively; (2) adding SMB and HML factors into the model meaningfully increases the explanatory power of the model; and (3) the model's factors, except for value factor, predict future gross domestic product (GDP) growth of Pakistan and remain robust. Our results are robust across sub-periods, risk regimes, and under three different methods of constructing the factors.

Keywords: emerging markets; KSE Pakistan; three-factor model; size and value premiums; future economic growth

JEL Classification: G11; G12; O10

1. Introduction

Asset pricing models are used to evaluate risk and return structure of stocks, and facilitate individual investors and institutions in planning and managing their portfolios. A list of models is available to assist investors and financial managers in predicting the expected return for their targeted stocks. However, two models are alternatively and widely used for this purpose. The first one is the Capital Asset Pricing Model (CAPM), developed by Sharpe (1964), Lintner (1965) and Mossin (1966). The second one is the three-factor model proposed by Fama and French (1993).

CAPM measures the sensitivity by a single factor: security's beta coefficient with a mean-variance coefficient of the market portfolio. In the early 1970s, CAPM, with its single factor to measure risk for a security, was widely used to facilitate the investors. Later, studies related to intertemporal asset pricing models (Merton 1973; Breeden 1979), arbitrage pricing theory (Ross 1976), size effect (Banz 1981; Reinganum 1981; Keim 1983), and book to market (value) effect (Rosenberg et al. 1985) and (Chan et al. 1991), highlighted some other variables having considerable effect on the relationship between average returns and systematic risk, that had remained unconsidered employing the single factor model, CAPM. These contributions helped to identify systematic risk empirically, which would not have been possible with the former abstracted and theoretical model.

The empirical validity of CAPM was struck down by the Fama and French (1992), which suggested that beta (β) is unable to fully capture the variations in cross-sectional expected returns. Later on, size (SMB) and book-to-market (HML) factors were also added as an extension of the CAPM (Fama and French 1993). It has been discussed that the three-factor model provides a better explanation as compared to CAPM in many countries.

Recently, Fama and French (2015) proposed a five-factor model which added investment (CMA) and profitability (RMW) as new factors into the existing three-factor model. However, the model is reportedly unable to explain the low average returns on small stocks, the returns of which are similar to those of firms with low profitability but high investment level. Elliot et al. (2016) discussed that such stocks are only a small fraction of the US market, but the case is different across global markets. They demonstrated that the newly added factors have limited explanatory power for these stocks. Moreover, the contribution of the value factor has been significantly diluted by the two new factors in terms of explaining the average returns; therefore, it has been suggested that the three-factor model generally fits well with Shanghai stock exchange (SSE) A-share market (Xie and Qu 2016).

The economic rationale (risk-based interpretation) behind the newly added factors (i.e., investment and profitability factors) has been criticized in recent studies (Ülkü 2017) and (Ali and Ülkü 2018). It has been explained that factors generally represent risk attributes (e.g., SMB and HM), while CMA and RMW are derived from the dividend discount model. Further, these factors capture mispricing away from 'value', caused by noise trading and the weekend sound-mind effect. Kubota and Takehara (2017) examined the five-factor model for the Japanese market. They concluded that the Fama-French's five-factor model is not the best benchmark for stocks traded at the Japanese stock market. Thus, the paper focuses on the three factors; size premium, value premium and the market risk premium.

In the context of Pakistan, Iqbal and Brooks (2007) analyzed the Fama-French three-factor model and CAPM for the stocks traded at Karachi stock exchange (KSE). They discussed that risk factors in the three-factor model are more significant. Mirza and Shahid (2008) deployed a multivariate framework to test the validity of the three-factor model. They included the stocks of financial firms as well; the results generally supported the three-factor model.

The Fama-French three-factor model has been widely applied to most of the developed and emerging markets; however, the model has been least applied to the emerging south-Asian market, Pakistan. This might be due to the small size of the market and the difficulty in assembling enough stocks to construct the underlying portfolios of this model in earlier decades. For instance, prior studies on KSE such as Iqbal and Brooks (2007), Mirza and Shahid (2008) and Javid and Ahmad (2008), which used a fixed number of stocks, ranging between 49 and 90 stocks, may have suffered from small sample problems. Moreover, the sample period in these studies either includes only bull rally between 2003 and 2007 or includes Asian-crises (1997), political instability in Pakistan (1999) and US-Afghan war (9/11); due to these events investment behaviors remained alert and risk averse. Hence, their results cannot be considered robust.

Fama-French excluded financial firms from their series of studies. They stated that "the stocks of financial firms are thinly traded and the financial firms tend to have higher financial leverage, but for non-financial firms, high leverage has a different meaning and can be considered as financial distress" (Fama and French 1992). Most of the studies followed the same approach and excluded the stocks of financial firms while empirically testing the three-factor model on various stock markets.

Pakistan shares the 'typical characteristics' and features of an emerging market, such as thick tails accompanied with excess kurtosis in the return distribution, high return with excessive volatility, and low market capitalization but high trading volume (Khwaja and Mian 2005). The special characteristics of financial firms in Pakistan, such as liquidity, active participation, and a large fraction of the market value of these firms to total market value of the index are rarely discussed in the literature. These characteristics are different as compared to the US and other developed stock markets discussed in Fama and French (1998, 2017), where stocks of financial firms are thinly traded and do not make up a large fraction of the total market value of the index.

Modigliani and Miller (1958, 1963) explain in theoretical language that the risk profile (beta) of the firm can be affected by leverage but it does not invalidate the fundamental principal of the asset pricing model. Therefore, it is better if the pricing model is generally applied, rather than restricted to nonfinancial firms only. Motivated by the Modigliani-Miller theory, Baek and Bilson (2015) assessed the size and value factors to measure the cross-section of expected stock return in financial and non-financial firms of US stock market. The empirical results suggested that size and value premiums commonly exist in both financial and non-financial firms. Therefore, we include both (financial and nonfinancial firms), as we believe that exclusion of financial sector firms is not justified in the case of Pakistan.

For the application of the three-factor model, factors formation methodology plays the most important role. In this regard, Xu and Zhang (2014) document the empirical evidence and identify some drawbacks that arise in the application of the three-factor model to Chinese stock returns. In order to evaluate the effect of several special features in China, they experiment with different ways to construct the three factors. Their results illustrate that the construction of the three factors can have a significant impact in empirical studies that apply the Fama-French's three-factor model. Further, Vo (2015) and Xie and Qu (2016) also discussed the applicability of the three-factor model by considering the special features of the Australian stock market and the SSE (A shares) China, respectively.

However, in the context of the Pakistani stock market, it is still unclear whether the portfolio construction should be based on Fama-French (i.e., to exclude the stocks of financial firms), or on adapting the strategy of keeping fixed number of stocks, similar to the previous studies on KSE, or on including stocks of both financial and non-financial companies as well as new firms.

To adjust for the small sample problem, a unique feature of KSE and the investment behaviors across the diverse economic conditions, this article uses a larger dataset (2002–2015) as compared to any previous study on KSE. A comparatively larger dataset containing all the liquid stocks to avoid the illiquidity factor (zero returns), is expected to improve the power of the tests and will capture variation in stock returns beyond any previous study on KSE. The paper argues for the importance of the special features in the Pakistani market and compares three different factors construction methodologies which may significantly affect the performance of the three-factor model. The three different constructed baskets of stocks are: 'fixed basket', 'non-financial basket' and 'variable basket'. The fixed basket includes only those stocks which survive the entire sample period, the non-financial basket and variable basket include (exclude) companies into (from) the basket every year upon meeting (differing from) the sample selection and criteria limitations. The variable basket includes all the stocks, whilst the non-financial basket only includes non-financial stocks.[1]

The summary statistics, reported in Table 1, confirm that the monthly returns on the factor portfolios in three different scenarios are somewhat different from each other. For example, the fixed basket generates approximately 5.66% per annum size premium, whereas the non-financial and variable baskets generate approximately 9.14% and 9.15% per annum, respectively. The value premium for the fixed basket is approximately 11.25% per annum, whereas the non-financial and variable baskets generate approximately 15.04% and 12.27% per annum, respectively. The significance of these factors also varies. The value premium is significant at a 5% level in each of the portfolio construction methodologies. Conversely, SMB is statistically insignificant for the fixed basket, significant at 10% level for the non-financial basket, and significant at 5% level for the variable basket.

1 See Section 3.4 of this paper for further details.

Table 1. Descriptive statistics: comparing three different methods of constructing factors.

	Fixed Basket		Non-Financial Basket		Variable Basket	
	SMB	HML	SMB	HML	SMB	HML
Mean (%)	0.471	0.938	0.762	1.254	0.763	1.022
STD (%)	5.252	6.197	5.759	7.017	5.323	6.529
t-statistic	1.163	1.961 **	1.715 ***	2.315 **	1.858 **	2.029 **

Note: Authors calculation. The table reports the comparison of descriptive statistics of size (SMB) and value (HML) premiums between the fixed basket, non-financial basket and variable basket. The sample period is 2002:01–2015:12, *** and ** indicate significance at 10 and 5% level, respectively. Source: the official website of the Pakistan stock exchange (https://www.psx.com.pk/) and the official website of the State Bank of Pakistan (http://sbp.org.pk/).

Liew and Vassalou (2000) analyzed the relationship between future economic growth and the Fama–French three-factor model. Their findings suggest that size and book-to-market factors are positively related to future economic growth. Vassalou (2003) and Petkova (2006) observed a moderated explanatory power of the Fama–French factors in the existence of macro-economic risk. The findings by Boamah (2015) provide a further indication of the relevance of SMB and HML to future economic growth.

There is no known study that has observed the predictive ability of these risk factors for future economic growth in the GDP of the Pakistani economy. However, Javid and Ahmad (2008) examine a set of macroeconomic variables in addition to market risk premium (single factor). The results support the proposal that a few economic variables play an additional role in explaining the variation in stock returns and this variability has some business cycle correlations.

The paper offers several pioneering contributions. It: (1) constructs and compares the risk factors and the three-factor model under three different methods; (2) examines the robustness of the model across different risk regimes and subsamples; (3) analyses the performance of the term structure premium augmented four-factor model; and (4) links the information content of the Fama–French factors and the business cycle variables to predict future economic growth of Pakistan. The evidence will enhance our understanding of whether or not these factors relate to underlying economic risk factors.

Our results show that: (1) size and value premiums exist in the KSE. In terms of returns, small size firms outperform big size firms while value stocks (high book-to market equity ratio) outperform growth stocks (low book-to-market equity ratio); (2) the three-factor model can explain the variations in average stock returns on six size-B/M portfolios, the average adjusted R squared meaningfully increased by including two additional factors into the model; (3) the three-factor model by constructing portfolios in different ways, is applicable to KSE, as all the models capture size and book-to-market effects significantly; (4) the significance of the regression coefficients are time variant. However, the existence of these factors is stable across the three sub-periods; (5) the three-factor model captures the size and book-to-market effects significantly for the six risk-based (categorized based on market beta) portfolios; (6) loadings on the term structure premium (TSP) mostly remain statistically significant but do not improve the explanatory power of the augmented four-factor model, contrarily it increases the significance of the intercept. However, SMB and HML remain robust in the presence of the TSP; and (7) the market and SMB factors possess the predictive ability for one-year ahead growth of the Pakistani economy and remain robust in the presence of the business cycle variables.

This paper proceeds as follows. Section 2 provides a related literature review of prior studies, Section 3 describes the data and the methodologies used in the paper. Section 4 discusses empirical results and analysis. Section 5 investigates the relevance of the risk factors to predict future economic growth. Section 6 summarizes the research findings and concludes the paper.

2. Prior Related Studies

Success of the Fama-French three factor model is, basically, a divergence in CAPM and emerged as a most popular explanation for the ongoing argument on asset pricing. However, several studies in the financial literature (e.g., Groenewold Fraser 1997; Beltratti and Tria 2002; Drew and Veeraraghan 2002; Mirza and Shahid 2008; Guo et al. 2008; Lischewski and Voronkova 2012; Cakici et al. 2013; Minović and Živković 2014; Baek and Bilson 2015; Boamah 2015; Ceylan et al. 2015; Zaremba and Konieczka 2015; Elgammal et al. 2016; Chung et al. 2016; Xie and Qu 2016; Kubota and Takehara 2017) attribute mixed evidence regarding the existence, significance, augmented versions and time varying behavior of the risk premiums and the three-factor model in the stock markets of USA, Europe, Australia, Asia and Africa by applying various models and portfolio construction methodologies.

Daniel and Titman (1997) examined the Fama and French (1993) and demonstrated that size and book-to-market factors are highly correlated with the average stocks returns but there is no separate distress and most of the co-movement of the value stocks is not due to distressed stocks being exposed to a unique distress factor. They explained that it is characteristics rather than factor loadings that appear to explain the cross-sectional variation in stock returns. Davis et al. (2000) thoroughly studied the characteristics, co-variances and average returns for the period (1929–1997). By dividing the sample into two sub-periods, their findings confirmed that value premium (HML) factor was 0.50% per month in the first sub-period (1929–1963) and 0.43% per month in the second sub-period (1963–1997). The Value premium observed in the first sub-period was statistically significant at (t = 2.8) while the second sub-period presented higher significance at (t = 3.38). They confirmed a strong relationship between value premium and average stock returns. They discovered that the results of Daniel and Titman (1997) appeared to be supporting characteristics of the model due to the shorter time span.

Connor and Sehgal (2001) analyzed the results of the Fama-French three-factor model and CAPM. Stocks traded at the CRISIL 500 Indian stock market were taken as a sample. The results after using wald statistics showed that three out of six portfolios had significant intercepts for CAPM, whereas, in the Fama-French model all six portfolios had insignificant intercepts. Finally, on the basis of their findings, it was concluded that the three-factor model performs better for the Indian stock market than the CAPM.

In their study of three developed markets, Griffin (2002) found that the three-factor model can significantly explain the variations in the cross-section of expected stock returns in the stock markets of Canada, England and Japan. Drew and Veeraraghan (2002) detected size and value premiums in the Malaysian stock market. De Groot and Verschoor (2002) analyzed the influence of size and value factors on stocks' average returns in five Asian emerging markets. Their findings suggested a strong size effect for all of the markets (India, Korea, Malaysia, Taiwan and Thailand), while value effect only exists in Thailand, Malaysia and Korea.

For the Australian stock market, O' Brien et al. (2008) compared the CAPM with the three-factor model. Their results suggested that the three-factor model explained nearly 70% of the variations in return and led to the formation of an opinion that the three-factor model is a very effective and useful model for explaining the variation in expected stock returns. Brown et al. (2008) detected time-varying value premium in the stock markets of Hong Kong, Korea and Singapore. However, they found a value discount in the Taiwanese stock market.

Malkiel and Jun (2009) studied the Chinese stocks and confirmed the existence of size and book-to-market effects for returns on Chinese stocks. Lischewski and Voronkova (2012) examined the factors determining the stock prices on the Polish stock market (WSE). Findings supported the existence of the size and value factors along with the market risk premium, while liquidity factor was not priced in Polish stocks.

Xu and Zhang (2014) empirically investigated the Fama-French three-factor model and identified some downsides that can arise in the application of the three-factor model to the Chinese stock returns. In order to evaluate the effect of several special features in China, they experiment with different ways to construct the three factors. They concluded that formation of the three factors can have a significant impact in empirical studies that apply the three-factor model to Chinese stock market. In the same way, Vo (2015) examined various approaches to construct portfolios and proposed further evidence for the Australian market.

Therefore, Xie and Qu (2016) performed an empirical study, by focusing on the unique features of the Chinese stock market. Their study consisted of stocks traded at SSE A-share between 2005 and 2012. The findings suggested that size and value premiums are significant for China's stock market (SSE A-share market) and the three-factor model generally fits well. They did not include the investment and profitability factors in the model as these factors dilute the value factor. Similarly, Kubota and Takehara (2017) empirically investigated and rejected the Fama-French's five-factor model as a benchmark for the Japanese stock market.

In a Pakistani context, Iqbal and Brooks (2007) analyzed the conditional Fama-French three-factor model and CAPM for the stocks traded at KSE-Pakistan. The GARCH and EGARCH methods are used on monthly, weekly and daily data of 89 stocks during the period between 1992 and 2006. They illustrated in a graphical analysis that conditioning variables generally result in upward bias. They concluded that the unconditional three-factor model performs better. Mirza and Shahid (2008) deployed a multivariate framework to test the validity of the three-factor model. The sample consisted of 81 stocks traded on KSE from January 2003 to December 2007. The results confirmed the size premium but reported a value discount. Their findings, in general, supported the three-factor model. Javid and Ahmad (2008) examined a set of macroeconomic variables along with the market risk premium on 49 stocks traded at KSE during the period between 1993 and 2004. The results supported that the economic variables play an incremental part in explaining the variation in stock returns and this variability has some business cycle correlations.

Within a broad international analysis Liew and Vassalou (2000) examined the relationship between the Fama–French's three factors and future economic growth in ten countries. The results indicated that SMB and HML are positively related to future economic growth. The predictive ability of the Fama–French factors is found independent on the market factor. They contended that their findings support the risk-based interpretation of the Fama–French factors. Further, a moderate explanatory power of the Fama–French factors for stock returns in the presence of macroeconomic risk factors is noticed by several studies (Aleati et al. 2000; Lettau and Ludvigson 2001; Vassalou 2003; Petkova 2006). Similarly, Boamah (2015) examined the applicability of the Fama-French factors and explore the ability of these factors to predict future economic growth (GDP) of South Africa. The findings show the relevance of small firms and value stocks on the South-African stock market. Additionally, the results show a significantly positive relationship between future economic growth and SMB, HML, and the market factor. The findings remain robust to the inclusion of business cycle variables in the model.

3. Data and Methodology

Emerging markets have their own dynamics, significantly different from developed markets (Bruner et al. 2002). KSE was declared as an open market in 1991 but the pace of the market was stagnant until 2001. However, the market has shown a tremendous growth in recent years; the index has grown by more than 715% in the last eight years (December 2008 to December 2016). Our dataset consists of stocks traded at KSE from January 2002 to December 2015 and GDP growth rates between 2003 and 2016.[2] We start from January 2002 due to a number of reasons, such as: (1) the availably of the data on the official website of the KSE; (2) the stocks remain actively traded at KSE in this period; and (3) in preceding years, the market was illiquid and influenced by other global and regional

[2] Pakistan has three stock markets, the other two stock markets are Islamabad stock exchange and Lahore stock exchange, however all these three markets were merged on 11 January 2016 and renamed as Pakistan stock exchange. Source: https://www.psx.com.pk/.

factors.[3] Thus, it is better to include a lag of a few months to avoid potential bias and begin taking data from January 2002. The study which spans the period of 168 months, including bearish, bull, super bull, recession, recovery and, again, rapid growth in the market, covers all characteristics of market performance and is long enough to ensure stability and efficacy of the model.

3.1. Types and Sources of Data

Data on stock prices and index closing points are obtained from the official website of KSE.[4] The cut-off yield on the Pakistani Treasury bill rate (T-bill), Pakistan investment bonds (PIBs), and financial statements of financial sector data are obtained from the official website of the State Bank of Pakistan (SBP).[5] The financial daily Business Recorder is used for the data related to number of outstanding shares, market capitalizations and any other missing information.[6] The KSE-100 index is a market capitalization weighted index and is used as the market return, whereas 6 month T-bills cut-off yields are converted into monthly values and used as a risk-free rate, similar to the previous studies on KSE (Iqbal and Brooks 2007; Mirza and Shahid 2008). Overall, more than 630 stocks are carefully observed. However, after screening the stocks as per criteria limitations, the number of stocks included are reduced to 330.[7] Table 2 shows the number of stocks considered in each case. A continuous change in the number of stocks can be noticed across different baskets and this may present different results. We include delisted firms in the sample up to the delisting year to control the survivorship bias. The dataset is modified on December 31 each year. In order to estimate the monthly returns, the closing price of the last day of each month is used.

Table 2. Year-over-year sample size (2002 to 2015).

Year	Fixed Basket	Non-Financial Basket	Variable Basket
2002	192	162	195
2003	192	168	202
2004	192	188	226
2005	192	200	249
2006	192	210	258
2007	192	212	269
2008	192	214	277
2009	192	234	305
2010	192	243	313
2011	192	248	320
2012	192	253	326
2013	192	254	327
2014	192	257	330
2015	192	257	330

Note: Author's calculation. The table reports the number of companies considered for the reformation of six size and book-to-market (B/M) sorted portfolios each year-end from 2002 to 2015.

3.2. Selection Criteria and Limitations

For selected companies, monthly price data, market value of equity, book value and other fundamental information should be available; selected stock must survive for a complete year and be traded for at least 85% of the trading days with non-zero returns during the year.

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3 These factors include, but are not limited to Asian crises (1997), political uncertainty in Pakistan (1999) and US-Afghan (9/11) war.
4 The official website of Karachi stock exchange is www.kse.com.pk (new: https://www.psx.com.pk/).
5 The official website of the State Bank of Pakistan (SBP) is www.sbp.org.pk.
6 Source: http://www.brecorder.com/market-data/karachi-stocks/.
7 See, Section 3.2 for selection criteria and limitations.

3.3. Model Specification

In order to test the significance and existence of the diverse factors on asset pricing in the Pakistani stock market (KSE), we employ numerous pricing models and follow a stepwise approach. We start with a standard CAPM:

$$E(R_i) - R_f = \alpha_i + \beta_i \left[E(R_m) - R_f \right] + \epsilon_i \tag{1}$$

Next, we add SMBL and HML factors into the CAPM:

$$E(R_i) - R_f = \alpha_i + \beta_i \left[E(R_m) - R_f \right] + s_i(SMB) + h_i(HML) + \epsilon_i \tag{2}$$

where, $E(R_i) - R_f$ is the portfolio *i's* return in excess of risk-free rate R_f, α_i is the intercept of the regression equation representing the non-market return component, $E(R_m) - R_f$ is the market risk premium (market portfolio return in excess of risk-free rate), SMB (small minus big) is the return on small size stocks minus return on big size stocks captures size premium, HML (high minus low) incorporates value premium that is the difference between returns of value stocks (high B/M ratio) and growth stocks (low B/M ratio). β_i, s_i and h_i, are the slopes of expected risk premium of portfolio i to the market, size and value factors in the regression, respectively, while ϵ_i represents the random return component due to unexpected events related to a particular portfolio. It is supposed that ϵ_i has a multivariate normal distribution and is identically and independently distributed over time.

3.4. Variable Construction and Portfolio Formation

In order to examine the three factors for Pakistani stocks, we experiment with three ways of constructing size and value factors to explore the impact of the special features in the Pakistani stock market. The three portfolio construction methods (baskets of stocks) are: 'fixed basket', 'non-financial basket' and 'variable basket'. By following the previous studies on KSE, we construct the fixed basket; which includes only those stocks which have survived the entire sample period. Next, we follow Fama and French (1993) and construct the non-financial basket. The non-financial basket excludes stocks of financial companies, however, every year new companies are included into the basket upon meeting the sample selection and criteria limitations. The variable basket is based on the special features of KSE, such as: liquidity of the financial companies, active participation, and fraction of the market value of the financial firms to the total market value of the index. It includes both non-financial and financial companies into the basket every year upon meeting the sample selection and criteria limitations. The variable and the non-financial baskets include delisted firms in the sample up to the delisting year to control the survivorship bias, whilst the fixed basket does not include.

The dependent variable of the three factor model is the excess return on equal weighted six portfolios. 2 pcs (small and big) portfolios are determined for size effect and 3 pcs (high, medium, low) portfolios are determined for value effect. A total of six intersection portfolios (SL, SM, SH, BL, BM, BH) are created with the following criteria: shares classified according to market value have been subdivided using the median market cap as breakpoint, while shares classified according to book-to-market have been divided by the 30th and 70th percentiles as breakpoints. In the case of risk-based portfolios, i.e., constructing portfolio by categorizing the stock's sensitivity to market movements, six portfolios on the basis of risk profile of the stocks are carefully considered as the dependent variables.

The independent variables consist of market, size and value premiums. For the market risk premium, we find the difference between the return on market portfolio and risk free rate, and show that it exists in both Fama-French three factor model and CAPM. Size premium (SMB) is the average return on three small portfolios SL, SM and SH minus the average return on the three big portfolios BL, BM and BH, while HML is the average return on two value portfolios SH and BH minus the average return on the two growth portfolios SL and BL. SMB and HML are computed as follows:

$$SMB = \frac{(SL + SM + SH)}{3} - \frac{(BL + BM + BH)}{3} \tag{3}$$

$$HML = \frac{(SH + BH)}{2} + \frac{(SL + BL)}{2} \tag{4}$$

4. Empirical Results and Discussion

The descriptive statistics in Table 1 report that the average monthly returns on the SMB are statistically insignificant in the fixed basket, and significant at 10% and 5% levels in non-financial and variable baskets, respectively. In contrast, value premium is significant at 5% level across all the methodologies. To understand the changes in the results caused by construction methodologies, we start with a detailed analysis of the variable basket, because it is significant for both factors at 5% level. Afterwards, we compare the performance of these factors obtained by three different portfolio construction methodologies. Table 3 reports the descriptive statistics of the monthly excess return and volatility of the six size-B/M sorted portfolios from January 2002 to December 2015 obtained by using variable basket.

Table 3. Descriptive statistics on the excess return (and volatility).

	Low B/M	**Medium B/M**	**High B/M**
Small Capitalization	1.384 (9.008)	1.689 (7.193)	3.462 (10.375)
Big Capitalization	1.427 (7.297)	1.426 (8.285)	1.394 (11.150)

Note: Author's calculation. The table reports the descriptive statistics on monthly average excess returns between six size-B/M portfolios for the Pakistani stock market. The values of standard deviation are reported in parentheses. The sample period is 2002:01–2015:12 (168 monthly observations). Source: the official website of the Pakistan stock exchange (https://www.psx.com.pk/) and the official website of the State Bank of Pakistan (http://sbp.org.pk/).

Holding group size constant, the average return and volatility of the portfolios increase with the portfolio's B/M ratio. The average monthly return on portfolios containing low B/M is 1.41% and the standard deviation is 8.15%, whereas stocks with high B/M ratio have an average return of 2.43% and a standard deviation of 10.76%. Conversely, when the B/M ratio is constant, the average return on small capitalization firms is 2.42% and the standard deviation is 9.69%, whereas stocks with big capitalization have an average return of 1.41% and a standard deviation 9.22%. Average returns on all portfolios are positive in our study, but are contradictory to the results reported by Mirza and Shahid (2008). Their results for KSE during the bull rally between 2003 and 2007 report negative average monthly returns on portfolios SH, BH and BM. The monthly average returns are the highest in the small value category (SH), approximately 3.46%, while the lowest in the small growth category (SL) is approximately 1.38%. The monthly standard deviation is the highest in the big value category (BH), approximately 11.15% and the lowest in the small medium-B/M category (SM), approximately 7.19%.

Table 4 represents the summary statistics of all three portfolios for time period from January 2002 to December 2015. The monthly average returns of the three explanatory variables are all positive and significant. The annual average return on the market, size and value factors is approximately 18.22%, 9.15% and 12.27%, respectively, whereas the standard deviation is approximately 7.60%, 5.32% and 6.53%, respectively. It is evident from the results that small stocks and values stocks outperform the big stocks and growth stocks, respectively.

Table 4. Summary statistics of independent variables (factors).

	$R_m - R_f$	SMB	HML
Mean (%)	1.518	0.763	1.022
STD (%)	7.596	5.323	6.529
t-statistic	2.591	1.858	2.029

Note: Author's calculation. The table reports the summary statistics of the market risk premium ($R_m - R_f$), size premium (SMB) and value premium (HML). The sample period is 2002:01–2015:12 (168 monthly observations). Source: the official website of the Pakistan stock exchange (https://www.psx.com.pk/) and the official website of the State Bank of Pakistan (http://sbp.org.pk/).

Table 5 reports the correlation coefficients among the independent variables. We did not notice any excessively high values of the correlation coefficients that may arise a concern about any multicollinearity problem. The observed correlation shows that SMB and HML can be regarded as separate measures of risk premium, which are not dependent on market risk premium. The correlation between SMB and HML also shows a valid justification for considering size and value risk factors separately.

Table 5. Correlation coefficients of monthly factor returns.

	$R_m - R_f$	SMB	HML
$R_m - R_f$	1		
SMB	−0.445	1	
HML	0.365	−0.176	1

Note: Author's calculation. The table reports the correlation coefficients between market, size and value factors. The sample period is 2002:01–2015:12 (168 monthly observations). Source: the official website of the Pakistan stock exchange (https://www.psx.com.pk/) and the official website of the State Bank of Pakistan (http://sbp.org.pk/).

4.1. Regression Results

In this section, we analyze the standard CAPM and the Fama-French three-factor model by employing time-series regression for each of the six size-B/M portfolios (SL, SM, SH, BL, BM, BH). The objective of this approach is to identify the role of size and value factors to capture variation in stock returns during the period from January 2002 to December 2015. We start from the traditional single factor CAPM in Table 6, in order to make a comparison with the three-factor model later.

Table 6. Capital Asset Pricing Model (CAPM) regressions on monthly excess returns of portfolios formed on size and B/M ratio (variable basket).

$R_i - R_f$	α	β	R^2	Adj. R^2
SL	0.006 (0.915)	0.528 (6.406) *	0.198	0.193
SM	0.008 (1.778) ***	0.597 (10.454) *	0.397	0.393
SH	0.023 (3.387) *	0.786 (9.070) *	0.331	0.327
BL	0.002 (0.682)	0.795 (18.971) *	0.684	0.682
BM	0.001 (0.208)	0.887 (18.014) *	0.662	0.659
BH	−0.004 (−0.698)	1.165 (16.789) *	0.629	0.627

Note: Author's calculation. The table reports the estimation results of the single factor CAPM. Stocks are sorted into six size-B/M portfolios (SL, SM, SH, BL, BM, BH). t-stats are in parenthesis, *** and * indicate significance at 10% and 1% level, respectively. The sample period is 2002:01–2015:12 (168 monthly observations). Source: the official website of the Pakistan stock exchange (https://www.psx.com.pk/) and the official website of the State Bank of Pakistan (http://sbp.org.pk/).

The results reported in Table 6 show that the average adjusted R^2 value of the CAPM is approximately 48%, suggesting that the CAPM does not explain most of the time-series variations in stock returns. The intercept of the CAPM is statistically significant for two out of six portfolios, i.e., small stocks with medium B/M ratio (SM) and small value stocks (SH). The portfolios containing small stocks generate higher average intercept and lower R^2. Thus, the results of the CAPM regressions provide some preliminary indication for a size premium.

Next, we include size and book-to-market factors into the model. Table 7 reports the results of the Fama-French three-factor model based on variable basket. The R^2 of the six regressions, with an average of approximately 71.74%, are much higher than those of the CAPM regressions. Usually, adding an independent factor into regression increases R^2. If the change is meaningfully higher, it is considered to be an improvement in the model. The average value of R^2 for small size group increases from approximately 30.88% to 71.08%, signifying that the three-factor model provides a massive improvement in the explanatory power over the CAPM. Therefore, our regression results support the argument that the three-factor model is a much better fit for KSE, Pakistan.

Table 7. Three factor regression on monthly excess returns of portfolios formed on size and B/M ratio (variable basket).

$R_i - R_f$	α	β	s	h	R^2	Adj. R^2
SL	−0.007 (−1.599)	0.988 (14.889) *	1.182 (13.197) *	−0.291 (−4.149) *	0.632	0.625
SM	−0.002 (−0.695)	0.762 (15.023) *	0.737 (10.764) *	0.205 (3.821) *	0.663	0.657
SH	0.004 (1.067)	0.906 (17.861) *	1.187 (17.330) *	0.796 (14.824) *	0.838	0.835
BL	0.003 (0.895)	0.860 (17.961) *	0.025 (0.381)	−0.183 (−3.615) *	0.708	0.703
BM	−0.001 (−0.220)	0.855 (14.952) *	0.061 (0.788)	0.164 (2.706) *	0.677	0.671
BH	−0.008 (−1.882) ***	0.942 (15.082) *	0.020 (0.235)	0.729 (11.036) *	0.787	0.783

Note: Author's calculation. The table reports the estimation results of the three-factor model (variable basket). Stocks are sorted into six size-B/M portfolios (SL, SM, SH, BL, BM, BH). *t*-Stats are in parenthesis, *** and * indicate significance at 10% and 1% level, respectively. The sample period is 2002:01–2015:12 (168 monthly observations). Source: the official website of the Pakistan stock exchange (https://www.psx.com.pk/) and the official website of the State Bank of Pakistan (http://sbp.org.pk/).

Theoretically, if a model satisfactorily explains the changes in the expected returns, then the intercept produced by regression results will tend towards zero. Table 7 reports that the six size-B/M portfolios produce intercepts, ranging from −0.0072 to 0.0037, are close to zero. Only the portfolio containing stocks with a high market capitalization and a high book-to-market value (BH) shows a significant (negative) intercept. The significant intercept for portfolio BH indicates that the big value firms have something not predicted by the model.

The loadings on the market factor are all significant at 1% level and thus reflect a positive sensitivity to market risk. HML has significantly positive coefficients for high B/M firms and significantly negative for low B/M firms. The coefficients of value stocks have both a large and positive sensitivity to HML, whereas growth stocks have a low and negative sensitivity to HML. Our results support the existence of value premium. Similarly, the coefficients of small firms have both a large and positive sensitivity to SMB, whereas the big firms have insignificant sensitivity. The coefficients of big firms are very small, ranging from approximately 0.019 to 0.061, whereas the coefficients of small firms range from approximately 0.737 to 1.187. Although the insignificant sensitivity of big firms to SMB is different from Fama-French's findings, the coefficient of small firms are highly significant both in the economic and statistically sense. This finding also indicates adequate evidence to support the existence of a size premium.

4.2. Comparative Analysis of the Three-Factor Model

In this section, we examine the three-factor model based on 'fixed' and 'non-financial' baskets. For comparison, Table 8 represents the three factor model regression results.

Table 8. Three factor regression on monthly excess returns of portfolios formed on size and B/M ratio (fixed basket and non-financial basket).

$R_i - R_f$	α	β	s	h	R^2	Adj. R^2
Panel A: Fixed basket						
SL	−0.002 (−0.341)	0.937 (14.412) *	1.286 (14.043) *	−0.442 (−5.945) *	0.657	0.651
SM	0.001 (0.397)	0.703 (13.838) *	0.704 (9.829) *	0.100 (1.717) ***	0.591	0.584
SH	0.007 (1.708) ***	0.876 (16.413) *	1.175 (15.623) *	0.758 (12.428) *	0.789	0.785
BL	0.007 (1.826) ***	0.789 (15.741) *	−0.003 (−0.044)	−0.240 (−4.180) *	0.635	0.629
BM	0.001 (0.343)	0.877 (15.481) *	0.060 (0.747)	0.095 (1.468)	0.648	0.641
BH	−0.002 (−0.355)	0.850 (13.821) *	0.108 (1.250)	0.561 (7.976) *	0.683	0.677
Panel B: Non-financial basket						
SL	−0.003 (−0.509)	1.076 (14.413) *	1.231 (13.013) *	−0.348 (−4.502) *	0.643	0.636
SM	0.000 (0.035)	0.690 (13.701) *	0.717 (11.221) *	0.135 (2.580) *	0.626	0.619
SH	0.008 (2.024) **	0.842 (15.513) *	1.145 (16.654) *	0.807 (14.367) *	0.813	0.810
BL	0.008 (1.997) **	0.748 (14.334) *	−0.007 (−0.103)	−0.200 (−3.705) *	0.582	0.574
BM	0.010 (0.220)	0.877 (15.0450) *	0.021 (0.280)	0.150 (2.480) **	0.653	0.647
BH	−0.003 (−0.635)	0.983 (14.338) *	0.079 (0.911)	0.645 (9.083) *	0.724	0.719

Note: Author's calculation. The table reports the estimation results of the three-factor model (fixed and non-financial basket). Stocks are sorted into six size-B/M portfolios (SL, SM, SH, BL, BM, BH). *t*-stats are in parenthesis, ***, ** and * indicate significance at 10%, 5% and 1% level, respectively. The sample period is 2002:01–2015:12 (168 monthly observations). Source: the official website of the Pakistan stock exchange (https://www.psx.com.pk/) and the official website of the State Bank of Pakistan (http://sbp.org.pk/).

The average R^2 value of fixed basket and non-financial basket is 66.71% and 67.72%, respectively. Two portfolios, namely SH and BL, represent statistically significant intercepts for both of the baskets. The intercepts of SH and BL range from −0.0016 to 0.0065 and −0.0027 to 0.0079, respectively. The coefficients of the market factor are all positive and significant at 1% level. The coefficients of small portfolios have a large and positive sensitivity to SMB, whereas big portfolios have a smaller and positive sensitivity to SMB. Finally, the coefficients of high B/M portfolios have a large and positive sensitivity to HML factor, while the low B/M portfolios have a smaller and negative sensitivity to HML. Our regression results are mostly similar to the variable basket. Similarly, we analyze CAPM based on fixed and non-financial baskets, in order to make a reasonable comparison with the CAPM-variable basket. However, the primary interest in the CAPM regression is the R^2 values and the intercept term. The results reported in Table A1 (Panel A and Panel B) in the appendix demonstrate that the fixed and non-financial baskets exhibit similar patterns as the variable basket. That is, the portfolios containing small stocks generate higher average intercept and lower R^2.

4.3. Model Performance Summary

One of our primary tasks is to test how well the three different types of factors construction explain average excess returns on the portfolios. Table 9 (Panel A and Panel B) examines the average absolute intercept (A$|\alpha_i|$), a measure of unexplained proportion of time series return variance $(1 - R^2)$, and the number of portfolios with statistically significant intercept (NPSIs). Panel C of Table 9 estimates the mean, standard deviation, Sharpe ratio and cumulative wealth of size and value factors.

Table 9. Summary statistics for tests of CAPM, three-factor model, and size and value premiums.

Factor Construction Type		A$\|\alpha_i\|$	A $(1 - R^2)$	NPSIs
Panel A: CAPM				
CAPM- fixed basket		0.008	0.568	2
CAPM- non-financial basket		0.009	0.565	2
CAPM- variable basket		0.007	0.516	2
Panel B: Three-factor model				
Fama-French- fixed basket		0.003	0.333	2
Fama-French- non-financial basket		0.004	0.327	2
Fama-French- variable basket		0.004	0.283	1
Panel C: Size and value premiums				
Factors	**Mean%**	**Std. Dev.%**	**Sharpe Ratio**	**Cumulative Wealth**
SMB (FB)	0.4714	5.252	0.089	1.792
SMB (NB)	0.7618 ***	5.759	0.132	2.279
SMB (VB)	0.7628 **	5.323	0.143	2.282
HML (FB)	0.9375 **	6.197	0.151	2.575
HML (NB)	1.2535 **	7.017	0.179	3.106
HML (VB)	1.0222 **	6.529	0.157	2.717

Note: Author's calculation. Panel A and Panel B show the average absolute intercept A$|\alpha_i|$, the measure of unexplained proportion of time-series return variance $(1 - R^2)$, and the number of portfolios with statistically significant intercepts NPSIs of CAPM and the three-factor model, respectively. Panel C reports the mean, standard deviation, Sharpe ratio and cumulative wealth of size and value factors based on three different portfolio construction methodologies. FB, NB and VB represent the fixed basket, non-financial basket and variable basket, respectively. *t*-stats are in parenthesis, *** and ** indicate significance at 10% and 5% level, respectively. The sample period is 2002:01–2015:12 (168 monthly observations). Source: the official website of the Pakistan stock exchange (https://www.psx.com.pk/) and the official website of the State Bank of Pakistan (http://sbp.org.pk/).

Panel A of Table 9 shows that the average absolute intercepts and the average unexplained portion of the time-series returns variance of CAPM are the lowest in the variable basket. Similarly, the average values of $(1 - R^2)$ across the 6 LHS portfolios, measuring the unexplained portion of the time-series return variance of the three-factor model are approximately 33.29%, 32.65% and 28.26% for fixed, non-financial and variable baskets, respectively. These findings confirm that the explanatory power of the variable basket for both the three-factor model and CAPM is higher than the other two methods of factors construction. Table 9 (Panel B) further validates that the average absolute intercepts and the average values of $(1 - R^2)$ of the three-factor model are generally smaller than those of the CAPM. The variable basket produces only one portfolio that generates statistical significant intercept, whereas the other two baskets produce two portfolios with significantly positive intercepts. Further, Panel C of Table 9 shows that the Sharpe ratio, cumulative wealth and the significance level (5%) of SMB are higher in variable basket than non-financial and fixed baskets. The HML is significant at 5% level in all the three baskets, however the Sharpe ratio and cumulative wealth are higher if HML is constructed by including only non-financial stocks.

Figure 1 plots the cumulated monthly value of one rupee (nPKR) invested at the start of January 2002 and compounded at the monthly returns of the two factors (SMB and HML) in the KSE, Pakistan. The solid lines represent the two factors constructed by using fixed basket (SMBf and HMLf). The round-dotted lines represent the non-financial basket (SMBn and HMLn), and the square-dotted lines represent the variable basket (SMBv and HMLv). The time period is from January 2002 to December 2015. Figure 1 shows that both factors follow the same pattern under all the three ways of constructing the factors. The cumulative wealth of SMB factor is the highest when it is constructed based on the variable basket, whereas the cumulative wealth of HML factor is the highest when it is constructed based on the non-financial basket.

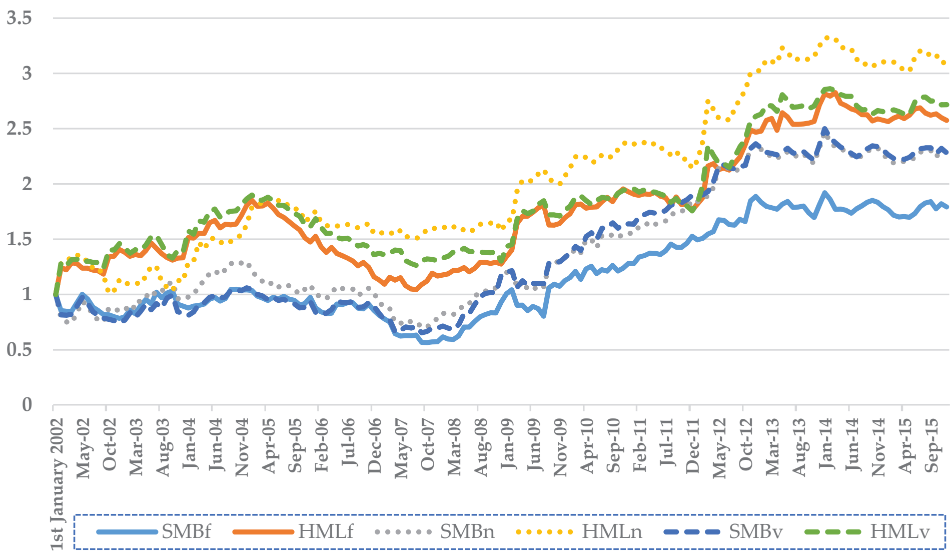

Figure 1. Cumulative value of the size and value factors using three different methodologies. Source: Author's own plotting. The sample period is 2002:01–2015:12. Source: the official website of the Pakistan stock exchange (https://www.psx.com.pk/) and the official website of the State Bank of Pakistan (http://sbp.org.pk/).

Overall, the results reveal that the three-factor model based on each of the basket of stocks explains the time-series variation in Pakistani stock returns very well. The fixed basket, used by most of the previous studies on the Pakistani stock market, performs the worst in terms of explanatory power and significance of the risk factors. The explanatory power of the three-factor model is relatively high when the portfolios include both financial and non-financial stocks (variable basket) as compared to when the portfolios include only non-financial stocks. Based on the explanatory power of the model, Sharpe ratio, cumulative wealth, and significance of the intercepts and the risk factors, we consider size and value factors constructed by using a variable basket of stocks for further analysis and robustness checks.

4.4. Robustness Test

As discussed earlier in this paper, our sample period includes the Global financial crises (2007–2009). Therefore, we break the sample into three sub-periods based on a combination of global and domestic market conditions, to confirm that our findings are robust. From January 2002 to December 2006 (pre-crises), from January 2007 to December 2010 (crises period) and from January 2011 to December 2015 (post-crises). Table A2 (Panel A, Panel B, and Panel C) in the appendix examines the time varying behavior of the three-factor model and size and book-to-market factors.

The R^2 of the six size-B/M portfolios' regressions in the post-crises period, with an average of approximately 81.82%, is higher than the other sub-periods, followed by crises (79.12%) and pre-crises (65.1%) periods, respectively. In the first sub-period (pre-crises), two out of six portfolios have statistically significant intercepts, whereas, in the second sub-period (crises), one portfolio has significant intercept, and in the third sub-period (post-crises), all the portfolios have insignificant intercepts. However, the magnitude of the intercepts is very nominal, ranging from 0.0001 to 0.0153 in the first sub-period, from -0.0143 to -0.0014 in the second sub-period, and from -0.0038 to 0.0039 in the third sub-period. All the coefficients on market factor across all the three sub-periods are significant at 1% level. With regard to size factor, the six size-B/M portfolios across the sub-periods exhibit varying degrees of sensitivity to the size factor, SMB. However, generally, the small portfolios have a large and positive sensitivity to SMB, whereas big portfolios have a small and negative sensitivity in first two sub-periods, and a nominal but positive sensitivity in the last sub-period. The average coefficients on small portfolios in each sub-period; pre-crises, crises and post-crises, are comparatively higher (0.762, 0.933 and 1.788, respectively) than the average coefficients on big portfolios (0.238, -0.067 and 0.288, respectively).

Our results show that size premium is getting stronger over the time period in terms of both the coefficients and the significance. Finally, value factor across the three sub-periods; pre-crises, crises and post-crises, high B/M ratio portfolios have a positive and large sensitivity to HML (0.908, 0.267 and 0.780, respectively), while low B/M stocks have a small and negative sensitivity to HML (-0.092, -0.733 and -0.220, respectively). The significance of the value factor is the highest in the post-crises period with approximately similar magnitude as in the pre-crises period. Our results for value factor confirm the findings of Davis et al. (2000), where significance of value premium increased from (t = 2.8) to (t = 3.38) in the recent sub-period. The value premium in our study is getting stronger over the time period. This is in contrast to the finding of Chung et al. (2016), where it was concluded that value premium is getting weaker over the time period in the Australian market.

It has been discussed that the data from the low-risk state are consistent with CAPM, whereas data from the high-risk state are inconsistent with CAPM (Huang 2000). The sample was divided into two different regimes (low risk and high risk). The results suggested that the data from the high risk regime violate CAPM. However, the data from the low risk state are consistent with CAPM. First, we regressed all the stocks on the market beta and classified them into 6 risk-based portfolios (B1 (high), B2, B3, B4, B5 and B6 (low)) to measure whether size and value premiums exist in all risk regimes. B1 represents stocks of the highest risk category (market beta), whereas B6 represents stocks at the lowest risk level. All portfolios contain an equal number of stocks.

Table 10 represents the estimation results of the three-factor model within a time-series context for each of the six risk-based portfolios. The regression results show that the coefficients of the market, size and value premiums are positive and significant at 1% level. The intercept is statistically insignificant for all the six portfolios and the R^2 values ranges between 36.56% and 74.68%. Our results support the existence and significance of the size and value premiums across all the risk profiles (regimes). However, the medium-ranked portfolios (B2, B3 and B4) have a higher explanatory power, and a higher level of significance for loadings on SMB and HML, with somewhat similar magnitude.

Table 10. Three factor regression on monthly excess returns of portfolios formed on risk profile (market beta).

$R_i - R_f$	α	β	s	h	R^2	Adj. R^2
B1 (High)	0.004 (0.697)	1.286 (19.073) *	0.644 (5.227) *	0.206 (2.132) **	0.606	0.599
B2	−0.004 (−0.976)	1.147 (18.865) *	0.528 (6.435) *	0.259 (4.026) *	0.747	0.742
B3	−0.003 (−0.900)	0.924 (17.903) *	0.545 (7.827) *	0.250 (4.585) *	0.730	0.725
B4	−0.002 (−0.539)	0.784 (14.738) *	0.460 (6.411) *	0.307 (5.453) *	0.673	0.667
B5	0.002 (0.387)	0.641 (10.930) *	0.559 (7.066) *	0.264 (4.261) *	0.536	0.528
B6 (Low)	0.005 (1.112)	0.454 (7.329) *	0.507 (6.070) *	0.213 (3.244) *	0.366	0.354

Note: Author's calculation. The table reports the estimation results of the three-factor model. Stocks are sorted into six risk-based portfolios. B1 contains securities of the highest risk level (highest market beta) whereas B6 contains the lowest risky securities. t-stats are in parenthesis, ** and * indicate significance at 5% and 1% level, respectively. The sample period is 2002:01–2015:12 (168 monthly observations). Source: the official website of the Pakistan stock exchange (https://www.psx.com.pk/) and the official website of the State Bank of Pakistan (http://sbp.org.pk/).

Petkova (2006) noticed a moderate explanatory power of the Fama–French factors on stock returns in the presence of macroeconomic risk factors. Elgammal et al. (2016) investigated the relationship between default premium and size and value premiums in the US market. They suggested that the default premium has explanatory power for value and size premiums. Baek and Bilson (2015) confirmed the existence of size and value premiums in both financial and nonfinancial firms. Additionally, they clarified that the financial firms are also sensitive to interest rate risk premium. Since our sample also includes financial firms, we examine the augmented four-factor model by including term structure premium into the Fama French three-factor model. The term structure premium (TSP) is calculated by finding the difference between the cut-off yield on ten-year Pakistan investment bonds (PIBs) and three-month Pakistani Treasury bill rate. By introducing TSP into the model, the relationship between excess returns and risk factors is modelled as:

$$E(R_i) - R_f = \alpha_i + \beta_i\left[E(R_m) - R_f\right] + s_i(SMB) + h_i(HML) + ts_i(TSP) + \epsilon_i \tag{5}$$

where, $E(R_i) - R_f$ is the portfolio i's return in excess of risk-free rate R_f, α_i is the intercept of the regression equation representing the non-market return component, $E(R_m) - R_f$ is the market risk premium (market portfolio return in excess of risk-free rate), SMB (small minus big) is the return on small size stocks minus return on big size stocks captures size premium, HML (high minus low) incorporates value premium that is the difference between returns of value stocks (high B/M ratio) and growth stocks (low B/M ratio), and TSP (term structure premium) is calculated by finding the difference between the cut-off yield on ten-year PIBs and three-month T-bills of Pakistan. β_i, s_i, h_i, and ts_i are the slopes of expected risk premium of portfolio i to the market factor, size factor, value factors and term structure premium in the regression, respectively, while ϵ_i represents the random return component due to unexpected events related to a particular portfolio.

Results reported in Table 11 show that there is a negligible increase in the average adjusted R^2 due to the addition of TSP (from 71.23% to 71.73%). In contrast, there is a huge increase in the significance of the average intercept (from one portfolio to three portfolios) and magnitude of the average intercept (from 0.004 to 0.008). Our results demonstrate that SMB, HML and market factors remain robust to the inclusion of the term structure premium. Our findings for the three-factor model are robust across various portfolio construction techniques.

Table 11. Augmented four-factor regression on monthly excess returns of portfolios formed on size and B/M ratio (variable basket).

$R_i - R_f$	α	β	s	h	ts	R^2	Adj. R^2
SL	−0.014 (−2.402) *	0.970 (14.544) *	1.186 (13.331) *	−0.294 (−4.220) *	3.735 (1.818) ***	0.639	0.630
SM	(−0.009 (−2.066) **	0.744 (14.697) *	0.741 (10.972) *	0.202 (3.817) *	3.707 (2.377) **	0.674	0.666
SH	−0.001 (−0.230)	0.894 (17.496) *	1.189 (17.454) *	0.794 (14.856) *	2.581 (1.640)	0.840	0.837
BL	−0.003 (−0.599)	0.845 (17.612) *	0.028 (0.434)	−0.186 (−3.695) *	2.978 (2.013) **	0.715	0.708
BM	−0.006 (−1.224)	0.840 (14.606) *	0.064 (0.833)	0.161 (2.680) *	2.914 (1.643) ***	0.682	0.675
BH	−0.016 (−2.836) *	0.921 (14.745) *	0.024 (0.291)	0.726 (11.102) *	4.131 (2.146) **	0.793	0.788

Note: Author's calculation. The table reports the estimation results of an augmented Fama-French four-factor model that includes term structure premium. Stocks are sorted into six size-B/M portfolios (SL, SM, SH, BL, BM and BH). Term structure premium is calculated by finding the difference between the cut-off yield on ten-year PIBs and three-month T-bill of Pakistan. *t*-stats are in parenthesis, ***, ** and * indicate significance at 10%, 5% and 1% level, respectively. The sample period is 2002:01–2015:12 (168 monthly observations). Source: the official website of the Pakistan stock exchange (https://www.psx.com.pk/) and the official website of the State Bank of Pakistan (http://sbp.org.pk/).

5. Predictive Ability of the Three Factors for Future Economic Growth

Fama and French (1992, 1993, 1996, 1998) argue that SMB and HML act as state variables that predict future variations in the investment opportunities established in the context of intertemporal capital asset pricing model (Merton 1973). Liew and Vassalou (2000) attempt to link the return-based factors with future growth in the macro-economy. They conclude that HML and SMB contain significant information about future GDP growth, and risk-based explanation for the returns of SMB and HML is plausible. The evidence will enhance our understanding of whether or not these factors relate to underlying economic risk factors.

In this section, we discuss the third main objective of the study. This objective is to examine the relevance of the market factor, SMB, and HML with future GDP growth of Pakistan using univariate and multivariate regression analysis. Along with these factors, we include Treasury bill rate and term structure premium to predict Pakistan's GDP growth one year ahead. That is, we explore the ability of these factors at year Y_{t-1} to forecast the GDP growth for year Y_t. The annual GDP data is obtained from the official website of the Asian development bank, whereas the data for T-bills and PIBs are obtained from the official website of the State Bank of Pakistan. Term structure premium is calculated by finding the difference between the cut-off yield on ten-year Pakistan investment bonds and three-month Pakistani Treasury bill rate, while GDP growth is calculated as the continuously compounded growth rate in Pakistan's gross domestic product. To obtain the yearly values, we have calculated the average (mean) of the monthly market risk premium (MKT), SMB, HML, Treasury bill rate (TB) and term structure premium (TSP) within each year (12 months).[8] The following equation represents the model:

$$GDP_{g,t} = \alpha + \beta\left[E(R_{m,t-1}) - R_{f,t-1}\right] + sSMB_{t-1} + hHML_{t-1} + fBCV_{t-1} + \epsilon_t \quad (6)$$

[8] See Boamah (2015) and Liew and Vassalou (2000) for an extensive overview of the methodology.

where, $GDP_{g,t}$ represents the GDP growth at time *t* and BCV_{t-1} represents the business cycle variables, which refers to the term structure premium and the three-month Treasury bill rate.

Before we proceed with the main test, we examine the stationarity of the variables. The market factor and HML are stationary, while SMB, GDP growth, T-bill and term structure premium are taken as first-order difference. The absence of a unit root in the series of returns is confirmed by augmented Dickey-Fuller test and Phillips-Perron test, with trend and intercept. It is carefully observed that all the variables are stationary at the time we perform regressions. Next, we examine various versions of Equation (6) and present the results in Table 12. To check whether the remaining residuals are independent and identically distributed (i.i.d.), we have conducted the BDS test by Brock et al. (1996) and no nonlinearity is found.

The evidence shows that in univariate regressions, the market factor and size premium show significant association with future growth of the Pakistani GDP, whereas value premium, Treasury bill and term structure premium indicate an insignificant relationship with future growth in GDP.

It is further evident that only the coefficient of the market factor is positive, whereas the coefficients of SMB, HML, TB and TSP are negative. The explanatory power of the univariate regressions is 63.03%, 32.79%, 1.30%, 9.32% and 1.02% for the market, SMB, HML, TB and TSP, respectively. The findings indicate that the predictive ability of the market factor and SMB for the growth of the Pakistan's GDP is non-trivial.

In a two-factor model consisting of market factor and SMB, HML, TB and TSP, the result indicates that the coefficients of market factor are all positive and statistically significant. The loadings on HML, SMB, Treasury bill and term structure are negative, but insignificant. The R^2 values are relatively higher in the two-factor regression, ranging from 63.32% (market and TSP) to 68.86% (market and TB). The two-factor model consisting of SMB and HML indicates that including HML into the regression model does not subsume the significance of SMB factor. The negative coefficients of SMB are similar to the findings of Liew and Vassalou (2000) for Switzerland and Japan.

Table 12. The information content of market, SMB and HML for future economic growth.

Model	α	MKT	SMB	HML	TB	TSP	R^2
1	0.095	0.170 *					0.630
2	0.040		−0.217 **				0.328
3	0.015			−0.003			0.013
4	0.018				−1.533		0.093
5	0.013					−0.647	0.010
6	0.093	0.155 *	−0.041				0.637
7	0.092	0.183 *		−0.040			0.659
8	0.100	0.166 *			−1.217		0.689
9	0.083	0.169 *				−0.342	0.633
10	0.011		−0.241 **		−2.566 **	−1.453	0.543
11	0.034			0.006	−2.046	−1.687	0.154
12	0.062		−0.250 **	0.068			0.412
13	0.075		−0.272 *	0.058	−1.988		0.562
14	0.065		−0.250 **	0.068		0.079	0.412
15	0.092	0.200 **	0.035	−0.052			0.662
16	0.096	0.170 **	0.023	−0.041	−1.397		0.730
17	0.073	0.206 **	0.049	−0.058		−0.541	0.669
18	0.036		−0.265 *	0.051	−2.361 ***	−1.156	0.588
19	0.049	0.177 *	−0.004	−0.054	−1.829	−1.411	0.769

Note: Author's calculation. The table reports the estimation results of the Fama-French three-factor model to predict future GDP growth of Pakistan. The MKT, SMB, HML and BC are correspondingly the excess return to the market risk premium, size premium, value premium, and business cycle variables (Treasury bill (TB) and term structure premium (TSP)). *t*-stats are in parenthesis, ***, ** and * are the 10%, 5% and 1% significance level, respectively. The sample period is 2002–2016 (168 monthly observations of risk factors (converted into annual values), and 14 annual observations of GDP growth). Source: the official website of the Pakistan stock exchange (https://www.psx.com.pk/), the official website of the State Bank of Pakistan (http://sbp.org.pk/) and the Asian development bank (https://www.adb.org/data/south-asia-economy).

In a multivariate regression analysis, Table 12 further reports that including Treasury bill, term structure premium or both in the model does not subsume the relevance of the SMB. The market factor has the strongest relevance with the GDP and deteriorates all the other factors. However, inclusion of HML and business cycle variables (TB and TSP) does not eliminate the forecasting of SMB. The evidence in this study suggests that the market factor and SMB possess the information content for one year ahead Pakistan's GDP growth. The negative relation of SMB with future economic growth, presumably, indicates that the investors would rather hold the big capitalization stocks when they notice that the economy is in bad state (low or instable growth).

6. Conclusions

Using monthly data from Pakistan's Karachi stock exchange (KSE) between 2002 and 2016, the article conducts an empirical investigation of the Fama-French's three-factor model. Specifically, this article inspects three different ways (fixed basket, non-financial basket, and variable basket) of constructing size and value factors in order to gauge the effects of the special features in Pakistani stock market. Our main findings are as follows.

First, the findings demonstrate that the formation of the Fama-French factors can have a significant impact in empirical studies that apply the Fama-French models to Pakistani stock returns. We recommend that the risk factors be constructed by including both financial and non-financial companies, where the model explains about 71.23% of the variations in the stock returns on Pakistani market. It is noticed that the average R^2 values of the three-factor model are meaningfully higher than those of the CAPM. Since our sample includes financial firms, an augmented four-factor model that includes term structure premium (TSP) is tested. Although the loadings on TSP are mostly significantly positive, but the relevance of size (SMB), value (HML) and market factors is not deteriorated. The four-factor model does not improve the explanatory power of the model, whilst it increases the significance and the magnitude of the average intercept.

Second, the study explores the ability of the SMB, HML and market factors to predict future growth of the Pakistani economy (GDP). The paper provides evidence of statistically significant and positive relation between future growth of the Pakistani economy and the market factor, which is robust in the presence of SMB, HML and the business cycle variables in the models. Further evidence shows negative and statistically significant relationship between future growth of the Pakistani economy and SMB, whilst the loadings on the HML, T-bill and term structure premium are negative, but statistically insignificant. The market and size factors are robust to the inclusion of the business cycle variables in the model. The negative relation of SMB with future economic growth, presumably, indicate that the investors would rather hold the big capitalization stocks when they notice that the economy is in a bad state (low or instable growth).

Third, the robustness test confirms that the three-factor model captures the time-series variations in stock returns across the three sub-periods (pre-, during-, and post-crises), six risk regimes (portfolios' risk profile), and across three different portfolio construction methodologies (baskets of stocks). However, the significance and coefficients vary over time, across risk-profile of the portfolio, and across portfolio construction methodology. The three-factor model performs better in the post-crises period (2010–2015): (1) the average value for R^2 is the highest, approximately 81.82%; (2) intercepts are statistically insignificant for all the six LHS portfolios; and (3) loadings on the market, SMB and HML factors are mostly significant at 1% level.

By and large, considering the empirical evidence, across the different estimation techniques and methodologies, we find that the size and book-to-market (value) are the factors significantly and consistently exist in the Pakistani equity returns; however, the significance and magnitude of these factors and the three-factor model vary. Most importantly, these factors, except for HML, have relevance with the future growth of the Pakistani economy. Being a small open economy, factors such as foreign investors trading (Ceylan et al. 2015) may have influence on the stock prices and future economic growth of Pakistan. The study of these factors will be worth doing in the future to further understand special characteristics of KSE, Pakistan.

Author Contributions: Fahad Ali and RongRong He contributed to data collection and management, and interpreted the results; YueXiang Jiang contributed to the analysis of the estimation results; Fahad Ali and YueXiang Jiang provided analytical materials and methodological tools; Fahad Ali, RongRong He and YueXiang Jiang wrote the manuscript. All authors read and approved the final manuscript.

Conflicts of Interest: The authors declare no conflict of interest.

Appendix A

Table A1. CAPM regression on monthly excess returns of portfolios formed on size and B/M ratio (fixed basket and non-financial basket).

$R_i - R_f$	α	β	R^2	Adj. R^2
Panel A: Fixed basket				
SL	0.007 (0.985)	0.503 (5.510) *	0.154	0.150
SM	0.008 (1.844) **	0.538 (9.367) *	0.346	0.342
SH	0.021 (3.177) *	0.727 (8.338) *	0.597	0.594
BL	0.005 (1.372)	0.739 (15.667) *	0.597	0.594
BM	0.002 (0.343)	0.881 (15.481) *	0.642	0.640
BH	0.003 (0.567)	0.940 (14.491) *	0.558	0.556
Panel B: Non-financial basket				
SL	0.009 (1.117)	0.661 (6.625) *	0.209	0.204
SM	0.009 (2.017) *	0.549 (9.074) *	0.332	0.328
SH	0.028 (3.770) *	0.792 (8.382) *	0.297	0.293
BL	0.006 (1.541)	0.691 (14.150) *	0.547	0.544
BM	0.002 (0.573)	0.916 (17.188) *	0.640	0.638
BH	0.003 (0.506)	1.154 (15.301) *	0.585	0.583

Note: Author's calculation. The table reports the estimation results of the CAPM (fixed and non-financial basket). Stocks are sorted into six size-B/M portfolios (SL, SM, SH, BL, BM, BH). *t*-stats are in parenthesis, ** and * indicate significance at 5% and 1% level, respectively. The sample period is 2002:01–2015:12 (168 monthly observations). Source: the official website of the Pakistan stock exchange (https://www.psx.com.pk/) and the official website of the State Bank of Pakistan (http://sbp.org.pk/).

Table A2. Three factor regression on monthly excess returns of portfolios formed on size and B/M ratio (subperiods).

$R_i - R_f$	α	β	s	h	R^2	Adj. R^2
Panel A: January 2002 to December 2006 (pre-crises)						
SL	0.002 (0.207)	0.796 (6.462) *	0.815 (4.369) *	−0.114 (−0.838)	0.449	0.420
SM	0.004 (0.687)	0.638 (7.145) *	0.652 (4.822) *	0.401 (4.057) *	0.637	0.618
SH	0.015 (2.226) **	0.695 (7.315) *	0.819 (5.690) *	0.852 (8.112) *	0.763	0.751
BL	0.014 (2.120) **	0.711 (8.054) *	−0.160 (−1.197)	−0.069 (−0.708)	0.658	0.639
BM	0.008 (0.941)	0.607 (5.180) *	−0.391 (−2.203) **	0.244 (1.883) ***	0.601	0.579
BH	0.000 (0.010)	0.812 (6.984) *	−0.164 (−0.930)	0.964 (7.502) *	0.802	0.791
Panel B: January 2007 to December 2010 (crises period)						
SL	−0.014 (−1.609)	1.001 (10.077) *	1.124 (6.863) *	−0.831 (−4.979) *	0.769	0.754
SM	−0.006 (−0.951)	0.804 (10.204) *	0.667 (5.131) *	−0.182 (−1.372)	0.705	0.685
SH	−0.001 (−0.233)	0.895 (13.075) *	1.009 (8.935) *	0.357 (3.106) *	0.816	0.803
BL	−0.002 (−0.379)	0.836 (12.792) *	−0.207 (−1.919) ***	−0.635 (−5.781) *	0.841	0.830
BM	−0.005 (−0.755)	0.923 (12.171) *	0.097 (0.776)	−0.198 (−1.553)	0.805	0.792
BH	−0.014 (−1.904) ***	0.942 (10.630) *	−0.091 (−0.626)	0.177 (1.191)	0.811	0.798
Panel C: January 2011 to December 2015 (post-crises)						
SL	−0.004 (−0.727)	1.152 (10.336) *	1.345 (12.522) *	−0.279 (−3.578) *	0.799	0.788
SM	0.001 (0.185)	0.799 (7.805) *	0.766 (7.755) *	0.206 (2.876) *	0.747	0.733
SH	0.003 (0.925)	1.128 (14.975) *	1.465 (20.171) *	0.825 (15.662) *	0.959	0.957
BL	0.004 (1.019)	0.987 (11.919) *	0.224 (2.809) *	−0.161 (−2.775) *	0.727	0.713
BM	−0.001 (−0.132)	1.080 (13.473) *	0.246 (3.186) *	0.177 (3.149) *	0.836	0.827
BH	−0.003 (−0.586)	1.011 (8.935) *	0.105 (0.963)	0.736 (9.299) *	0.841	0.833

Note: Author's calculation. The table reports the estimation results of the three-factor model. Stocks are sorted into six size-B/M portfolios (SL, SM, SH, BL, BM, BH). *t*-stats are in parenthesis, ***, ** and * indicate significance at 10%, 5% and 1% level, respectively. The sample period is 2002:01–2015:12 (168 monthly observations). Source: the official website of the Pakistan stock exchange (https://www.psx.com.pk/) and the official website of the State Bank of Pakistan (http://sbp.org.pk/).

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Which Liquidity Proxy Measures Liquidity Best in Emerging Markets?

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Abstract: This study empirically investigates the low-frequency liquidity proxies that best measure liquidity in emerging markets. We carry out a comprehensive analysis using tick data that cover 1183 stocks from 21 emerging markets, while also comparing various low-frequency liquidity proxies with high-frequency spread measures and price impact measures. We find that the Lesmond, Ogden, and Trzcinka (*LOT*) measure is the most effective spread proxy in most emerging markets. Among the price impact proxies, the Amihud measure is the most effective.

Keywords: liquidity proxy; emerging market; transaction cost; price impact

JEL Classification: G12; G15; G20

1. Introduction

The importance of liquidity extends far beyond the traditional domain of market microstructure research. There is mounting evidence that liquidity is important in asset pricing. Numerous studies document the pricing of illiquidity, and how it affects stock returns (Amihud and Mendelson 1986; Brennan and Subrahmanyam 1996; Chalmers and Kadlec 1998; Eleswarapu 1997; Amihud 2002), among others. Other studies report that liquidity commonality systematically affects expected returns (Acharya and Pedersen 2005; Pástor and Stambaugh 2003; Sadka 2006). The importance of liquidity is not limited to asset pricing; it is an important factor in corporate finance as well. When the liquidity of a company affects its required return and cost of capital, it has important implications for corporate financial policies. Empirical studies examine how liquidity is linked to capital structure decisions (Lesmond et al. 2008; Lipson and Mortal 2007; Bharath et al. 2009), payout policies (Amihud and Li 2006; Banerjee et al. 2007), information disclosure (Coller and Yohn 1997), and corporate governance (Brockman and Chung 2003).

Most literature on liquidity, including the studies mentioned above, focuses on the markets in the United States (U.S.) or developed markets. However, liquidity may have even greater impacts on emerging markets, as emphasized by Bekaert et al. (2007). Emerging markets are generally characterized by low transparency and limited portfolio choices due to a lack of diversity in available securities (Bekaert et al. 2007). When compared to investors in developed markets, investors in emerging markets tend to be more short-term oriented. Short-term investors are more likely to be concerned about the liquidity of securities. Besides, corporations in emerging markets are characterized by more concentrated ownership than those in developed markets, and they often face severe corporate governance problems. All of these considerations imply that liquidity may have a greater role to play in emerging markets than in developed markets.

While the role of liquidity is instrumental in emerging markets, research on emerging market liquidity is scant at best. This is in contrast to the attention being paid to liquidity in emerging markets lately, due to the dramatic growth of these markets, and the steady global capital market liberalization that has been underway for the past two decades. The primary reason for this lack of research is the paucity of transaction level data on emerging stock markets. To circumvent this problem, some researchers use proxies for liquidity that were obtained from daily return and/or volume data. However, the efficacy of their analysis critically hinges upon the effectiveness of the liquidity proxies that they employ. The most comprehensive study so far regarding the effectiveness of various low-frequency liquidity proxies is by Goyenko et al. (2009).[1]

The study by Goyenko et al. (2009) considers horse races with more than a dozen low-frequency liquidity proxies. It evaluates the correlation between each of the proxies and various benchmark liquidity measures that were retrieved from high-frequency data on the U.S. markets. The study concludes that many low-frequency liquidity measures perform reasonably well, but also adds a caveat by pointing out that the results may not apply to international markets, particularly emerging markets. Goyenko et al. (2009) state, "We do not know whether the measures are effective on international data, especially in relation to those stocks with extremely thin trading" (p. 180).

Our study takes up the analysis of this statement and evaluates whether some popular low-frequency liquidity proxies capture high-frequency liquidity measures effectively in emerging markets, and if they do, which proxy best measures liquidity.

This study is not the first to analyze the effectiveness of low-frequency liquidity proxies in emerging markets. Lesmond (2005) carries out comprehensive stock level comparisons of low-frequency liquidity proxies in 23 emerging markets. Lesmond's (2005) high-frequency liquidity benchmark relies on quarterly recorded quoted spreads. The quoted spread recorded at the end of the day (more specifically, the last day of each quarter) may overstate the average spread in the market because of its well-known U-shaped intraday pattern (McInish and Wood 1992). This problem is exacerbated in the case of small firms and infrequently traded stocks, both of which are common attributes of firms in emerging markets. More importantly, the quoted spread reveals only partial information about liquidity. The quoted spread measures the pre-trade transaction costs (i.e., potential transaction costs) but not the post-trade costs (i.e., actual transaction costs). The actual transaction costs that are borne by investors are measured more accurately by the effective spread, and there is no guarantee that a liquidity proxy that measures the quoted spread best would also measure the effective spread most efficiently. Moreover, extant literature on market microstructure breaks up the spread into post-trade price reversal, and adverse price change—the former being pure immediacy costs and the latter being the loss to the informed, or, simply, price impact.

Understanding these two sources of liquidity costs is of particular importance for emerging markets investors. Since many stocks in emerging markets are traded infrequently, the levels of immediacy costs could be multiple times higher than usually observed in developed markets. Investors in emerging markets could also face substantial information costs because of the lack of transparency in the information environment. Knowledge of the effectiveness of various low-frequency liquidity measures as proxies for different aspects of liquidity costs, such as the effective spread, pure immediacy costs, and price impact, offers invaluable information to emerging market investors.

This paper uses unique and comprehensive tick-by-tick data sets on 1183 stocks from 21 emerging stock markets, spanning four continental regions. The data are electronically fed by the *Bloomberg Terminals* in real time for about three months, and include all quote revisions and transactions at the

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[1] Hasbrouck (2009) also evaluates the effectiveness of transaction costs estimated from daily data using the Bayesian Gibbs sampling approach that he developed (Hasbrouck 2004, 2009).

individual stock level. The comprehensiveness of our data allows us to estimate various intraday measures for transaction costs and the price impact for each trade. We then use these estimates as the benchmarks against which we compare various low-frequency liquidity proxies.

We analyze two groups of benchmark liquidity measures that are calculated using the intraday data. Our classification is motivated by the study of Goyenko et al. (2009). The first group includes spread measures such as effective spread (*ES*), quoted spread (*QS*), and realized spread (*RS*). We call this group the "spread benchmarks." The second group consists of trade induced price impacts, the lambda coefficient *LAMBDA* (Hasbrouck 2009), the five-minute price impact *IMP* (Goyenko et al. 2009), and adverse selection costs *ASC* (Huang and Stoll 1996). This group is called the "price impact benchmarks."

The low-frequency liquidity proxies are all calculated using daily data. Specifically, we select three spread proxies, and three price impact proxies that are relatively easy to calculate, and have been widely used in empirical studies.[2] The three spread proxies include *ROLL* (Roll 1984), *HASB* (Hasbrouck 2009), and *LOT* (Lesmond et al. 1999), while the three price impact proxies include *AMIHUD* (Amihud 2002), *AMIVEST* (Cooper et al. 1985), and *PASTOR* (Pástor and Stambaugh 2003).

To assess the effectiveness of spread proxies, we compare low-frequency spread proxies with high-frequency spread benchmarks. Similarly, to assess the effectiveness of price impact proxies, we compare low-frequency price impact measures with high-frequency price impact benchmarks. We partition 21 emerging markets into four groups (G1 to G4) that are based on the cross-sectional average of the daily turnover of all the stocks within each country. We implement the analysis for each group individually and sort the values by average daily turnover. We consider three measures to examine the effectiveness of liquidity proxies. First, we measure the absolute difference between the median of the liquidity benchmark value and of liquidity proxy from each group. We interpret a smaller difference as evidence of a more effective proxy. Furthermore, we measure the absolute difference between the liquidity benchmark and liquidity proxy at the individual stock level, and we carry out a variety of Wilcoxon rank-sum tests. Second, we calculate the average cross-sectional correlation between a benchmark and a proxy across individual stocks within each group. Third, using regression, we compute the proxy-induced improvement in the coefficient of determination R^2. The regression originally includes only popular determinants of liquidity, such as stock price, firm size, country dummies, and industry dummies. Thereafter, we add liquidity proxies one at a time, and see how much the adjusted R^2 has improved.

When we compare spread benchmarks and spread proxies, all three measures (absolute difference, correlation, and incremental R^2) generate meaningful economic interpretation. This is because three spread proxies (*ROLL*, *HASB*, and *LOT*) measure round-trip trading costs as a percentage of stock price in a similar manner, and can be directly compared with three spread benchmarks (*ES*, *QS*, and *RS*). We can also arrive at meaningful economic interpretations of the second and third measures (correlation and incremental R^2) when we compare the price impact benchmarks and price impact proxies. The first measure, which is absolute difference, is interpreted with care. For example, *LAMBDA* captures the sensitivity of return of the signed squared volume. *IMP* is measured as continuously compounded return. *ASC* is the percentage change of returns. *AMIHUD* captures the average ratio of absolute return to the U.S. dollar trading volume. The inverse of *AMIVEST* is similar to the *AMIHUD* measure. *PASTOR* captures the sensitivity of excess return on the lagged signed U.S. dollar trading volume. Therefore, in our empirical analysis of the price impact benchmark and price impact proxies, the correlation and incremental R^2 measures carry more weight.

In our study, we analyze 21 emerging markets comprising eight stock markets in the Asia Pacific, four in Eastern Europe, six in Latin America, and three in Africa and the Middle East. While many of these markets show similarities in that they have generally low levels of liquidity, lack of transparency,

[2] The selection of proxies is made from the set of low-frequency measures evaluated in Goyenko et al. (2009).

and poor investor protection, they also display substantial dissimilarities in terms of trading rules and systems, legal systems, the degree of market openness, and investor composition. We run cross-sectional regressions to examine what factors influence the effectiveness of the liquidity proxies.

The remaining paper is organized as follows. Section 2 explains various high-frequency liquidity benchmarks and low-frequency liquidity proxies. Section 3 describes the datasets and sample construction, while Section 4 contains the empirical results. Finally, Section 5 concludes the paper.

2. Liquidity Variables

2.1. Liquidity Benchmarks Using High-Frequency Data

2.1.1. Spread Benchmarks

We use three spread benchmarks—the quoted spread (*QS*), the effective spread (*ES*), and the realized spread (*RS*). For easier comparison across different countries, we measure the spread as the percentage of the quote midpoint for all the three spread measures. As discussed in detail below, the three spread measures distinctly represent the different aspects of transaction costs.

The quoted spread at time t is calculated as follows, as the difference between the ask quote and the bid quote at time t, divided by the average of the two quotes.

$$QS_t = (a_t - b_t)/m_i,$$

where a_t and b_t are the posted ask price and bid price, respectively at time t, and m_t is the quote midpoint, or the mean of a_t and b_t.

The quoted spread measures the pre-trade transaction costs. Even when the quoted spread provides important information about transaction costs, it is not necessarily translated into actual transaction costs. For example, in a quote driven market, where market makers intervene in the trading process, transactions are frequently made within the bid and ask price. Even in an order driven market where most trades take place either at the ask or bid price, traders who are wary of transaction costs will avoid trading on a wide bid-ask spread, waiting until the spread narrows sufficiently. This implies that the transaction costs that investors actually bear could be different from the quoted spread.

Thus, the actual transaction costs that are borne by investors are measured better using the effective spread. The effective spread is defined as the absolute value of the difference between the transaction price and the midpoint of the quotes prevailing at the time of the transaction, divided by the midpoint quote. The round-trip effective spread conditional on a trade that takes place at time t is:

$$ES_t = 2D_t(p_t - m_t)/m_t,$$

where p_t is the transaction price at time t, and D_t is an indicator variable that equals one for customer buy orders, and negative one for customer sell orders.

Our third spread benchmark is the realized spread. The realized spread matches the price of a trade with its post-trade true value. More specifically, it is the effective spread net of the price impact of a trade. We calculate the percentage realized spread as:

$$RS_t = 2D_t(p_t - m_{t+\tau})/m_t,$$

where $m_{t+\tau}$ is the midpoint of the bid and ask quotes recorded τ minutes after transaction time t. τ is between 5 and 15 min after the trade. The quote midpoint serves as a proxy for the true economic value of the stock after the trade. This spread measure can be interpreted as compensation to the liquidity providers. In other words, it is the price that the liquidity consumers pay to liquidity providers for their immediacy of consumption.

2.1.2. Price Impact Benchmarks

In this study, we employ three high-frequency price impact measures: Hasbrouck's (2009) λ coefficient (*LAMBDA*), Goyenko et al.'s (2009) five-minute price impact (*IMP*), and Huang and Stoll's (1996) adverse selection costs (*ASC*). Hasbrouck (2009) estimates that, while using a regression of returns, the slope of the price function is measured over five-minute time intervals while considering the aggregate signed square root of the dollar volume during the same intervals. It is measured as the coefficient λ in the following regression model:

$$r_n = \lambda\left[\sum_t sign(volume_{t,n})\sqrt{volume_{t,n}}\right] + \varepsilon_n,$$

where r_n is the return over the nth five-minute interval, $volume_{t,n}$ is the dollar volume of the tth trade during the nth interval, and $sign(volume_{t,n})$ takes the value +1 if the tth transaction is a buy order, and -1 if it is a sell order.

Our next price impact benchmark is the five-minute price impact that was introduced by Goyenko et al. (2009). This measure captures the permanent price change over a five-minute window subsequent to a trade. It measures the change in quote midpoints from the time of the trade to five minutes after the trade.

$$IMP_t = 2D_t[\ln(m_{t+5}) - \log(m_t)],$$

In the above specification, m_t and m_{t+5} are the quote midpoints at t and five minutes after t, respectively.

Our last price impact benchmark is adverse selection costs, as developed by Huang and Stoll (1996). Huang and Stoll (1996) calculate adverse selection costs by subtracting the realized spread from the effective spread. This measure captures the portion of investors' transaction costs attributable to the permanent price change, as follows:

$$ASC_t = ES_t - RS_t = 2D_t(m_{t+\tau} - m_t)/m_t.$$

2.2. Liquidity Proxies from Low-Frequency Data

2.2.1. Spread Proxies

We choose three spread proxies—Roll's (1984) spread (*ROLL*), Hasbrouck's (2009) Gibbs estimate (*HASB*), and Lesmond et al.'s (1999) *LOT* measure. Our choice of the proxies is based on whether the measures are commonly used and are relatively easy to estimate. Roll (1984) develops a spread measure that is based on serial covariance in daily returns. Roll's spread is defined as:

$$ROLL = \begin{cases} 2\sqrt{-COV(r_t, r_{t-1})}, & \text{if } COV(r_t, r_{t-1}) \leq 0, \\ 2\sqrt{COV(r_t, r_{t-1})}, & \text{if } COV(r_t, r_{t-1}) > 0, \end{cases}$$

where COV denotes covariance, and r_t, r_{t-1} are daily returns on day t and $t-1$, respectively. In accordance with the study by Lesmond (2005), we calculate the spread separately depending on the sign of the serial covariance. This is to avoid the problem of a negative serial return covariance, resulting in an undefined spread.[3]

The next proxy we use is a spread estimate that is generated numerically using the Gibbs sampler, a simulation procedure based on the Markov Chain Monte Carlo simulation technique. Hasbrouck (2009)

[3] Roll (1984), and Goyenko et al. (2009) assign 0 to the value of the spread when the covariance is negative.

applies the Bayesian Gibbs sampling method to compute the effective costs of trading based on the following variant of Roll's (1984) model:

$$r_t = c\Delta q_t + \beta_m r_{mt} + \mu_t,$$

where r_t is the change in observed trade prices on day t, Δq_t is the change in trade directions from $t-1$ to t (i.e., $q_t - q_{t-1}$), and r_{mt} is the market return on t. The last term, μ_t, is an innovation in the efficient price m (i.e., $m_t - m_{t-1}$) or the change in the efficient price due to the arrival of new public information. The model has two parameters c and β_m along with latent data on trade direction indicators $q = \{q_1, \ldots, q_T\}$, and efficient prices $m = \{m_1, \ldots, m_T\}$. We use the programs that are available on Hasbrouck's website.[4] The estimated parameter c is the half spread that is implied by the model. Thus, our spread proxy for the round-trip spread is:

$$HASB = 2c.$$

Our third spread proxy is the *LOT* measure developed by Lesmond et al. (1999). The *LOT* measure estimates the effective spread while considering the notion that informed trading takes place only on nonzero return days. The idea behind it is simple. A zero return on a day implies that the accumulated value of information generated during the day is not large enough to justify the transaction costs imposed during the day. Lesmond et al. (1999) assume the market model as the return generating process for informed traders. Specifically, r_t, the observed return of the firm on day t, and, r_t^*, the unobserved true return of the firm on the same day, are given below in the framework of a limited dependent variable model:

$$r_t^* = \beta \times r_{mt} + \varepsilon_t,$$

where

$$r_t = \begin{cases} r_t^* - \alpha_1, & \text{if } r_t^* < \alpha_1 \\ 0, & \text{if } \alpha_1 \leq r_t^* \leq \alpha_2 \\ r_t^* - \alpha_2, & \text{if } r_t^* > \alpha_1. \end{cases},$$

In the above equation, r_{mt} is the market return on day t. ε_t is the random error term representing the public information shock. α_1 and α_2 are the sell-side transaction cost and the buy-side transaction cost, respectively. The round-trip transaction cost for informed traders can be calculated as the gap between α_2 and α_1, as follows:

$$LOT = \alpha_2 - \alpha_1.$$

Given r_t and r_{mt}, parameters, including α_1, α_2, β, and σ can be estimated by maximizing the following log-likelihood function:

$$\begin{aligned} \ln L(\alpha_1, \alpha_2, \beta, \sigma | r_t, r_{mt}) = & \sum_{region=1} \ln \frac{1}{(2\pi\sigma^2)^{1/2}} - \sum_{region=1} \frac{1}{2\sigma^2}(r_t + \alpha_1 - \beta \times r_{mt})^2 + \\ & \sum_{region=2} \ln \frac{1}{(2\pi\sigma^2)^{1/2}} - \sum_{region=1} \frac{1}{2\sigma^2}(r_t + \alpha_2 - \beta \times r_{mt})^2 + \\ & \sum_{region=0} \ln(\Phi_2 - \Phi_1), \end{aligned}$$

where 0, 1, and 2 represent the regions where the measured daily return is zero, nonzero negative, and nonzero positive, respectively. σ is the standard deviation based on nonzero returns. Lastly, Φ_1 and Φ_2 are the standard normal cumulative distribution functions evaluated at Regions 1 and 2, respectively.[5]

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4 Gibbs sampler estimation programs are available at www.stern.nyu.edu/~{}jhasbrou. We draw 2000 times for each Gibbs sampler. Like Hasbrouck (2009), we discard the first 200 draws to "burn in the sampler" (Hasbrouck 2009, p. 1451). Hasbrouck points out that 1000 sweeps are sufficient to produce reliable estimates.

5 Lesmond et al. (1999) also develop measures (ZEROS and ZEROS2) that are similar to, but much simpler than the *LOT* measure, utilizing zero return days. ZEROS and ZEROS2 are based on the rationale that low liquidity and less-informed

2.2.2. Price Impact Proxies

For price impacts, we examine three well-known low-frequency proxies, including the Amihud (2002) measure or *AMIHUD*, the Amivest measure (Cooper et al. 1985) or *AMIVEST*, and the Pástor and Stambaugh (2003) estimate *PASTOR*. *AMIHUD* captures the lack of liquidity by dividing the daily returns by the daily dollar volume. The measure shows the price shock that is triggered by a unit of dollar volume. For a given stock, *AMIHUD* is calculated as

$$AMIHUD = \frac{1}{T}\sum_{t=1}^{T}\frac{|r_t|}{Dollar\ Volume_t},$$

where T is the number of days with trading volume and r_t is the return on day t.

AMIVEST compares the daily returns with daily volume measured as the number of shares:

$$AMIVEST = \frac{1}{T}\sum_{t=1}^{T}\frac{|Share\ Volum|e_t}{|r_t|},$$

where T includes only the days with nonzero returns. The above two measures, even if constructed in a similar manner, differ in several aspects. For example, one uses the dollar volume, while the other uses the share volume. While *AMIHUD* represents illiquidity, *AMIVEST* shows liquidity. Besides, *AMIHUD* does not incorporate the days without trading, which contain important information regarding illiquidity. Although *AMIVEST* does not suffer from this particular limitation, it is limited in that it does not include information from days with a zero return. We use both proxies, since they complement each other.

Our third price impact proxy is a measure that was developed by Pástor and Stambaugh (2003). This measure is obtained after regression of the daily returns in excess of the daily market index returns on signed daily dollar volume. The Pástor and Stambaugh measure is calculated as the coefficient γ, using the following regression model:

$$r_{t+1}^e = \alpha + \beta \times r_t + \gamma \times Sign(r_t^e) \times Volume_t + \varepsilon_t,$$

where r_t and r_t^e are a stock's return and the stock's excess return net of the market index return on day t, respectively. $Sign(r_t^e)$ is the sign of the excess return. $Volume_t$ is the dollar volume on day t. The value of the coefficient γ proxies for the magnitude of the price impact:[6]

$$PASTOR = |\gamma|.$$

3. Data and Sample

This section describes the data sources and the construction of the sample that we use in this study. The data are derived from three different sources. We collect intraday trade and quote data from real time data feeds in the *Bloomberg Terminals*. The tick data contain detailed trade and quote information, including the time of quotes to the nearest second, bid and ask prices, bid and ask sizes, trade price and size in number of shares, as well as the condition codes of the bid and ask quotes. We use various filters to ensure that the trade and quote information that we use is not erroneous or affected by outliers:

(1) Quotes and transactions are used only if they are recorded during the exchange opening hours, and if the quotes or trades have positive prices and positive shares.

trading lead to a zero daily return. The result using ZEROS and ZEROS2 are slightly weaker than the results using the *LOT* measure.

[6] Originally, Pástor and Stambaugh (2003) used the coefficient to measure the liquidity. They anticipated the minus (−) value of the coefficient, where the lower minus value represented the lower liquidity. We take the absolute value to measure the degree of illiquidity in this study. Moreover, we confirm that the latter performs better than the former in the analyses.

(2) Only valid quotes and trades are used, where a valid quote or trade is defined, as follows:

   (a) If a quote is not the first quote of the day, its price should be within the range of 50–150% of its previous quote.
   (b) If a trade is not the first trade of the day, its price should be within the range of 50–150% of the price of the trade prior to it.

(3) To obtain a reliable time series average of the daily average spreads, we impose a condition that there should be at least 20 valid trading days for each stock during the entire investigation window. A valid trading day is a day that has at least one valid quoted spread and one valid effective spread. A valid quoted spread is a spread whose size in currency unit is within 0.2 × (quote midpoint) and a valid effective spread is an effective spread whose size in currency unit is within 0.2 × (quote midpoint in effect at the time of the trade).
(4) For the quoted, effective, and realized spreads, we calculate the daily average spread first (an equal weight average of all spreads, not time weighted), and then calculate the average of these daily spreads over the entire period. For each stock, these average spreads in currency units must be smaller than 10% the time series average of the daily prices during the period.

We also use Standard and Poor's (S&P) Emerging Markets Database (EMDB) for information on emerging markets. We retrieve stock codes, security type codes, market capitalization, and industry sector classification codes from the database. Furthermore, we screen out sample firms by deleting the stocks that experienced stock splits during our sample period, while using the stock split information available from the EMDB database.

We rely on the *Datastream International* (DS) data to retrieve daily returns. Even if the DS data provide daily volume information, we use the *Bloomberg Terminals* tick data as the primary source of information on the daily volume. The reason is as follows. All volume information from the DS data is given in units of 1000 shares. However, a unit of 1000 shares is sometimes too large to accurately capture the daily volumes of many stocks in our sample. This is a result of infrequent trading, wherein only a few hundred shares of these stocks are typically traded per day. The DS data record 0 or 1 in the daily trading volume cells for these firms. This eventually leads to too small a variation in the daily volume to guarantee a reasonable estimation of some of the liquidity proxies that utilize daily volume information.

Initially, we collect the trade and quote information for 2105 firms in 23 countries from the *Bloomberg Terminal* data feed. However, only 1629 of these firms are covered by the EMDB. Furthermore, many of the 1629 firms whose information is available on both the *Bloomberg Terminal* and EMDB are not covered by the DS data. Even if they are covered in the DS data, some liquidity benchmarks or proxy variables cannot be estimated for various reasons. In our sample, we discard any firm that is not fully covered by all three databases, or it does not produce all liquidity benchmarks and proxies. Finally, two markets, Russia and Turkey, are excluded, since the number of the surviving firms is too small to carry out a reasonable intra-country analysis. Our final sample consists of 1183 firms from 21 emerging markets.

Among the above countries, China has the largest sample with 222 stocks, followed by South Korea with 145 stocks. Czech Republic has the smallest number of stocks at only seven. The number of stocks in each country is reported in Table 1. The *Bloomberg Terminal* tick data cover relatively large and liquid firms. This, along with the availability of information from the other data sources, and our restrictive data screening and sample selection procedure, leads to the composition of our final sample of firms. This composition tends to include more liquid firms than average emerging market firms. Nevertheless, even for these more liquid and representative firms, spreads are, in general, substantially higher when compared to the levels that were observed in developed markets.

Table 1. Country-by-Country Summary Statistics. Panel A of Table 1 reports the cross-sectional medians of the spread benchmarks calculated using intraday data, and the spread proxies estimated using daily data. The high-frequency spread benchmarks include the quoted spread *QS*, effective spread *ES*, and realized spread *RS*. The low-frequency spread proxies include *ROLL* (Roll 1984), *HASB* (Hasbrouck 2009), and *LOT* (Lesmond et al. 1999). Panel B of the table reports the cross-sectional medians of price impact benchmarks calculated using intraday data and price impact proxies estimated using daily data. The high-frequency price impact benchmarks include *LAMBDA* (Hasbrouck 2009), *IMP* (Goyenko et al. 2009), and *ASC* (Huang and Stoll 1996). The low-frequency spread proxies include *AMIHUD* (Amihud 2002), *AMIVEST* (Cooper et al. 1985), and *PASTOR* (Pástor and Stambaugh 2003). Panel C of the table reports the cross-sectional median values of firm characteristics (stock price, firm size, turnover, volatility, and investability), and market features (market volatility, legal origin, and trading mechanism). The legal origin takes a value of one if the country's legal system is based on common laws, and is considered zero otherwise. The trading mechanism takes the value of one for a pure limit-order system, and zero for a dealer or a hybrid system. Panel D of the table reports the minimum tick size, whether tick size varies by stock price, currency code, and average month-end exchange rates during our sample period. The sample covers 1183 firms from 21 emerging markets. The sample period is from February to May 2004.

Panel A: Spread Benchmarks and Spread Proxies								
Market			**High-Frequency Spread Benchmark**			**Low-Frequency Spread Proxy**		
Region	**Country**	**N**	***QS* (%)**	***ES* (%)**	***RS* (%)**	***ROLL***	***HASB***	***LOT***
Asia	China	222	0.180	0.177	0.036	1.086	2.239	0.176
	India	101	0.318	0.234	0.103	2.506	2.942	0.001
	Indonesia	43	2.973	1.996	1.036	2.246	3.372	4.075
	South Korea	145	0.301	0.273	0.096	1.539	2.654	0.515
	Malaysia	89	0.929	0.706	0.524	1.324	2.298	1.265
	Philippines	39	2.590	1.760	0.879	1.797	2.995	4.514
	Taiwan	106	0.464	0.463	0.211	1.956	2.841	0.674
	Thailand	57	0.710	0.656	0.262	1.593	2.632	1.030
Eastern Europe	Czech Republic	7	1.672	0.612	0.241	1.526	2.092	0.263
	Greece	63	0.740	0.647	0.238	1.176	2.192	0.554
	Hungary	13	0.916	0.765	0.378	1.691	2.550	0.473
	Poland	26	0.534	0.450	0.229	1.067	2.041	0.602
Latin America	Argentina	12	0.938	0.643	0.141	1.694	1.573	0.527
	Brazil	23	2.471	1.486	0.273	1.830	2.302	0.132
	Chile	35	1.933	1.568	0.583	0.732	1.905	1.333
	Mexico	35	1.053	0.701	0.145	1.076	1.967	0.269
	Peru	18	4.097	2.914	0.591	1.340	2.552	4.297
	Venezuela	11	6.761	4.500	1.211	1.150	3.748	8.635
Others	Egypt	48	2.187	1.479	0.779	1.710	2.535	0.699
	Israel	40	0.429	0.299	0.121	1.068	1.726	0.103
	South Africa	50	0.707	0.560	0.185	1.124	2.062	0.583

Table 1. *Cont.*

Panel B: Price Impact Benchmarks and Price Impact Proxies								
Market			**High-Frequency Price Impact Benchmark**			**Low-Frequency Price Impact Proxy**		
			LAMBDA	*IMP*	*ASC*	*AMIHUD*	*AMIVEST*	*PASTOR*
Asia	China	222	1.216	0.140	0.136	0.140	0.017	0.011
	India	101	1.477	0.177	0.119	0.233	0.027	0.007
	Indonesia	43	0.020	1.180	1.159	0.004	1.166	0.000
	South Korea	145	0.073	0.217	0.185	0.000	4.415	0.000
	Malaysia	89	1.984	0.241	0.182	1.639	0.002	0.070
	Philippines	39	0.438	0.968	0.832	4.292	0.001	0.059
	Taiwan	106	0.321	0.237	0.234	0.009	0.310	0.000
	Thailand	57	0.157	0.420	0.394	0.040	0.038	0.004
Eastern Europe	Czech Republic	7	0.458	0.370	0.311	0.093	0.128	0.002
	Greece	63	12.519	0.459	0.358	10.120	0.000	0.813
	Hungary	13	0.789	0.402	0.194	0.097	0.038	0.002
	Poland	26	2.869	0.293	0.226	1.385	0.002	0.045
Latin America	Argentina	12	5.207	0.530	0.503	3.187	0.001	0.145
	Brazil	23	0.046	1.281	0.954	0.253	0.010	0.020
	Chile	35	0.053	0.694	0.564	0.013	1.017	0.000
	Mexico	35	0.807	0.561	0.468	0.146	0.031	0.010
	Peru	18	11.545	1.703	1.712	31.924	0.000	0.893
	Venezuela	11	1.887	2.493	2.293	0.267	0.014	0.007
Others	Egypt	48	4.924	0.534	0.487	7.518	0.000	0.512
	Israel	40	0.140	0.266	0.162	0.366	0.009	0.015
	South Africa	50	0.054	0.382	0.340	0.231	0.030	0.008

Table 1. *Cont.*

Panel C: Firm and Market Characteristics									
Market		**Stock Price ($)**	**Firm Size ($ Million)**	**Turnover**	**Volatility**	**Investability**	**Market Volatility**	**Legal Origin**	**Trading Mechanism**
Asia	China	0.89	571	0.343	0.018	0.000	1.147	0	1
	India	5.70	719	0.123	0.032	0.490	2.210	1	1
	Indonesia	0.07	166	0.168	0.026	0.000	1.742	0	1
	South Korea	13.63	676	0.663	0.022	0.837	1.690	0	1
	Malaysia	1.04	496	0.101	0.014	0.503	0.890	1	1
	Philippines	0.28	228	0.024	0.018	0.000	1.155	0	1
	Taiwan	0.78	1521	0.840	0.025	0.707	1.951	0	1
	Thailand	0.40	507	0.296	0.023	0.435	1.933	1	1
Eastern Europe	Czech Republic	15.09	2658	0.218	0.019	0.569	1.133	0	0
	Greece	7.46	622	0.142	0.020	0.759	1.079	0	1
	Hungary	18.13	289	0.241	0.015	0.000	1.342	0	0
	Poland	13.94	656	0.147	0.014	0.684	1.124	0	1
Latin America	Argentina	1.18	427	0.048	0.020	0.000	2.561	0	0
	Brazil	0.93	949	0.126	0.023	0.923	2.211	0	0
	Chile	1.90	986	0.047	0.014	0.643	0.634	0	1
	Mexico	1.97	1612	0.110	0.016	0.718	1.184	0	1
	Peru	0.56	181	0.039	0.027	0.000	0.983	0	0
	Venezuela	0.26	189	0.005	0.021	0.000	0.906	0	1
Others	Egypt	2.97	86	0.121	0.022	0.000	0.602	0	1
	Israel	10.58	698	0.243	0.014	0.663	0.904	1	1
	South Africa	3.48	909	0.166	0.014	0.877	1.007	1	1

Table 1. *Cont.*

Panel D: Minimum Tick Size and Foreign Exchange Rates						
Market		**Minimum Tick in Local Currency**	**Minimum Tick in US Currency (Cents)**	**Tick Size Varies by Stock Price**	**Local Currency**	**Exchange Rate (Local Currency/USD)**
Asia	China	0.01	0.1208	No	CNY	8.28
	India	0.01/0.05	0.0224/0.1120	Yes	INR	44.63
	Indonesia	1	0.0114	Yes	IDR	8768.88
	South Korea	1	0.0858	Yes	KRW	1165.19
	Malaysia	0.005	0.1316	Yes	MYR	3.80
	Philippines	0.0001	0.0002	Yes	PHP	56.10
	Taiwan	0.01	0.0301	Yes	TWD	33.21
	Thailand	0.01	0.0251	Yes	THB	39.79
Eastern Europe	Czech Republic	0.01	0.0377	Yes	CZK	26.50
	Greece	0.001	0.1220	Yes	EUR	0.82
	Hungary	1	0.4852	Yes	HUF	206.12
	Poland	0.01	0.2564	Yes	PLN	3.90
Latin America	Argentina	0.001	0.0345	Yes	ARS	2.90
	Brazil	0.01	0.3367	No	BRL	2.97
	Chile	0.001	0.0002	Yes	CLP	616.77
	Mexico	0.001	0.0089	Yes	MXN	11.26
	Peru	0.001	0.0288	Yes	PEN	3.48
	Venezuela	0.01	0.0004	No	VEF	3067.58
Others	Egypt	0.01	0.1616	No	EGP	6.19
	Israel	0.01	0.2203	Yes	ILS	4.54
	South Africa	1	15.1286	No	ZAR	6.61

Our data spans approximately three months from February to May 2004. However, the data periods for each country do not exactly match. For most countries, the starting date is one of 25, 26, or 27 February, while the ending date is one of 3, 4, or 5 May. The number of trading days ranges from approximately 46 to 51 for most countries.

All variables are measured in terms of U.S. dollars. We obtain exchange rates from Factset. During our sample period from February to May 2004, the changes in exchange rates are small. The maximum and minimum in average monthly exchange rate returns from the 21 emerging markets are 1.97% for the Indian Rupee and −0.44% for the Korean Won, respectively.

Our study focuses on the cross-sectional relation between high-frequency liquidity benchmarks and low-frequency liquidity proxies. Existing studies on the U.S. equity markets demonstrate that the cross-sectional patterns of forecasting errors and the correlation between various liquidity proxies have been stable over time (Chung and Zhang 2014; Abdi and Ranaldo 2017). The results from these two studies clearly indicate that the cross-sectional pattern of the effectiveness of liquidity proxies is time invariant. Therefore, we believe that, despite the limitation in our sample period, our analysis still gives valid and valuable information to researchers and practitioners.

4. Empirical Results

4.1. Spread Benchmarks and Spread Proxies

4.1.1. Spread Benchmarks and Spread Proxies

Panel A of Table 1 presents the median spread benchmarks and median spread proxies for each of the 21 emerging markets in our sample. The reported quoted spread displays rich cross-country variation. For example, Venezuela has the highest median quoted spread at 6.76%, while China has the lowest median quoted spread at 0.18%. In fact, for many countries, the median quoted spreads are substantial, reaching as high as 3%. Meanwhile, not all emerging markets have large transaction costs. There are a number of markets with substantially low spreads. While South Korea has the second largest number of sample stocks, its median quoted spread is only 0.30%. Spreads are generally higher in South America than in other regions.

The median quoted spreads that are shown in Table 1 are significantly smaller than those reported by Lesmond (2005). There are two possible reasons for this substantial difference. First, quoted spreads that are reported in Lesmond's study are based on daily closing quotes, which could overstate the median quoted spread level during the day. The median quoted spreads in our sample are all complied from intraday quotes. Second, our stringent requirements in the sampling and the data filtering process may exclude many firms with extremely large spreads.

The effective spread also exhibits rich cross-sectional dispersion across markets. As expected, a substantial gap exists between the quoted spread and the effective spread for most countries. Furthermore, the proportion of the effective spread to the quoted spread differs dramatically from country to country. In the case of the Czech Republic, the effective spread is slightly more than one-third, or 37% (0.612%/1.672%) of the quoted spread. China is at the other extreme, with an effective spread to quoted spread ratio of 98% (0.177%/0.180%). The median proportion for the whole sample is 76%, which indicates that, in general, post-trade transaction costs are significantly smaller than pre-trade transaction costs. The realized spread also displays an interesting cross-country distribution. The realized spread is interpreted as the proportion of the effective spread attributable to the cost of immediacy. The proportion of the realized spread in the effective spread also shows large variations, ranging from 11% (0.273%/2.471%) for Brazil to 56% (0.524%/0.929%) for Malaysia.

Panel A of Table 1 also reports the medians of the three low-frequency proxies of the spreads. Among the three proxies, *ROLL* and *HASB* display the least amount of cross-country dispersion. Both measures are generally between 1% and 2% for most countries. This is in contrast to the rich cross-country dispersion in the effective spread, in which both measures are intended proxies. The *LOT* measure displays greater variation. For example, the median *LOT* measure for Venezuela (8.64) is much larger than the median *LOT* measure for China (0.18). While the magnitudes of the proxies differ significantly from market to market, they show some consistency in that countries with a larger *ROLL* measure also have generally larger *HASB* and *LOT* measures.

4.1.2. Price Impact Benchmarks and Price Impact Proxies

Now, we turn to the summary statistics for price impact benchmarks and price impact proxies. Panel B of Table 1 shows the medians of both high-frequency benchmarks (*LAMBDA*, *IMP*, and *ASC*) and low-frequency proxies (*AMIHUD*, $1/AMIVEST$, and *PASTOR*). Rich cross-country dispersion is evident in the price impact benchmarks. *IMP* and *ASC* are quite similar in magnitude, while *LAMBDA* is somewhat different from *IMP* and *ASC*. Greece has the largest *LAMBDA* with a value of 12.52. Venezuela has the largest *IMP* at 2.49 and the largest *ASC* at 2.29. The larger the price impact measures, the more illiquid the market is.

With respect to price impact proxies, Peru has the largest *AMIHUD* at 31.92. A larger value of *AMIHUD* indicates greater illiquidity. It does not take much volume to move the stock price and generate large returns. On the other hand, *AMIVEST* measures liquidity. South Korea has the highest *AMIVEST* at 4.42, and the lowest *AMIHUD* value at 0.00. This indicates that South Korea is the most liquid market among the 21 countries in our sample. A high *PASTOR* value indicates illiquidity. Peru has the highest *PASTOR* value at 0.89. While Pástor and Stambaugh (2003) warn against using their measure for individual stocks, the *PASTOR* measure is constructed keeping in mind liquidity at the portfolio level.

4.1.3. Firm Characteristics, Market Features, Minimum Tick Size, and Foreign Exchange Rate

Panel C of Table 1 reports the cross-sectional median values of firm characteristics (stock price, firm size, turnover, volatility, and investability), and market features (market volatility, legal origin, and trading mechanism). The legal origin takes a value of one if the country's legal system is based on common laws or it is zero otherwise. The trading mechanism takes the value one for a pure limit-order system, and zero for a dealer or a hybrid system. Panel D of Table 1 reports the minimum tick size, whether tick size varies by stock price, currency code, and the average month-end exchange rates during our sample period.

4.2. The Best Liquidity Proxies

4.2.1. The Best Spread Proxies

In this section, we examine which liquidity proxies act as the best proxies for liquidity benchmarks. We first partition all countries four groups (G1 to G4) based on the average daily turnover of each country.[7] G1, which has the highest turnover, includes China, South Korea, Taiwan, and Thailand. G2 includes Brazil, Hungary, Indonesia, Israel, Mexico, and Poland. G3 includes Argentina, Czech Republic, Egypt, Greece, India, Malaysia, and South Africa. G4, which has the lowest turnover, includes Chile, Peru, Philippines, and Venezuela. The number of stocks in each group are 530, 180, 370, and 103, respectively.

To examine which among *ROLL*, *HASB*, and *LOT* more accurately proxy spread benchmarks (*ES*, *QS*, and *RS*), we calculate a minimum gap measure, which is the smallest absolute difference between the median spread proxy and median spread benchmark.

$$GAP_{ROLL} = |Median\,(ROLL_i) - Median\,(Benchmark_i)|,$$

$$GAP_{HASB} = |Median\,(HASB_i) - Median\,(Benchmark_i)|,$$

$$GAP_{LOT} = |Median\,(LOT_i) - Median\,(Benchmark_i)|,$$

[7] Turnover is calculated as the daily average number of traded shares divided by market capitalization.

where the median is calculated using sample stocks in each group, for example, $i = 1, 2, \ldots, 530$ for the G1 group. The results are reported in Panel A of Table 2 under the headings *ROLL*, *HASB*, and *LOT*. For each group, the spread proxy that has the smallest gap is indicated by **. The three proxies exhibit stark differences in their effectiveness. The *LOT* measure is by far the most effective one, dominating the other two proxies in three out of the four groups when the spread benchmark is *ES*. Furthermore, *LOT* dominates the other two proxies in two out of the four groups when the spread benchmark is *QS*, and in three out of the four groups when the spread benchmark is *RS*. Thus, it appears that *LOT* is more effective, particularly in active and liquid markets from Groups G1 to G3.

Table 2. The Best Spread Proxies and Price Impact Proxies of Countries sorted by Turnover. All countries are partitioned into four groups (G1 to G4) based on the average daily turnover of each country. G1, which has the highest turnover, includes China, South Korea, Taiwan, and Thailand. G2 includes Brazil, Hungary, Indonesia, Israel, Mexico, and Poland. While G3 includes Argentina, Czech Republic, Egypt, Greece, India, Malaysia, and South Africa, G4, which has the lowest turnover, incudes Chile, Peru, Philippines, and Venezuela. Panel A of the table reports the cross-sectional medians of spread benchmarks and spread proxies. Spread benchmarks include *QS*, *ES*, and *RS*. Spread proxies include *ROLL*, *HASB*, and *LOT*. Panel B of the table reports the cross-sectional medians of price impact benchmarks, and price impact proxies. Price impact benchmarks include *LAMBDA*, *IMP*, and *ASC*. Price impact proxies include *AMIHUD*, the inverse of *AMIVEST*, and *PASTOR*. The median spread (price impact) proxy that best approximates the median spread (price impact) benchmark in each group is indicated by **. In Panel A for example, the gap $GAP_{LOT} = |Median\ (LOT_i) - Median\ (ES_i)|$ is smallest in G1. Furthermore, in Panel B, the gap $GAP_{AMIHUD} = |Median\ (AMIHUD_i) - Median\ (LAMBDA_i)|$ is smallest in G1. The sample covers 1183 firms from 21 emerging markets. The sample period is from February to May 2004.

Panel A: Spread Benchmarks and Spread Proxies				
Group	***ES* (%)**	***ROLL***	***HASB***	***LOT***
G1	0.274	1.380	2.490	0.396 **
G2	0.760	1.423	2.204	0.454 **
G3	0.599	1.532	2.422	0.522 **
G4	1.909	1.210	2.492 **	3.368
	QS (%)			
G1	0.297	1.380	2.490	0.396 **
G2	1.074	0.423 **	2.204	0.454
G3	0.792	1.532	2.422	0.522 **
G4	2.620	1.210	2.492 **	3.368
	RS (%)			
G1	0.096	1.380	2.490	0.396 **
G2	0.263	1.423	2.204	0.454 **
G3	0.313	1.532	2.422	0.522 **
G4	0.783	1.210 **	2.492	3.368
Panel B: Price Impact Benchmarks and Price Impact Proxies				
Group	***LAMBDA***	***AMIHUD***	***1/AMIVEST***	***PASTOR***
G1	0.365	0.029 **	0.010	0.002
G2	0.184	0.213 **	0.046	0.007
G3	2.087	1.135 **	0.336	0.054
G4	0.268	0.404	0.225 **	0.008
	IMP			
G1	0.191	0.029 **	0.010	0.002
G2	0.560	0.213 **	0.046	0.007
G3	0.277	1.135	0.336 **	0.054
G4	0.955	0.404 **	0.225	0.008
	ASC			
G1	0.179	0.029 **	0.010	0.002
G2	0.390	0.213 **	0.046	0.007
G3	0.224	1.135	0.336 **	0.054
G4	0.832	0.404 **	0.225	0.008

Now, we repeat the analysis and calculate GAP_{ROLL}, GAP_{HASB}, and GAP_{LOT} for each of the 21 emerging markets. Figure 1 plots the dominating proxy against the average daily turnover in each market. If *LOT* dominates the other proxies in a specific market, then the market is plotted with a circle symbol (●) on the upper parallel line. If *ROLL* is dominant in a market, then the market is plotted with a triangular delta symbol (▲) on the middle parallel line. If *HASB* is dominant, then the market is plotted with a diamond symbol (⧫) on the bottom parallel line. For example, South Korea, which has a daily turnover of 1.24, the highest among the countries in the sample, and, at the same time, has *LOT* as the dominating proxy, is plotted as a circle to the far right on the upper parallel line. The pattern in Figure 1 clearly indicates that *LOT* is the best proxy for effective spread *ES* in 14 out 21 emerging markets. Our unreported results indicate that *LOT* is the best proxy for quoted spread *QS* and realized spread RS in 14 and 16 out of 21 emerging markets, respectively.

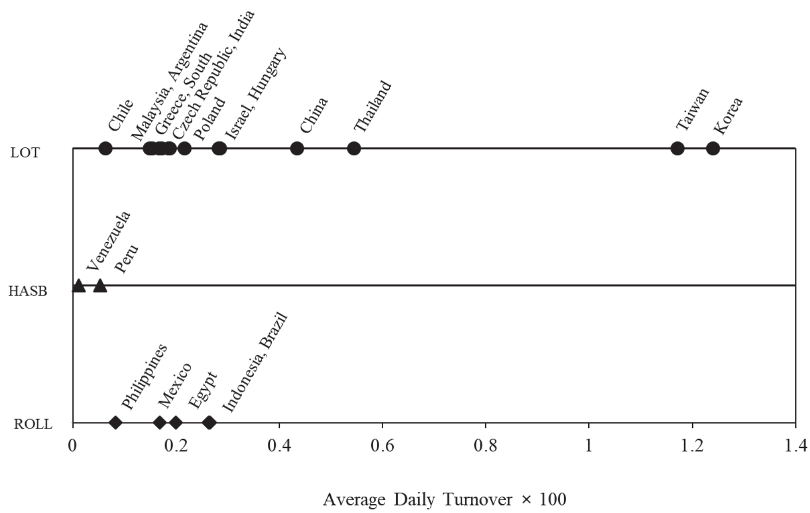

Figure 1. Turnover and the Best Proxy for Effective Spread in each Country. This figure plots the best proxy for the effective spread in each of the 21 emerging markets against the average daily turnover of the market. The spread proxies include *ROLL*, *HASB*, and *LOT*. The effectiveness, or minimum gap, is measured as the absolute difference in median values between the proxy, and the effective spread. $GAP_{ROLL} = |Median\ (ROLL_i) - Median\ (ES_i)|$, $GAP_{HASB} = |Median\ (HASB_i) - Median\ (ES_i)|$, and $GAP_{LOT} = |Median\ (LOT_i) - Median\ (ES_i)|$, where the median is calculated from sample stocks indexed by subscript *i* in each country.

Figure 1 also suggests that *LOT* is more accurate in markets with the highest turnover. For each of the four markets in Group G1, i.e., China, Korea, Taiwan, and Thailand, with the highest turnover, *LOT* is the dominating proxy for ES. The number of stocks in G1 is 530. This accounts for 45% of the total sample of 1183 stocks. *ROLL* is the dominating proxy for *ES* in Venezuela and Peru, while *HASB* is the dominating proxy for *ES* in Philippines, Mexico, Egypt, Indonesia, and Brazil.

4.2.2. The Best Price Impact Proxies

To examine which among *AMIHUD*, 1/*AMIVEST*, and *PASTOR* is a more accurate proxy for price impact benchmarks (*LAMBDA*, *IMP*, and *ASC*), we also calculate the following minimum gap measures:

$$GAP_{AMIHUD} = |Median\left(AMIHUD_i\right) - Median\left(Benchmark_i\right)|,$$

$$GAP_{1/AMIVEST} = |Median\left(1/AMIVEST_i\right) - Median\left(Benchmark_i\right)|,$$

$$GAP_{PASTOR} = |Median\left(PASTOR_i\right) - Median\left(Benchmark_i\right)|,$$

where the median is calculated using sample stocks in each group. The results are reported in Panel B of Table 2 under the headings *AMIHUD*, 1/*AMIVEST*, and *PASTOR*. Here, notice that we use the inverse of *AMIVEST* because this has a positive correlation with *AMIHUD*. For each group, the price impact proxy that has the smallest gap is indicated by **. The pattern is clear. *AMIHUD* is by far the most effective measure, dominating the other two proxies in three out of the four groups, when the price impact benchmark is *LAMBDA*. *AMIHUD* also dominates the other two proxies in three out of the four groups when the price impact measures are *IMP* and *ASC*, respectively.

Similarly, we repeat the analysis and calculate GAP_{AMIHUD}, $GAP_{1/AMIVEST}$, and GAP_{PASTOR} for each of the 21 emerging markets. Figure 2 plots the dominating proxy against the average daily turnover in each market. If *PASTOR* dominates the other proxies in a specific market, then the market is plotted with a circle symbol (●) on the upper parallel line. If 1/*AMIVEST* is dominant in a market, then the market is plotted with a triangular delta (▲) on the middle parallel line. If *AMIHUD* is dominant, then the market is plotted with a diamond symbol (⧫) on the bottom parallel line. For example, South Korea, which has a daily turnover of 1.24, the highest among the countries in the sample, and, at the same time, has *AMIHUD* as the dominating proxy, is plotted with a circle to the far right on the lower parallel line. The pattern in Figure 2 clearly indicates that *AMIHUD* is the best proxy for the price impact benchmark *LAMBDA* in 16 out 21 emerging markets. Our unreported results indicate that *AMIHUD* is the best proxy for *IMP* and *ASC* in 14 and 12 out of 21 emerging markets, respectively.

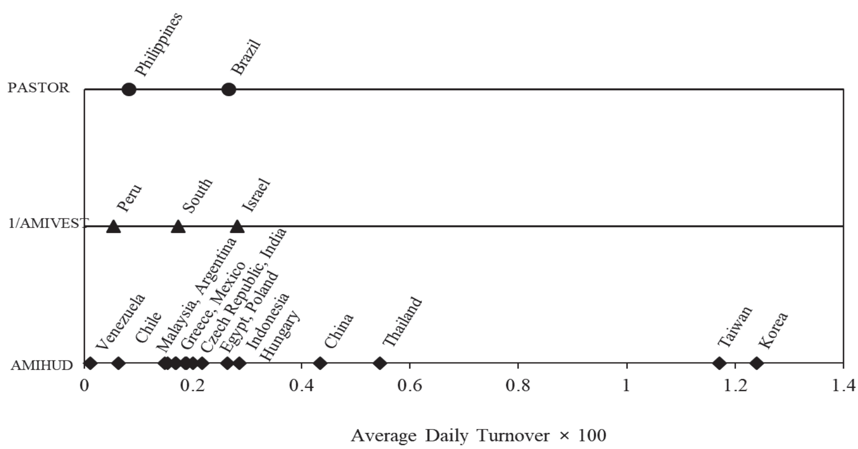

Figure 2. Turnover and the Best Proxy for Price Impact *LAMBDA* in each Country. This figure plots the best proxy for the price impact *LAMBDA* in each of the 21 emerging markets against the average daily turnover of the market. The price impact proxies include *AMIHUD*, 1/*AMIVEST*, and *PASTOR*. The effectiveness, or minimum gap, is measured as the absolute difference in median values between the proxy, and the price impact *LAMBDA*. $GAP_{AMIHUD} = |Median\ (AMIHUD_i) - Median\ (LAMBDA_i)|$, $GAP_{1/AMIVEST} = |Median\ (1/AMIVEST_i) - Median\ (LAMBDA_i)|$, and $GAP_{PASTOR} = |Median\ (PASTOR_i) - Median\ (LAMBDA_i)|$, where the median is calculated from sample stocks indexed by subscript *i* in each country.

Figure 2 also suggests that *AMIHUD* is more accurate in markets with the highest turnover. For each of the four markets in Group G1, i.e., China, Korea, Taiwan, and Thailand, with the highest turnover, *AMIHUD* is the dominating proxy for *LAMBDA*.

4.3. Wilcoxon Rank-Sum Tests for the Effectiveness of Liquidity Proxies

4.3.1. Effectiveness of Spread Proxies

An analysis of the accuracy of the spread proxies in Figures 1 and 2 is descriptive, without any formal statistical test. To see whether the pattern that is described above is statistically discernible, we calculate the absolute difference (*MERR*) between the spread proxies (*ROLL*, *HASB*, and *LOT*), and spread benchmarks (*ES*, *QS*, and *RS*) for each stock i, as follows:

$$MERR_{ROLL,i} = |ROLL_i - Benchmark_i|,$$

$$MERR_{HASB,i} = |HASB_i - Benchmark_i|,$$

$$MERR_{LOT,i} = |LOT_i - Benchmark_i|.$$

MERR is similar to the *GAP* measure introduced earlier except that, for each group from G1 to G4, *GAP* calculates the difference in cross-sectional medians between a spread proxy and a spread benchmark, while *MERR* calculates the difference for each individual stock.

Panel A of Table 3 displays the median *MERR* for each stock group partitioned by turnover. The results are generally consistent with those that are displayed in Panel A of Table 2 and Figure 1. LOT is the most accurate proxy for *ES*, *QS*, and *RS*. For example, in the top section of Panel A where the spread benchmark is *ES*, and the turnover is the highest (G1), the median $|LOT_i - ES_i|$ is 0.181%. The median $|ROLL_i - ES_i|$, and $|HASB_i - ES_i|$ are 1.029% and 2.193%, respectively. We implement the Wilcoxon rank-sum test to see if the median $|ROLL_i - ES_i|$, and the median $|LOT_i - ES_i|$ are statistically different. The result indicates that the difference between 1.029% and 0.181% is highly significant. A significance level of *** is assigned to the corresponding number corresponding number in the $|ROLL_i - ES_i|$ column. The median $|HASB_i - ES_i|$ of 2.193% and the median $|LOT_i - ES_i|$ of 0.181% are also statistically different. A significance level of *** is assigned to the corresponding number in the $|HASB_i - ES_i|$ column.

Table 3. Measurement Errors of Spread Proxies and Price Impact Proxies of Countries sorted by Turnover. All countries are partitioned into four groups (G1 to G4) based on the average daily turnover of each country. Panel A of the table reports the median values of the measurement error (*MERR*) between the spread benchmarks (*ES*, *QS*, and *RS*), and spread proxies (*ROLL*, *HASB*, and *LOT*), respectively. For example, $MERR_{ROLL,i} = |ROLL_i - ES_i|$. Panel A then implements the Wilcoxon rank-sum tests for equality between (i) the median $|ROLL_i - ES_i|$ and median $|LOT_i - ES_i|$, and (ii) the median $|HASB_i - ES_i|$ and median $|LOT_i - ES_i|$. The significance levels are assigned to the $|ROLL_i - ES_i|$ and $|HASB_i - ES_i|$ columns, respectively. Panel B reports the measurement error between the price impact benchmarks (*LAMBDA*, *IMP*, and *ASC*), and price impact proxies (*AMIHUD*, 1/*AMIVEST*, and *PASTOR*), respectively. For example, $MERR_{AMIHUD,i} = |AMIHUD_i - LAMBDA_i|$. Panel B also implements the Wilcoxon rank-sum tests for equality between (i) the median $|AMIHUD_i - LAMBDA_i|$ and median $|1/AMIVEST_i - LAMBDA_i|$, and (ii) the median $|AMIHUD_i - LAMBDA_i|$ and median $|PASTOR_i - LAMBDA_i|$. The significance levels are assigned to the $|1/AMIVEST_i - LAMBDA_i|$ and $|PASTOR_i - LAMBDA_i|$ columns, respectively. The sample covers 1183 firms from 21 emerging markets. The sample period is from February to May 2004. *, **, and *** represent statistical significance at 10%, 5%, and 1%, respectively.

Panel A: Spread Proxies			
Group	**Median Measurement Error**		
	$\lvert ROLL_i - ES_i\rvert$	$\lvert HASB_i - ES_i\rvert$	$\lvert LOT_i - ES_i\rvert$
G1	1.029 ***	2.193 ***	0.181
G2	0.811 ***	1.316 ***	0.464
G3	0.877 ***	1.673 ***	0.300
G4	1.008 **	1.195 ***	1.604

Table 3. *Cont.*

Panel A: Spread Proxies			
Group	**Median Measurement Error**		
	$\mid ROLL_i - QS_i \mid$	$\mid HASB_i - QS_i \mid$	$\mid LOT_i - QS_i \mid$
G1	1.003 ***	2.165 ***	0.181
G2	0.892 *	1.162 ***	0.656
G3	0.752 ***	1.545 ***	0.399
G4	1.760	1.199	1.442
	$\mid ROLL_i - RS_i \mid$	$\mid HASB_i - RS_i \mid$	$\mid LOT_i - RS_i \mid$
G1	1.273 ***	2.388 ***	0.290
G2	1.066 ***	1.839 ***	0.256
G3	1.149 ***	1.997 ***	0.328
G4	0.921 ***	1.793 **	2.398
Panel B: Price Impact Proxies			
Group	**Median Measurement Error**		
	$\mid AMIHUD_i - LAMBDA_i \mid$	$\mid 1/AMIVEST_i - LAMBDA_i \mid$	$\mid PASTOR_i - LAMBDA_i \mid$
G1	0.326	0.360	0.366
G2	0.355	0.188 *	0.145 *
G3	1.515	1.645	2.028
G4	0.957	0.740	0.682
	$\mid AMIHUD_i - IMP_i \mid$	$\mid 1/AMIVEST_i - IMP_i \mid$	$\mid PASTOR_i - IMP_i \mid$
G1	0.184	0.171	0.185 **
G2	0.598	0.522	0.524
G3	0.847	0.265 ***	0.230 ***
G4	1.902	0.953	0.928 ***
	$\mid AMIHUD_i - ASC_i \mid$	$\mid 1/AMIVEST_i - ASC_i \mid$	$\mid PASTOR_i - ASC_i \mid$
G1	0.170	0.156	0.171 *
G2	0.546	0.423 **	0.372 ***
G3	0.878	0.265 ***	0.183 ***
G4	1.702	0.874	0.784 ***

4.3.2. Effectiveness of Price Impact Proxies

Now, we calculate the absolute difference (*MERR*) between the price impact proxies (*AMIHUD*, 1/*AMIVEST*, and *PASTOR*), and price impact benchmarks (*LAMBDA*, *IMP*, and *ASC*) for each stock *i*, as follows:

$$MERR_{AMIHUD,i} = |AMIHUD_i - Benchmark_i|,$$
$$MERR_{1/AMIVEST,i} = |1/AMIVEST_i - Benchmark_i|,$$
$$MERR_{PASTOR,i} = |PASTOR_i - Benchmark_i|.$$

Panel B of Table 3 displays the median *MERR* for each stock group partitioned by turnover. The results are notably different from those displayed in Panel B of Table 2 and Figure 2, wherein *AMIHUD* is the dominating proxy for the price impact benchmarks *LAMBDA*, *IMP*, and *ASC*. When we examine the effectiveness of the price impact proxies at the individual stock level, there is no clear winner, when the price impact benchmark is *LAMBDA* in the top section of Panel B. However, there is some evidence that when the price impact benchmark is either *IMP* or *ASC*, *PASTOR* turns out to be the winner for less liquid markets in G3 and G4. We conjecture that the results might be driven by larger dispersion in price impact proxy measures, as compared to the results for spread proxy measures. We examine this issue further when we analyze the correlation structure and conduct regression analysis.

4.4. Correlation Analysis

In this section, we examine the cross-sectional correlations between the spread benchmarks and the spread proxies. The correlation is calculated across firms in each country group for each pair of spread benchmark and spread proxy. The correlations with both a predicted sign and statistical significance at the 5% level are indicated with **. In addition, if the correlation is greater than 0.50, it is further indicated with a bold color. We consider that, even if somewhat arbitrary, a correlation of 0.50 or greater is a good indication that the proxy captures the benchmark reasonably well.

Panel A of Table 4 reports the pairwise correlation between the spread proxies (*ROLL*, *HASB*, and *LOT*), and the spread benchmarks (*ES*, *QS*, and *RS*) for each stock group from G1 to G4. It is clear that *LOT* dominates both *ROLL* and *HASB*. The correlation between *ROLL* and the spread benchmarks are in general between 0.20 and 0.40. The same conclusion can be drawn for *HASB*, except in Group G2.[8] The correlation between *LOT* and the spread benchmarks are much higher. In general, the correlations are between 0.50 and 0.80 for all four stock groups from G1 to G4. In the unreported results, we repeat the correlation analysis on a country-by-country basis. Overall, the results confirm that the *LOT* measure tends to do better than either *ROLL* or *HASB*. The evidence from the correlation structure is consistent with that based on measurement error at the individual stock level from Panel A of Table 3.

Table 4. Cross-Sectional Correlations between Liquidity Benchmarks and Liquidity Proxies. All countries are partitioned into four groups (G1 to G4) based on the average daily turnover of each country. Panel A of the table reports the Spearman cross-sectional correlations between spread benchmarks (*ES*, *QS*, and *RS*), and spread proxies (*ROLL*, *HASB*, and *LOT*). Panel B reports the Spearman cross-sectional correlations between price impact benchmarks (*LAMBDA*, *IMP*, and *ASC*), and price impact proxies (*AMIHUD*, 1/*AMIVEST*, and *PASTOR*). Among the spread proxies that have a significant correlation, the ones larger than 0.50 are in bold. The sample covers 1183 firms from 21 emerging markets. The sample period is from February to May 2004. ** indicates statistical significance at the 5% level.

Panel A: Correlation between Spread and Spread Proxies				
	Spread	**Spread Proxy**		
	Benchmark	***ROLL***	***HASB***	***LOT***
G1	*ES*	0.274 **	0.255 **	**0.582** **
	QS	0.265 **	0.246 **	**0.575** **
	RS	0.210 **	0.118 **	**0.544** **
G2	*ES*	0.351 **	**0.609** **	**0.622** **
	QS	0.311 **	**0.578** **	**0.576** **
	RS	0.260 **	**0.503** **	**0.691** **
G3	*ES*	−0.081	0.062	**0.636** **
	QS	−0.077	0.054	**0.551** **
	RS	−0.084	0.055	**0.620** **
G4	*ES*	0.261 **	0.449 **	**0.818** **
	QS	0.258 **	0.438 **	**0.802** **
	RS	0.060	0.211 **	**0.457** **
Panel B: Correlation between Price Impact and Price Impact Proxies				
	Price Impact	**Price Impact Proxy**		
	Benchmark	***AMIHUD***	***1/AMIVEST***	***PASTOR***
G1	*LAMBDA*	**0.800** **	**0.787** **	**0.713** **
	IMP	−0.113	−0.115	−0.168 **
	ASC	−0.079	−0.080	−0.137 **
G2	*LAMBDA*	**0.606** **	**0.633** **	**0.550** **
	IMP	0.069	0.006	−0.026
	ASC	−0.049	−0.090	−0.098
G3	*LAMBDA*	**0.715** **	**0.759** **	**0.716** **
	IMP	**0.705** **	**0.613** **	**0.583** **
	ASC	**0.636** **	**0.563** **	**0.534** **
G4	*LAMBDA*	0.487 **	0.490 **	**0.504** **
	IMP	**0.510** **	0.475 **	0.467 **
	ASC	**0.534** **	**0.502** **	0.498 **

[8] The generally low Spearman correlations of the HASB estimate are somewhat unexpected. Hasbrouck (2009) reports a Spearman correlation of 0.89 for the U.S. markets. The difference might be due to differences in liquidity characteristics between the U.S. and emerging markets.

Panel B of Table 4 presents the pairwise correlations between price impact proxies (*AMIHUD*, $1/AMIVEST$, and *PASTOR*), and price impact benchmarks (*LAMBDA*, *IMP*, and *ASC*). Two clear patterns emerge. First, there is no clear winner among the three price impact proxies when we examine their correlations with price impact benchmarks. Therefore, evidence from the correlation structure confirms the evidence from the measurement error in Panel B of Table 3, regarding the effectiveness of price impact proxies. Second, in the more liquid markets of Groups G1 and G2, the correlation between the price impact proxies and *LAMBDA* is much higher than the correlation between price impact proxies and either *IMP* or *ASC*. Third, the performance of *PASTOR* is as good as either *AMIHUD* or $1/AMIVEST$. This result is in contrast to the findings by Hasbrouck (2009) and Goyenko et al. (2009), although these two studies draw their conclusions from the U.S. market.

4.5. Incremental Regression R^2

4.5.1. The Determinants of Spread Benchmarks

The correlation analysis offers some interesting results. However, these results alone may not fully reveal how much variation in a liquidity benchmark is captured by a variation in a liquidity proxy. This is because a covariate variable can affect both the benchmark and the proxy, spuriously increasing or decreasing the correlation. One needs to control for covariate variables while examining the associations between liquidity benchmarks and liquidity proxies.

One variable is known to affect measured liquidity is price. Another variable is firm size. We include both the log of stock price (*PRICE*) and the log of firm size (*SIZE*) as control variables in a cross-sectional regression framework. The dependent variable is one of the high-frequency liquidity benchmarks, while the independent variables are the control variables and a low-frequency liquidity proxy, added one at a time. We run the regressions using all sample stocks. Specifically, the regression takes the following form:

$$SPREAD_i = \varphi_0 + \varphi_1 PRICE_i + \varphi_2 SIZE_i + \sum CDUMs + \sum IDUMs + \varepsilon_i, \quad (1)$$

where *SPREAD* = *QS*, *ES*, and *RS*, respectively. Subscript i refers to individual stocks, i = 1, ..., 1183. Country dummies and industry dummies are included. We obtain the adjusted R^2, R^2_{ADJ1} from the above regressions. Subsequently, we run the following regressions, adding spread proxies:

$$\begin{aligned} SPREAD_i = \varphi_0 \quad & +\varphi_1 \log(PRICE)_i + \varphi_2 \log(SIZE)_i + \varphi_3 SPREAD\_PROXY_i \\ & +\sum CDUMs + \sum IDUMs + \varepsilon_i, \end{aligned} \quad (2)$$

where *SPREAD_PROXY* = *ROLL*, *HASB*, and *LOT*, respectively. The corresponding adjusted R^2 is R^2_{ADJ2}. The incremental adjusted R^2 is calculated as:

$$Incremental\ R^2 = R^2_{ADJ2} - R^2_{ADJ1}. \quad (3)$$

Panel A of Table 5 summarizes the regression results. The estimated coefficient of log(*PRICE*) is insignificant, but the estimated coefficient of log(*SIZE*) has the predicted negative sign, and is highly significant in all regressions. In the case when ES is the dependent variable, the benchmark regression of Equation (1) has an adjusted R^2 of 0.325. When *ROLL*, *HASB*, and *LOT* are added one at a time as in Equation (2), then the corresponding estimates (t-statistics) are 0.296 (3.84), 0.256 (4.73), and 0.122 (3.94), respectively. Furthermore, the corresponding adjusted R^2 increases to 0.361, 0.343, and 0.464, respectively. The incremental R^2 are 0.036, 0.018, and 0.139, respectively. The notable largest incremental R^2 comes from adding *LOT* in the regression. The results that were obtained using *QS* and *RS* as dependent variables are similar. The largest incremental R^2 values, 0.134 and 0.082, respectively, again come from adding *LOT* in the regression. The conclusion from the incremental R^2 analysis is fully consistent with the conclusions drawn from measurement error and the correlation structure analysis.

Table 5. Incremental Regression R^2s. Panel A of the table examines the incremental explanatory power of spread proxies in predicting spread benchmarks, after controlling for stock price and firm size. In the first regression, the dependent variable is one of the spread benchmarks (*ES*, *QS*, and *RS*), while the independent variables are the control variables, namely the stock price (*PRICE*) and firm size (*SIZE*). The corresponding adjusted R^2 is R^2_{ADJ1}. In the second regression, the dependent variable is one of the spread benchmarks (*ES*, *QS*, and *RS*), while the independent variables are the control variables, stock price and firm size in addition to one of the spread proxies (*ROLL*, *HASB*, and *LOT*). The corresponding adjusted R^2 is R^2_{ADJ2}. The incremental adjusted R^2 is calculated as: $R^2_{ADJ2} - R^2_{ADJ1}$. Panel B examines the incremental explanatory power of price impact proxies (*AMIHUD*, 1/*AMIVEST*, and *PASTOR*) in predicting price impact benchmarks (*LAMBDA*, *IMP*, and *ASC*). The sample covers 1183 firms from 21 emerging markets. The sample period is from February to May 2004. The *t*-statistics are in parenthesis. *, **, and *** represent statistical significance at 10%, 5%, and 1% levels, respectively.

Panel A: The Incremental Explanatory Power of Spread Proxies								
	Intercept	***PRICE***	***SIZE***	***ROLL***	***HASB***	***LOT***	**Adjusted R^2**	**Incremental R^2**
ES	5.956 ***	0.009	−0.306 ***				0.325	
	(10.23)	(0.22)	(−6.48)					
	5.345 ***	0.022	−0.252 ***	0.296 ***			0.361	0.036
	(8.97)	(0.57)	(−7.17)	(3.84)				
	4.879 ***	0.023	−0.265 ***		0.256 ***		0.343	0.018
	(8.45)	(0.53)	(−5.66)		(4.73)			
	3.699 ***	−0.001	−0.175 ***			0.122 ***	0.464	0.139
	(5.69)	(−0.01)	(−5.61)			(3.94)		
QS	8.852 ***	0.026	−0.402 ***				0.439	
	(11.26)	(0.63)	(−8.24)					
	8.242 ***	0.040	−0.348 ***	0.295 **			0.463	0.024
	(10.15)	(1.02)	(−9.12)	(3.74)				
	7.671 ***	0.041	−0.357 ***		0.280 ***		0.453	0.014
	(9.88)	(0.98)	(−7.34)		(4.91)			
	6.197 ***	0.015	−0.248 ***			0.144 ***	0.573	0.134
	(7.79)	(0.57)	(−6.91)			(4.27)		
RS	2.431 ***	0.017	−0.187 ***				0.133	
	(4.32)	(0.49)	(−4.59)					
	1.971 ***	0.027	−0.146 ***	0.223 ***			0.165	0.032
	(3.52)	(0.83)	(−4.87)	(3.19)				
	1.860 ***	0.024	−0.165 ***		0.136 ***		0.140	0.007
	(3.15)	(0.69)	(−4.00)		(2.75)			
	1.042	0.011	−0.107 ***			0.075 ***	0.215	0.082
	(1.44)	(0.41)	(−3.95)			(2.94)		

Table 5. *Cont.*

Panel B: The Incremental Explanatory Power of Price Impact Proxies								
	Intercept	***PRICE***	***SIZE***	***AMIHUD***	***1/AMIVEST***	***PASTOR***	**Adjusted R^2**	**Incremental R^2**
LAMBDA	19.550 ***	−1.313 *	−3.495 **				0.087	
	(2.73)	(−1.76)	(−2.25)					
	15.592 ***	−1.454 *	−2.724 **	0.047			0.160	0.073
	(2.62)	(−1.91)	(−2.15)	(1.51)				
	6.907 ***	−0.713 **	−0.767 **		0.403 ***		0.671	0.584
	(2.69)	(−2.18)	(−2.23)		(3.12)			
	17.158 **	−1.274 *	−3.007 **			0.914	0.114	0.027
	(2.45)	(−1.72)	(−1.98)			(1.42)		
IMP	6.561 ***	0.024	−0.159 ***				0.405	
	(3.48)	(0.64)	(−5.99)					
	6.534 ***	0.023	−0.153 ***	0.001			0.406	0.001
	(3.46)	(0.62)	(−5.72)	(0.71)				
	6.486 ***	0.028	−0.142 ***		0.002 *		0.414	0.009
	(3.43)	(0.74)	(−5.44)		(1.93)			
	6.471 ***	0.026	−0.140 ***			0.034 ***	0.423	0.018
	(3.43)	(0.68)	(−5.41)			(3.92)		
ASC	3.433 ***	−0.009	−0.111 ***				0.523	
	(6.12)	(−0.63)	(−7.59)					
	3.383 ***	−0.011	−0.101 ***	0.001			0.539	0.016
	(6.00)	(−0.76)	(−7.51)	(1.06)				
	3.337 ***	−0.004	−0.090 ***		0.003 *		0.569	0.046
	(5.91)	(−0.31)	(−7.34)		(1.72)			
	3.310 **	−0.007	−0.086 ***			0.047 ***	0.621	0.098
	(5.85)	(−0.50)	(−7.24)			(14.54)		

4.5.2. The Determinants of Price Impact Benchmarks

Now, we examine the determinants of price impact benchmarks. We first run the following regression:

$$PRICE\_IMPCT_i = \varphi_0 + \varphi_1 \log(PRICE_i) + \varphi_2 \log{(SIZE)}_i + \sum CDUMs + \sum IDUMs + \varepsilon_i, \quad (4)$$

where PRICE_IMPACT = *LAMBDA*, *IMP*, and *ASC*, respectively. Subscript *i* refers to individual stocks, *i* = 1, ..., 1183. Country dummies and industry dummies are included. Thereafter, we run the following regressions, adding price impact proxies:

$$\begin{aligned} PRICE\_IMPACT_i = \quad & \varphi_0 + \varphi_1 \log(PRICE_i) + \varphi_2 \log{(SIZE)}_i + \varphi_3 PRICE\_IMPACT\_PROXY_i \\ & + \sum CDUMs + \sum IDUMs + \varepsilon_i, \end{aligned} \quad (5)$$

where *PRICE_IMPACT_PROXY* = *AMIHUD*, $1/AMIVEST$, and *PASTOR*, respectively. The incremental adjusted R^2 is calculated as in Equation (3).

Panel B of Table 5 summarizes the regression results. Overall, the results for price impacts are weaker than those for spreads. In the case when *LAMBDA* is the dependent variable, the basic regression in Equation (4) yields an adjusted R^2 of 0.087. When *AMIHUD*, $1/AMIVEST$, and *PASTOR* are added one at a time as in Equation (5), the corresponding estimates (*t*-statistics) are 0.047 (1.51), 0.403 (3.12), and 0.914 (1.42), respectively. The corresponding adjusted R^2 increase to 0.160, 0.671, and 0.114, respectively. The incremental R^2 values are 0.073, 0.584, and 0.027, respectively. The notable largest incremental R^2 come from adding $1/\text{AMIVEST}$ in the regression.

To understand why the results from adding price impact proxies are weaker when LAMBDA is used as the price impact benchmark, we run the same regressions for each of the four country groups partitioned by turnover. Group G1 has a total of 530 stocks. The regression results from the G1 group now become much stronger. When *AMIHUD*, $1/AMIVEST$, and *PASTOR* are added one at a time, the corresponding estimates (*t*-statistics) are 1.097 (13.21), 1.988 (10.15), and 5.045 (7.12), respectively. The incremental R^2 values become 0.389, 0.396, and 0.319, respectively. Therefore, for emerging liquid markets in the G1 group, all three price impact proxies do a very good job in predicting the price impact benchmark, *LAMBDA*. The weak results are driven by less liquid markets. The notably large incremental R^2 value of 0.587, by adding $1/AMIVEST$ in the regression, is driven by stocks in the G3 group.

The results using *IMP* and *ASC* as dependent variables yield a different conclusion. Panel B shows that the largest incremental R^2 values at 0.018 and 0.098, respectively, come by adding *PASTOR* in the regression. Both of these results are driven by the stocks in the G3 group, where the countries are less liquid. To some extent, the conclusion regarding *PASTOR* is consistent with the measurement error analysis for price impact in Panel B of Table 3, where *PASTOR* turns out to be the better proxy for less liquid markets in the G3 and G4 groups.

4.6. Firm and Market Characteristics and Accuracy of Liquidity Proxies

The analysis so far focuses on how accurately various low-frequency liquidity proxies predict high-frequency liquidity variables. Here, we examine which firm and market characteristics determine the effectiveness of liquidity proxies. Specifically, we run regressions to see if the accuracy of individual liquidity proxies depends on firms and market characteristics that are known to affect liquidity. The dependent variable in the regression is calculated as:

$$ACCURACY_i = \log(1/|Low\,Frequency\,\mathrm{Pr}oxy_i - High\,Frequency\,Benchmark_i|) \quad (6)$$

Since the denominator of $Accuracy_i$ is the measurement error of a liquidity proxy, the smaller the error, the larger the value of $Accuracy_i$. We apply log transformation because $Accuracy_i$ exhibits extreme distribution. The regression is run as follows:

$$ACCURACY_i = \phi_0 + \phi_1 \log(PRICE_i) + \phi_2 Turnover_i + \phi_3 Stock\ Volatility_i + \phi_5 \log(SIZE_i) + \phi_6 Investability_i + \phi_7 MarketVolatility_i + \phi_8 Legal\ Origin_i + \phi_9 Trading\ Mechanism_i + CDUMs + IDUMs + \varepsilon_i. \quad (7)$$

In constructing the dependent variables, spread proxies include *ROLL*, *HASB*, and *LOT*. Spread benchmarks include *ES*, *QS*, and *RS*. Furthermore, price impact proxies include *AMIHUD*, 1/*AMIVEST*, and *PASTOR*, while price impact benchmarks include *LAMBDA*, *IMP*, and *ASC*. The independent variables include five firm characteristic variables and three market characteristic variables. The firm characteristics include stock price, turnover, return volatility, firm size, and investability. The investability portrays accessibility by foreign investors and takes a value between zero (non-accessible to foreigners) and one (fully accessible).

The variables that capture market characteristics include market volatility, legal origin, and trading mechanism. Market volatility is the daily return standard deviation of the leading market index in each market. A country's legal origin is from La Porta et al. (1998). The legal origin variable takes the value of one if the country's legal system is based on common laws, and zero otherwise. La Porta et al. (1998) report that countries with common law systems generally have a stronger investor protection system than those with other legal systems. The degree of information asymmetry is lower. The data on trading mechanisms are from Jain (2005). We assign a value of one for a pure limit-order system, and zero for a dealer or a hybrid system.

The regression results of Equation (6) for spread proxies appear in Panel A of Table 6. For brevity, we only report the results when the spread benchmark is ES. The evidence shows that volatility is significantly related to the accuracy of spread proxies. Individual firms' return volatilities have significant and negative signs for all the three spread proxies. Obviously, volatility adds noise to the estimates of the proxies. Thus, high volatility is associated with less accuracy. Firm size has a positive sign and it is highly significant. Spread proxies are more accurate when the firms are larger. Investability has a positive sign and is highly significant. This suggests that spread proxies are more accurate when firms are more accessible to foreign investors. When *LOT* is used as a proxy for *ES*, the model performs the best with an R^2 exceeding 0.40. *LOT* portrays spread better when a firm has a higher stock price, a higher turnover, a smaller return volatility, a larger market capitalization, and is more accessible to foreigners.

Among the market characteristics, market volatility displays a positive and highly significant coefficient in all three models with *ROLL*, *HASB*, and *LOT* being the spread proxies, respectively. The results show that when individual stock volatility is accounted for, greater market volatility increases the accuracy of a spread proxy. One possible explanation is that higher market volatility is an indicator of market development (Bekaert and Harvey 1995). Greater market level volatility increases the effectiveness of spread proxies. The legal origin exhibits a significant and positive coefficient in models when *ROLL* and *HASB* are used as the proxies for *ES*.

Now, we turn to the regressions for price impact proxies in Panel B of Table 6. For brevity, we only report the results when the price impact benchmark is *LAMBDA*. Overall, the set of firm and market characteristics explains the variations in the accuracy of price impact proxies reasonably well. The R^2 values range from 0.529 to 0.816, much higher than the R^2 values from the regressions for spread proxies that range from 0.316 to 0.409. In general, the accuracy increases with turnover, firm size, and investability. The accuracy decreases with individual stock return volatility. The indicator variable for legal origin is positive and highly significant in all three regressions. This suggests that all the three price impact proxies are more effective in markets with common law legal systems. The indicator variable for the trading mechanism is positive and highly significant in all three regressions as well. This suggests that all three price impact proxies work better in a limit-order based system than in dealer or hybrid systems.

Table 6. Determinants of accuracy of Liquidity Proxies. The table presents the coefficients (t-statistics) from the cross-sectional regressions of the accuracy measures of liquidity proxies on firm and market characteristics. The accuracy measure is calculated as log(1/ | Proxy − Benchmark |). The spread benchmark is *ES*. The spread proxies include *ROLL*, *HASB*, and *LOT*. The price impact benchmark is *LAMBDA*. The price impact proxies include *AMIHUD*, 1/*AMIVEST*, and *PASTOR*. Firm characteristics include stock price, turnover, return volatility, firm size, and investability. Market characteristics include market volatility, legal origin, and trading mechanism. Country dummies and industry dummies are also included. *, **, and *** represent statistical significance at the 10%, 5%, and 1% levels, respectively. The sample covers 1183 firms from 21 emerging markets. The sample period is from February to May 2004.

	The Dependent Variable Is log(1/ | Proxy − Benchmark |)					
	Proxy = *ROLL*	**Proxy = *HASB***	**Proxy = *LOT***	**Proxy = *AMIHUD***	**Proxy = 1/*AMIVEST***	**Proxy = *PASTOR***
	Benchmark = *ES*	**Benchmark = *ES***	**Benchmark = *ES***	**Benchmark = *LAMBDA***	**Benchmark = *LAMBDA***	**Benchmark = *LAMBDA***
Intercept	−2.079 ***	−2.625 ***	−2.90 ***	−6.163 ***	−4.189 **	−5.389 ***
	(−2.58)	(−3.46)	(−3.56)	(−8.93)	(−5.02)	(−10.14)
Stock Price	0.052	0.004	0.120 ***	−0.046	0.038	−0.016
	(1.15)	(0.08)	(2.64)	(−1.19)	(0.82)	(−0.53)
Turnover	5.186	6.535	22.193 ***	34.789 ***	4.937	33.427 ***
	(0.64)	(0.85)	(2.70)	(5.00)	(0.59)	(6.23)
Stock Volatility	−13.734 ***	−11.402 **	−15.984 ***	−2.128	−12.097 **	−11.668 ***
	(−2.71)	(−2.39)	(−3.12)	(−0.49)	(−2.31)	(−3.49)
Firm Size	0.091 *	0.158 ***	0.158 ***	0.699 ***	0.042	0.599 ***
	(1.85)	(3.40)	(3.17)	(16.52)	(0.82)	(18.37)
Investability	0.371 **	0.091	0.371 **	0.803 ***	0.313 *	0.532 ***
	(2.04)	(0.53)	(2.01)	(5.14)	(1.66)	(4.42)
Market Volatility	1.437 ***	1.775 ***	1.253 **	−0.857 *	1.616 ***	−0.441
	(2.64)	(3.46)	(2.28)	(−1.84)	(2.87)	(−1.23)
Legal Origin	0.443 *	0.481 **	−0.032	1.952 ***	1.119 ***	1.656 ***
	(1.78)	(2.06)	(−0.13)	(9.16)	(4.35)	(10.09)
Trading Mechanism	−0.193	−0.696	0.177	2.678 ***	2.155 ***	2.379 ***
	(−0.27)	(−1.04)	(0.25)	(4.40)	(2.93)	(5.07)
Country Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Industry Dummies	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.316	0.324	0.409	0.699	0.529	0.816
Observations	1183	1183	1183	1183	1183	1183

5. Conclusions

This paper empirically investigates whether popular low-frequency liquidity proxies capture liquidity effectively in emerging markets, and, if they do, which proxy measures liquidity best. We carry out a comprehensive analysis using tick-by-tick trade and quote data covering 1183 stocks from 21 emerging markets, spanning four continental regions. Our study complements those by Lesmond (2005), and Goyenko et al. (2009) in important ways. While Lesmond (2005) relies on quarterly quoted spreads, we use comprehensive market microstructure data, which allows us to compare various low-frequency liquidity proxies using various measures of transaction costs and price impact, exclusively from market microstructure data. Our study extends the analysis of Goyenko et al. (2009) for the U.S. market to emerging markets.

Our major findings are summarized as follows. We find rich dispersion in transaction costs and price impacts across emerging markets. Furthermore, we find that most of the spread proxies, including the Roll's (1984) spread, Hasbrouck's (2009) estimate, and Lesmond et al.'s (1999) *LOT* measure performs relatively well. The *LOT* measure has an obvious edge over the other two spread proxies in a majority of the markets. With respect to price impact proxies, the Amihud (2002) measure, Cooper et al.'s (1985) Amivest measure and Pástor and Stambaugh's (2003) measure are close substitutes, with the Amihud measure being more effective in some cases. Our regression analysis shows that certain firm and market characteristics significantly influence how accurately a low-frequency spread proxy captures a high-frequency spread benchmark. Turnover, stock volatility, firm size, openness to foreign investors, market volatility, legal origin, and trading mechanism all affect the measurement accuracy of a proxy significantly.

Our coverage of emerging market stocks is quite comprehensive. However, the timeseries is limited to about three to four months in the year 2004. Studies by Abdi and Ranaldo (2017) and Chung and Zhang (2014) show that the cross-sectional pattern of the effectiveness of liquidity proxies, is quite stable over time. Therefore, the findings of our paper should still hold valid and offer valuable information to researchers and practitioners.

Our sample firms represent a greater number of liquid firms than the average firms in emerging markets. One distinct characteristic of emerging markets is that a small number of large corporations often make up the majority of the total market capitalization and trading activity. Therefore, although in some of the markets, our sample includes only the largest firms, they represent their respective markets reasonably well. Further, foreign investors in emerging markets generally deal with large firms because of better liquidity, greater visibility, and easier access to firm-specific information (Kang and Stulz 1997; Chiyachantana et al. 2004). Our sample stocks are likely to become primary targets of global investments. In this regard, our findings offer useful information to global investors.

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Market Efficiency and News Dynamics: Evidence from International Equity Markets

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Abstract: This paper examines the efficient market hypothesis by applying monthly data for 15 international equity markets. With the exceptions of Canada and the U.S., the null for the absence of autocorrelations of stock returns is rejected for 13 out of 15 markets. The evidence also rejects the independence of market volatility correlations. The null for testing the absence of correlations between stock returns and lagged news measured by lagged economic policy uncertainty (EPU) is rejected for all markets under investigation. The evidence indicates that a change of lagged EPUs positively predicts conditional variance.

Keywords: efficient market; economic policy uncertainty; random walk; news; Asian market; G7 market

1. Introduction

The aim of this paper is to present empirical evidence to evaluate the efficient market hypothesis (EMH) by using economic policy uncertainty (EPU) as a news variable. Specifying a regression model with longer lags of EPU allows us to test whether the EPU has a prolonged negative effect or being able to track a phenomenon for markets to rebound. A successful empirical finding from this study will help to inform investors of whether market damage is continually worsening or if they are to be rewarded by an uncertainty premium. Departing from conventional approaches that have focused on risk variables derived from financial market (Bali et al. 2009; Chen et al. 2018)[1], this study employs a broader definition of news variables by including consideration for EPU, which contains information of social event, political risk, or headline commentary news that can influence stock market. Thus, the results will be enriched by using EPU innovations to derive empirical regularities that can provide insight to investors about the stock return behavior.

In a highly integrated financial market system, a shock in one market will soon spillover to other markets. For instance, headline news on 10 October 2018 that the Nasdaq index suddenly dropped 4.08% in the U.S. market led to a corresponding 1.62% plunge in the UK FTSE and a drop of 1.09%, 1.54%, and 2.2.66%, in the German DAX 30, French CAC 40 and Russia MOER indices, respectively. The retreat in the U.S. caused declines in the Asian markets where China's Shanghai stock A-share plunged 5.22%, Hong Kong HSI fell 3.54%, and Japanese's Nikkei index was down 3.89%.

The above news observations provide us with some insight for analyzing the global market behavior. As news is released, regardless of whether its focus is financial or political, it will create uncertainty and hence fear among investors, regardless of whether the news comes from the domestic

[1] This may stem from Frank Knight's statement (Knight 1921) regarding uncertainty that suggests economic agents have no historical data from which a probability distribution is developed. If there is any measure of uncertainty, which can be used as a proxy for the unexpected component of the state variable (Cornell 1983; Chiang 1985; Lauterbach 1989), then the omitted variable problem may arise.

market or the foreign market. By employing the monthly data to test the news-based EPU indices (Baker et al. 2016; Davis 2016) on stock returns, this study finds that EPUs are positively correlated with stock returns beyond the current period, which allows us to reject the EMH and suggests the existence of an uncertainty premium. This is the case for nearly all markets, although the evidence is more consistent for the G7 markets. Further, with some minor exceptions, the evidence suggests that EPU innovations provide significant information that can be used to predict variance in a subsequent period. This finding leads us to reject the assumption that the error series is independently and identically distributed on monthly data. Following this introduction, Section 2 presents the essence of efficient market theory and sets up hypotheses to test the uncertainty premiums; Section 3 describes the data; Section 4 tests the monthly return autocorrelations. Section 5 presents a regression model to examine the effect of news on stock returns and reports the empirical results. Section 6 concludes the findings.

2. News and Market Efficient Market Theory

2.1. Efficient Market Hypothesis

In his Foundations of Finance (1976), Fama wrote: "An efficient capital market is a market that is efficient in processing information. The prices of securities observed at any time are based on 'correct' evaluation of all information available at that time. In an efficient market, prices 'fully reflect' available information." (Fama 1976, p. 134). This statement provides a central message regarding the importance of the timing of price information and market efficiency. Under this mechanism, stock prices provide an accurate signal to traders, which allows them to evaluate the value of firms. That is, firms can raise funds to finance their activities by selling securities at fair prices, and investors are able to acquire these assets at prices that fully reflect their underlying intrinsic values. In this sense, prices play a significant and effective function in allocating resources.

The essence of efficient market can be seen from its pricing process. This assumes that market participants at time $t-1$ use market information $\phi_{m,t-1}$ to assess a joint distribution of security prices for time t as of $f_m\{p_{1t}, p_{2t}, \ldots, p_{nt} \mathrm{I}\, \phi_{m,t-1}\}$, where p_{it} is the price of security i at time t and i = 1, 2, ..., n. From this assessment of the distribution of prices, the market observes appropriate prices $\{p_{1t-1}, p_{2t-1}, \ldots, p_{nt-1}\}$ for individual securities, which in turn gives rise to the aggregate market price, P_{t-1}. Note that the information given by $\phi_{m,t-1}$ includes not only the prices per se, but also the process that describes the evolution of the state of the market over time. It follows that the market price, P_{t-1}, can be used to predict the expected price in t given by:

$$E_{t-1}[P_t \,\mathrm{I}\, \phi_{m,t-1}] = P_{t-1}. \quad (1)$$

The above expression can be written as:

$$E_{t-1}[P_t - P_{t-1} \mathrm{I}\, \phi_{m,t-1}] = E_{t-1}[\varepsilon_t \mathrm{I}\, \phi_{m,t-1}] = 0. \quad (2)$$

This expression implies that errors in forecasting P_t using P_{t-1} on average approach zero. This also informs investors that if there are deviations by using P_{t-1} in predicting the future stock price, P_t, the errors must be associated with random news that hits the market between time $t-1$ and t.[2]

Since price is sensitive to news, which arrives randomly in the market, the stock price can be said to wander along a random course. An analysis of an efficient market then tends to explore whether or not the market does, in fact, use available information in setting stock prices. One way to approach

[2] This statement is based on Fama's perception (1976) of market efficiency. However, Ohlson (1995); Glezakos et al. (2012) and Jianu et al. (2014) find that financial statements provide a significant source information for predicting the stock price.

this issue is to explore whether the source of information for future price movements is associated with past prices. Let us consider that the one-period price evolves with a constant equilibrium rate, μ, as:

$$P_t = P_{t-1}e^{(\mu+\varepsilon_t)} \tag{3}$$

Taking the natural logarithm using $p_t = ln(P_t)$, we obtain:

$$p_t = \mu + p_{t-1} + \varepsilon_t \tag{4}$$

where μ is the constant rate of an expected price change in the natural logarithm, ε_t is independently and identically distributed (iid) with mean 0 and variance σ^2 and is expressed as $\varepsilon_t \sim$ iid (0, σ^2). The above expression in Equation (4) can be called a random walk with a drift, which can be alternatively expressed as:

$$R_{mt} = \mu + \varepsilon_t$$

where $R_{mt} = p_t - p_{t-1}$.

Taking expectation on prices, the notion of Equation (2) then can be expressed as:

$$E_{t-1}[R_{mt}\mathrm{I}\,\phi_{m,t-1}] - \mu = E_{t-1}[\varepsilon_t\mathrm{I}\,\phi_{m,t-1}] = 0. \tag{5}$$

Equation (5) suggests that an expected stock return deviates from its equilibrium is expected to be zero, which implies there are no systematic excess profits that can be explored by checking the evolution of stock returns over time. To test this proposition, a linear regression function can be used and expressed as:

$$E_{t-1}[R_{mt}\mathrm{I}\,\phi_{m,t-1}] = \mu + \rho_s R_{mt-s}. \tag{6}$$

It follows that market efficiency, in combination with the assumption of constant expected returns over time, implies an absence of autocorrelation of the returns with s order of lags. Thus, the null hypothesis is: $\rho_s = 0$ for $s = 1, 2, \ldots, S$. A further test of market efficiency can be achieved by examining whether $\{E_{t-1}[R_{mt}\mathrm{I}\,\phi_{m,t-1}] - \mu\}$ is orthogonal to any lagged news.

In analyzing the market efficiency, researchers opt to apply the random walk process to describe the possible correlations of information dependency. Campbell et al. (1997) clearly distinguish the notion of independent assumption from that of a serial correlation and note that the assumption of incremental iid is too strong (Campbell et al. 1997), since even though $\mathrm{Cov}[\varepsilon_t, \varepsilon_{t-s}] = 0$ for all $s \neq 0$ cannot be rejected, $\mathrm{Cov}[\varepsilon_t^2, \varepsilon_{t-s}^2] = 0$ for some $s \neq 0$ is usually rejected. This has been displayed in stock return series where large returns tend to be followed by large returns, or the volatility of stock returns appears to be highly dependent, presenting a clustering phenomenon shown in most GARCH-type conditional variance (Ding et al. 1993; Chen and Chiang 2016; Chen et al. 2018).

2.2. The Model with News Information

Empirical analysis of the impact of news on stock returns follows two approaches. The first is to derive a news variable from rational expectations. Known as an efficient markets-rational expectations hypothesis (Mishkin 1982), it posits that investors are rational, and are able to use econometric models and available information to form an optimal forecast of a state variable. Thus, the unpredicted component is nothing but the result of news hitting market. This approach has been proposed by Mishkin (1982); Cornell (1983); Chiang (1985); Pearce and Roley (1985) and Lauterbach (1989). Clearly, this approach simply relies on a policy/state variable, such as an unexpected change in money supply or a change in interest rates as a proxy for measuring monetary policy uncertainty, which in turn is used to test the news impact on stock returns.

The second approach is based on survey data of market participants or headline news, which forms the future economic prospects that influence stock returns. For instance, McQueen and Roley (1993) find that good news in an industrial production index raises stock prices. Boyd et al. (2005); Leduc and Liu (2016) and Caggiano et al. (2014) report that news of rising unemployment leads to contraction and lower expected earnings and hence results in lower stock prices. Birz and Lott (2011) choose newspaper articles as a measure of news. These authors indicate that news about GDP and unemployment affects stock returns.

Despite their success in linking macroeconomic news (Birz and Lott 2011) to the stock returns, their choice of news variables is restricted to macroeconomic indicators and fails to include broad coverage of news, such as the political risk, changes in immigration policy, and trade wars among others, which could significantly disrupt prevailing economic conditions and therefore affect investors' expectations and investment decisions. To alleviate the weakness arising from narrow news content, this study employs EPU indices which reflect broader news coverage as described in earlier. Further, most studies are focused on daily data; as a result, the impact of news has been treated as short lived. This approach ignores the longer-term effects on stock returns without investigating the delayed reactions to news. Finally, with the exception of Flannery and Protopapadakis (2002), very few studies pay attention to the issue of stock return heteroskedasticity. From an efficient market point of view, examining the dependency of volatility appears to be an integral part of analyzing investors' behavior.

Motivated by the above empirical issues, this study employs EPU indices to serve as news variables. The literature suggests that EPU affects both stock returns (Bansal et al. 2005; Ozoguz 2009; Antonakakis et al. 2013; Lopez de Carvalho 2017) and stock variance (Liu and Zhang 2015; Chiang 2019). To incorporate this notion into the test equations, we write:

$$R_{mt} = \alpha + \sum_{i=0}^{n} \beta_i \eta_{t-i} + \sum_{i=0}^{n} \gamma_i z_{t-i} + \rho_1 R_{m,t-1} + \varepsilon_t \tag{7}$$

$$\sigma_t^2 = \omega + b_1 \varepsilon_{(t-1)}^2 + b_3 \Delta\eta_{t-1} + b_4 \Delta z_{t-1} \tag{8}$$

where Equation (7) is the mean equation, R_{mt} is the stock return, η_t denotes the local EPU$_t$ and z_t represents the global EPU$_t$. The AR(1) term is included in Equation (7) to capture either the momentum effect resulted from a price ceiling or the positive feedback of trading. Equation (8) is the variance equation, which assumes the GARCH(1,1)[3] process. However, the EPU innovations from respective local markets and the global market are included in the variance equation to capture the local news shock and contagious effect from global markets (Chiang et al. 2007; Forbes 2012; Bali and Cakici 2010). Finally, following Nelson (1991); Li et al. (2005); Chiang and Zhang (2018), the error series is assumed to follow the GED distribution, specified as $\varepsilon_t \Omega_{t-1}$ ~ GED($0, \sigma_t^2, \nu$), which accommodates the thickness of the tails of a distribution.

2.3. Uncertainty Premium Hypotheses

Equation (7) provides a dynamic regression framework pertinent to test uncertainties and stock returns, this section outlines each hypothesis as follows:

(i) *Local uncertainty premium hypothesis*

If a rise in η_{t-i} signifies a potential deterioration of economic activities that endangers future cash flows (Bloom 2009; Leduc and Liu 2016), it is expected that $E_{t-1}[R_{mt}, \eta_{t-i}] = 0$ would be rejected. Note a rejection of $E_{t-1}[R_{mt}, \eta_t] = 0$ is consistent with the EMH (Li 2017; Chen et al. 2017; Lopez de Carvalho 2017). However, if $E_{t-1}[R_{mt}, \eta_{t-i}] = 0$ for $i \geq 1$ is rejected and there is a positive relation,

[3] The popularity of this model is due to Bollerslev et al. (1992). Bollerslev (2010) provides different specifications of the conditional volatility models. In addition, some papers (Glosten et al. 1993; Chiang and Doong 2001) prefer to add an asymmetric term to the conditional variance equation to capture the bad news, which has a more profound impact on variance as compared to an equal amount of good news. Our specification indicates that this is redundant, since the inclusion of $\Delta\eta_{t-1}$ and Δz_{t-1} already captures the effect arising from bad news.

then the market is inefficient and investors will be rewarded by an uncertainty premium from the local market.

(ii) *Global uncertainty premium hypothesis*

It is observed that an increase in uncertainty over the global market is soon learned by local investors via mass media, digital devices, trade connections or financial institution linkages, which will induce investors to reassess their portfolio positions (Chiang et al. 2007; Forbes 2012; Klößner and Sekkel 2014; Chen et al. 2018). This spillover hypothesis can be tested by examining $E_{t-1}[R_{mt}, z_{t-i}] = 0$. A rejection of $E_{t-1}[R_{mt}, z_t] = 0$ is consistent with the efficient-market hypothesis. However, if $E_{t-1}[R_{mt}, z_{t-i}] = 0$ is rejected, that is, $\gamma_i = 0$ for $i \geq 1$ is rejected and $\gamma_i > 0$, evidence would go against the EMH, and investors will be rewarded by an uncertainty premium from a rise in lagged global EPU.

(iii) *Uncertainty innovation hypothesis*

The literature suggests that uncertainty causes higher stock market volatility. Liu and Zhang (2015) show that the inclusion of EPU helps to improve forecasting ability of existing volatility models; and Tsai (2017) reports that EPU has a predictive ability not only to explain local stock volatility but also to describe cross market volatility. Testing these phenomena involves examining Cov$[\sigma_t^2, \Delta\eta_{t-1}]$ = 0 and Cov$[\sigma_t^2, \Delta z_{t-1}]$ = 0. In terms of Equation (8), the null hypothesis tests joint significance of $\Delta\eta_{t-1} = \Delta z_{t-1} = 0$ in a variance equation, which can be examined by Lagrange Multiplier (LM) test using the chi-squared distribution.

3. Description of Data and Variables

The empirical analyses in this study cover the data of the world stock index and 15 individual country/market indices, which include G7: Canada (CA), France (FR), Germany (GM), Italy (IT), Japan (JP), the United Kingdom (UK), the United States (US); Asian-Pacific markets: Australia (AU), China (CN), Hong Kong (HK), India (IN), South Korea (KO) and Singapore (SG); South American markets: Brazil (BR) and Chile (CL). Since most global EPU data start from January 1997, the estimations mainly use a sample for the period from January 1997 to June 2016. However, the stated times of stock indices for China and Brazil are later than other markets. The stock indices (including the total return index (RI) as defined in Datastream includes dividends, interest, rights offerings and other distributions realized over a given month) are downloaded from the database of DataStream, and the EPU news indices are obtained from www.PolicyUncertainty.com provided by Baker et al. (2016) and Davis (2016). The U.S. EPU index is constructed from three underlying components: (i) newspaper coverage of policy-related economic uncertainty based on major local newspapers; (ii) the number of tax code provisions set to expire in future years; (iii) disagreement among economic forecasters, which is used as a proxy for uncertainty. In constructing the EPU, Baker et al. (2016) search the digital archives of each paper to obtain a monthly count of articles that contain the following terms: "uncertainty" or "uncertain"; "economic" or "economy"; and one or more of the terms "deficit", "the Fed," or "uncertainties" or its variants. They find this uncertainty index is reliable, unbiased, and consistent since the uncertainty index is highly correlated with a market's implied volatility, VIX (Whaley 2009), and closely related to other measures of policy uncertainty. Following Bekaert and Harvey (1995), the stock prices are measured using the U.S. dollar.[4]

Table 1 reports summary statistics of monthly stock returns for the G7 market (Panel A) and Asian-Pacific and Latin American (APLA) markets (Panel B). The statistics indicate that the U.S. market performs well as compared with the other advanced markets; Japan, on the other hand, displays a negative return and high volatility as indicated by the standard deviation. The statistics in Panel B

[4] Appendix A provides a description of a list of variables and data sources.

show that Chile, which has the highest return, performs very well, while China and South Korea, which have moderate returns, are relatively more volatile. In general, the returns in the group of APLA are much higher than those in G7 markets for the period of investigation.

Table 1. Summary statistics of monthly stock market returns: September 1990–June 2016.

Panel A. G7 Market								
	CA	**FR**	**GM**	**IT**	**JP**	**UK**	**US**	**Global**
Mean	0.55	0.30	0.55	0.11	−0.19	0.37	0.57	0.39
Median	0.62	0.90	0.95	0.04	0.24	0.66	1.00	0.78
Maximum	13.89	12.59	19.37	21.09	18.29	9.89	10.58	10.35
Minimum	−25.53	−19.23	−29.33	−16.80	−27.22	−13.95	−18.56	−21.13
Std. Dev.	5.56	5.30	6.02	6.00	6.02	3.95	4.08	4.23
Skewness	−0.62	−0.50	−0.94	0.15	−0.49	−0.62	−0.84	−0.94
Kurtosis	4.77	3.58	6.22	3.80	4.40	3.93	5.17	5.56
Jarque-Bera	60.37	17.49	179.73	9.47	37.72	31.28	97.13	130.74
Observations	310	310	310	310	310	310	310	310
Panel B. Asian-Pacific and Latin America markets								
	AU	**CN**	**HK**	**IN**	**KO**	**SG**	**BZ**	**CL**
Mean	0.79	0.75	0.90	1.11	0.67	0.50	1.11	1.27
Median	1.25	0.63	1.51	1.04	0.26	0.84	1.54	0.52
Maximum	9.73	92.34	25.30	53.79	42.89	21.33	20.54	17.44
Minimum	−22.58	−32.94	−34.50	−38.14	−33.29	−26.61	−35.56	−26.06
Std. Dev.	4.02	10.63	7.17	9.28	8.21	5.78	7.24	5.29
Skewness	−0.89	2.33	−0.30	0.13	0.41	−0.47	−0.81	0.14
Kurtosis	5.99	23.54	5.66	7.74	6.23	5.89	6.30	5.62
Jarque-Bera	156.67	4898.77	96.29	291.48	142.93	118.76	148.43	89.56
Observations	310	265	310	310	310	310	263	310

To visualize the stock returns, the monthly stock returns are plotted in Figures 1 and 2. These time series evidently present some degree of comovements and capture the major turning points, especially for the G7 markets, suggesting that these series could be driven by some common factors.

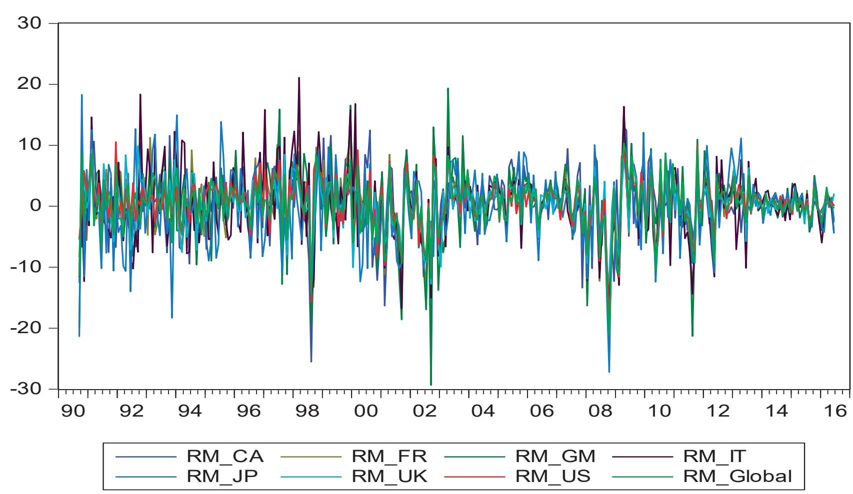

Figure 1. Time series plots of the percentage of stock returns (vertical axis) vs. time for G7 and global markets.

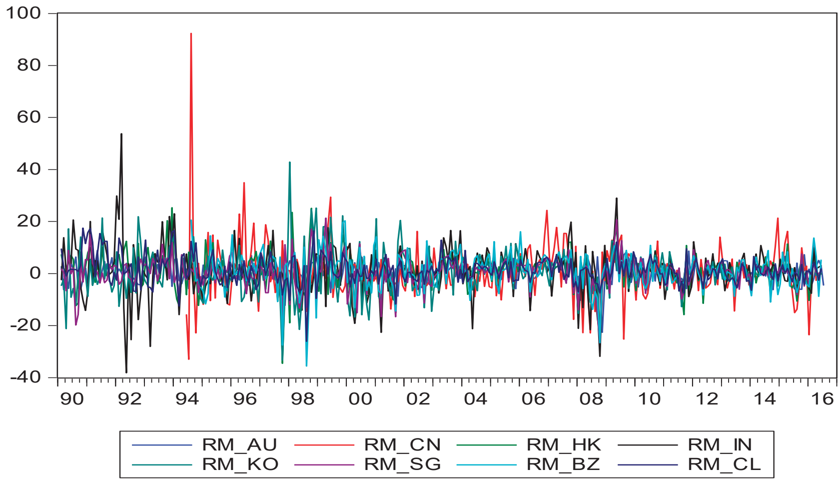

Figure 2. Time series plots of the percentage of stock returns (vertical axis) vs. time for Asia-Pacific and Latin American markets.

Let us turn to the EPU series, which are plotted in Figure 3 for the G7 market and Figure 4 for the APLA markets. The time paths of G7 markets exhibit some degree of comovements over time, and their correlations with global EPU (GEPU) are in the range from 0.48 (for Italy) to 0.88 (for the U.S.). It is evident that the EPU index for the UK spiked during the time of Brexit. Similarly, correlation coefficients of EPUs shown in the APLA group in Figure 4 range from 0.67 (for India) to 0.98 (for Singapore); the high correlation may reflect some sort of global contagions as shocks occur in the global markets (Chiang et al. 2007; Forbes 2012). The time paths show that EPUs for China, Hong Kong and South Korea occasionally act more volatile.

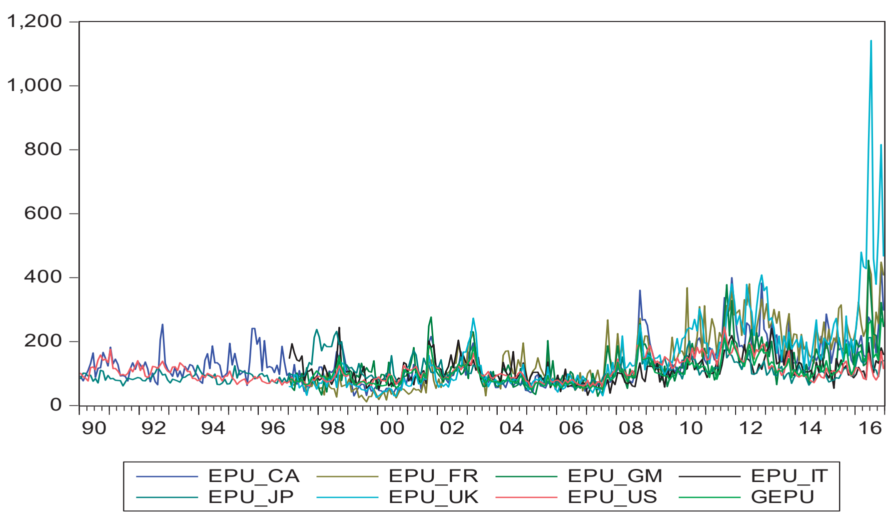

Figure 3. Time series plots of EPU (vertical axis) vs. time for G7 and global markets.

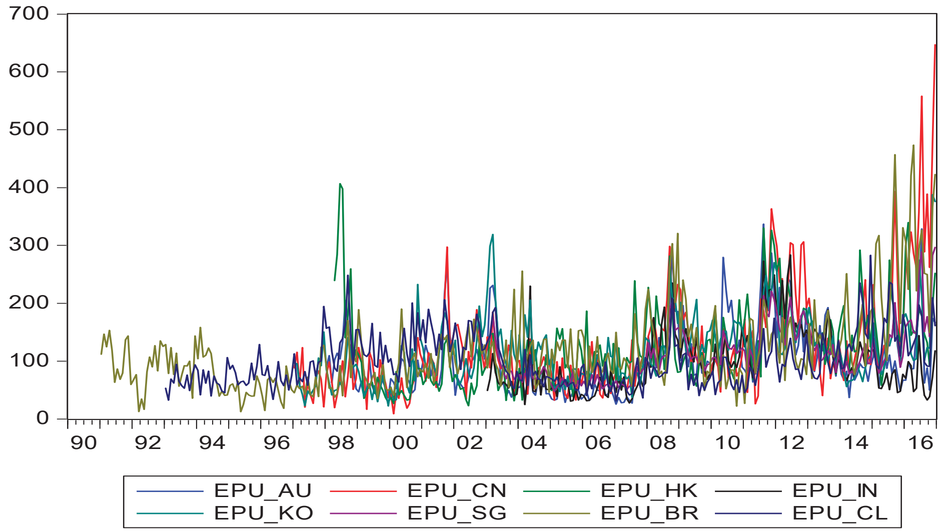

Figure 4. Time series plots of EPU (vertical axis) vs. time for Asia-Pacific and Latin American markets.

4. Test of Return Autocorrelations

A simple approach to testing the EMH is to examine the autocorrelations at the lagged s periods by t-statistics or examine the joint significance for $\rho_s = 0$ for s = 1, 2, ..., S by χ^2 distribution. Tables 2 and 3 report the autocorrelations of monthly stock market returns up to 12 orders for the G7 and APLA markets, respectively. Interestingly, only Canada and the U.S. lack autocorrelations, regardless of whether testing is on the individual lags or the lagged coefficients as a group. The results for Canada and the U.S. seem consistent with the EMH if we just look at the autocorrelation pattern. For the other markets, the evidence shows that at least some autocorrelations are significant, which leads to a rejection of the EMH. However, conclusions for the other G7 markets, with the exception of Italy, should be made with caution, since they do not display a consistent pattern, but rather exhibit significant autocorrelations in higher orders. This may result from a spurious correlation due to an omitted variable. If we look at the autocorrelations of the APLA markets in Table 3, five markets are statistically significant at the AR(1) term, which could result from price ceilings imposed by government or some sort of market frictions.

In testing whether the volatility is independent, that is, $\mathrm{Cov}[\varepsilon_t^2, \varepsilon_{t-s}^2] = 0$ for $s \neq 0$ as noted by Campbell et al. (1997), Table 4 reports the autocorrelations for absolute values of R_{mt}. Apparently, the null is uniformly rejected, as evidenced by the level of significance of the Ljung-Box Q-statistics up to 12 lags. Thus, the testing results show an absence of an independent assumption for volatility is invalid and suggest some type of GARCH model may be considered to describe the return residuals.

Table 2. Autocorrelations of monthly stock market returns up to 12 orders: Group 7 markets.

Market	ρ_1	ρ_2	ρ_3	ρ_4	ρ_5	ρ_6	ρ_7	ρ_8	ρ_9	ρ_{10}	ρ_{11}	ρ_{12}	Q_{12}
CA	0.086	0.097	0.092	−0.002	−0.081	−0.062	−0.017	0.100	0.046	0.018	0.047	−0.081	18.58
	1.47	1.64	1.55	−0.03	−1.37	−1.06	−0.28	1.70	0.78	0.30	0.81	−1.38	[0.10]
FR	0.125	−0.081	0.095	0.029	−0.006	0.025	−0.076	0.146	−0.072	0.110	−0.050	0.101	13.18
	2.13 *	−1.37	1.62	0.49	−0.10	0.43	−1.32	2.53 *	−1.23	1.90	−0.86	1.77	[0.36]
GM	0.068	0.006	0.045	0.035	0.017	0.037	−0.079	0.098	−0.049	0.005	−0.004	0.116	10.00
	1.17	0.11	0.76	0.60	0.29	0.64	−1.36	1.68	−0.83	0.09	−0.06	2.03 *	[0.62]
IT	0.036	0.004	0.120	0.099	−0.111	−0.004	−0.119	0.148	0.099	−0.019	0.034	0.040	23.46
	0.61	0.06	2.03 *	1.68	−1.90	−0.07	−2.05 *	2.55 *	1.70	−0.33	0.58	0.70	[0.02] *
JP	0.086	−0.021	0.103	0.032	0.004	−0.128	−0.027	0.053	0.028	0.038	−0.012	−0.037	7.36
	1.46	−0.35	1.76	0.54	0.07	−2.17 *	−0.45	0.91	0.48	0.66	−0.22	−0.67	[0.83]
UK	0.044	−0.034	−0.022	0.136	−0.015	−0.011	0.005	0.068	0.015	−0.003	−0.024	0.036	12.63
	0.75	−0.58	−0.38	2.31 *	−0.26	−0.18	0.08	1.16	0.25	−0.05	−0.42	0.62	[0.40]
US	0.073	−0.017	0.105	0.047	0.052	−0.079	0.051	0.035	−0.010	0.010	0.038	0.070	11.47
	1.24	−0.29	1.79	0.80	0.88	−1.34	0.87	0.60	−0.17	0.18	0.66	1.20	[0.49]

Notes: This table examines stock market efficiency by testing the dependency of stock returns; ρ_s is the coefficient of autocorrelation with order s ($s = 1, 2, \ldots, 12$). Q_{12} is the Ljund-Box statistics for testing joint significance of 12 order lags. The numbers in the brackets are the p-values. The values in the first row are the estimated coefficients and in the second row are the t-statistics. * indicates statistically significant at the 5% level.

Table 3. Autocorrelations of monthly stock market returns up to 12 orders: Asian-Pacific and Latin American markets.

Market	ρ_1	ρ_2	ρ_3	ρ_4	ρ_5	ρ_6	ρ_7	ρ_8	ρ_9	ρ_{10}	ρ_{11}	ρ_{12}	Q_{12}
AU	0.002	0.079	0.130	0.041	−0.062	−0.045	0.126	0.019	0.061	−0.035	−0.056	0.061	8.68
	0.04	1.35	2.23	0.70	−1.05	−0.77	2.17 *	0.33	1.04	−0.61	−0.96	1.04	[0.73]
CN	0.131	0.136	−0.059	0.123	0.033	−0.138	0.073	0.002	0.002	−0.041	0.068	−0.024	9.44
	2.05 *	2.12 *	−0.92	1.90	0.51	−2.11 *	1.11	0.03	0.04	−0.79	1.33	−0.47	[0.67]
HK	0.084	0.037	0.004	−0.032	0.023	−0.019	0.132	0.026	0.050	0.049	−0.110	−0.076	21.25
	1.44	0.64	0.06	−0.56	0.41	−0.32	2.32 *	0.45	0.87	0.85	−1.90	−1.32	[0.05] *
IN	0.121	0.050	−0.010	−0.068	0.097	0.061	−0.046	−0.034	−0.038	0.003	0.043	−0.083	16.96
	2.08 *	0.86	−0.17	−1.16	1.66	1.03	−0.79	−0.58	−0.65	0.05	0.75	−1.45	[0.15]
KO	0.152	−0.069	0.030	−0.092	0.030	0.010	0.040	−0.016	0.061	−0.063	0.060	−0.084	9.75
	2.61 *	−1.18	0.52	−1.58	0.52	0.18	0.69	−0.28	1.07	−1.12	1.05	−1.49	[0.64]
SG	0.120	0.142	−0.043	0.058	−0.031	−0.037	0.036	0.007	−0.005	−0.042	−0.091	0.042	17.38
	2.06 *	2.43 *	−0.73	0.99	−0.53	−0.64	0.63	0.12	−0.08	−0.74	−1.60	0.74	[0.14]
BR	0.089	0.046	0.033	0.108	−0.099	−0.069	0.057	0.003	−0.003	0.124	0.026	−0.013	15.17
	1.38	0.71	0.50	1.66	−1.52	−1.06	0.87	0.04	−0.04	1.93	0.41	−0.20	[0.23]
CL	0.201	−0.012	−0.005	0.170	−0.036	0.009	0.148	0.057	0.041	−0.025	−0.017	0.014	43.84
	3.48 *	−0.20	−0.09	2.93 *	−0.61	0.15	2.53 *	0.96	0.70	−0.43	−0.29	0.25	[0.00] *

Notes: This table tests the dependency of stock returns; ρ_s is the coefficient of autocorrelation up to the 12th order. Q_{12} is the Ljund-Box statistics for testing joint significance of 12 order lags. The numbers in the brackets are the p-values. The values in the first row are the estimated coefficients and in the second row are the t-statistics. * indicates statistically significant at the 5% level or better.

Table 4. Autocorrelations of monthly absolute values of stock market returns up to 12 orders.

Market	ρ_1	ρ_2	ρ_3	ρ_4	ρ_5	ρ_6	ρ_7	ρ_8	ρ_9	ρ_{10}	ρ_{11}	ρ_{12}	$Q(12)$	$P(s)$
Panel A														
CA	0.231	0.291	0.255	0.149	0.269	0.266	0.215	0.276	0.170	0.168	0.218	0.142	195.88	0.00
FR	0.203	0.242	0.189	0.092	0.164	0.170	0.142	0.085	0.147	0.124	0.064	0.133	90.84	0.00
GM	0.124	0.222	0.195	0.084	0.167	0.191	0.123	0.098	0.169	0.148	0.046	0.118	84.33	0.00
IT	0.134	0.140	0.241	0.090	0.076	0.174	0.088	0.113	0.139	0.068	0.030	0.079	66.36	0.00
JP	0.147	0.101	0.101	0.101	0.098	0.019	0.043	0.047	0.110	0.032	0.040	0.050	26.49	0.01
UK	0.177	0.177	0.222	0.117	0.155	0.153	0.101	0.090	0.091	0.132	0.038	0.005	69.11	0.00
US	0.235	0.213	0.215	0.241	0.231	0.216	0.175	0.110	0.089	0.182	0.050	0.125	128.92	0.00
Panel B														
Au	0.081	0.152	0.064	0.055	0.108	0.003	0.033	−0.036	0.119	0.045	0.052	0.012	22.16	0.04
CN	0.142	0.159	0.048	0.087	0.105	0.044	0.13	0.041	0.124	0.1	0.117	0.034	34.69	0.00
HK	0.049	0.118	0.162	0.126	0.099	0.15	0.16	0.19	0.086	0.03	0.125	0.11	59.96	0.00
IN	0.109	0.328	0.101	0.119	0.202	0.101	0.139	0.084	0.018	0.073	0.031	0.155	79.69	0.00
KO	0.053	0.19	0.265	0.189	0.219	0.209	0.169	0.163	0.29	0.092	0.175	0.127	137.45	0.00
SG	0.227	0.122	0.081	0.091	0.102	0.207	0.222	0.183	0.155	0.100	0.024	0.049	80.73	0.00
BZ	0.148	0.094	0.125	0.112	0.065	0.036	0.152	0.124	0.095	0.125	0.114	0.088	40.29	0.00
CL	0.247	0.167	0.25	0.183	0.123	0.164	0.331	0.133	0.093	0.082	0.004	0.085	119.24	0.00

Notes: The standard error for the estimated coefficient is $1/\sqrt{T} = 1/\sqrt{310} = 0.05679$, e.g., the t-statistic of ρ_1 for CA is $0.231/0.05679 = 4.068$. Testing for absence of autocorrelations of the absolute R_{mt} with 12 lags by $Q(12)$, the null is uniformly rejected at the 1% level for all markets shown in p-values.

5. Empirical Results

5.1. Evidence from the Regression Method

The regression results of Equation (7), which use the Newey–West estimator (Newey and West 1987), are reported in Tables 5 and 6 that show negative and statistically significant values for all the coefficients of news variables, except those for Australia and Singapore in the global news at the current period. In the case of Australia, however, the negative impact has been extended to the lagged one period. The testing results also show that none of the AR(1) terms is significant. The evidence seems inconsistent with our earlier finding in testing the autocorrelations. In fact, this may be attributable to the fact that the AR(1) effect has been picked up by the lagged news variables in a multivariate regression procedure. In addition, the use of the Newey–West method also helps to reduce the significance of AR(1). However, the significance of the lagged news variables can be viewed as evidence against the EMH.

Table 5. Regression results of stock returns on domestic EPU (η_t) and global EPU (z_t) for G7 markets for the period of January 1997–June 2016.

Markets	α	η_t	η_{t-1}	η_{t-2}	z_t	z_{t-1}	z_{t-2}	ρ_1	$\bar{R}^2$
CA	1.751	−0.042	0.009	0.024	−0.082	0.052	0.020	0.05	0.11
	1.87	−3.57	0.78	2.38	−3.46	2.00	0.90	0.71	
FR	0.745	−0.029	0.019	0.006	−0.111	0.073	0.016	0.01	0.14
	1.11	−4.27	2.34	0.90	−5.60	2.91	0.80	0.14	
GM	0.676	−0.072	0.046	0.024	−0.130	0.059	0.033	−0.07	0.16
	0.63	−5.14	2.40	1.96	−5.09	1.73	1.24	−1.08	
IT	−0.198	−0.070	0.031	0.041	−0.093	0.063	0.003	−0.07	0.16
	−0.16	−5.34	1.91	3.09	−5.05	2.56	0.14	−1.03	
JP	2.006	−0.089	0.029	0.043	−0.062	0.032	0.043	−0.02	0.19
	1.92	−4.47	1.34	2.57	−3.85	1.24	1.81	−0.30	
UK	−0.334	−0.017	0.022	−0.001	−0.081	0.037	0.015	−0.09	0.15
	−0.75	−2.42	2.48	−0.21	−4.98	1.77	0.95	−1.27	
US	0.975	−0.053	0.020	0.030	−0.053	0.043	0.034	−0.02	0.12
	1.11	−5.22	1.16	2.38	−1.85	1.49	1.37	−0.18	

Notes: The dependent variable is stock return. The values in the first row are the estimated coefficients and in the second row are the *t*-statistics.

Table 6. Regression results of stock returns on domestic EPU (η_t) and global EPU (z_t) for G7 markets for the period of January 1997–June 2016.

Markets	α	η_t	η_{t-1}	η_{t-2}	z_t	z_{t-1}	z_{t-2}	ρ_1	$\bar{R}^2$
AU	2.079	−0.010	−0.039	0.035	−0.007	−0.042	0.054	−0.089	0.15
	3.71	−1.04	−2.46	5.64	−0.33	−1.93	3.14	−0.96	
CN	0.848	−0.026	0.005	0.018	−0.076	0.030	−0.009	0.058	0.03
	0.90	−2.44	0.33	1.61	−2.44	0.92	−0.22	0.86	
HK	1.539	−0.038	0.009	0.022	−0.087	0.068	0.009	0.052	0.13
	1.62	−4.45	0.68	2.15	−3.40	1.99	0.38	0.72	
IN	3.956	−0.080	0.024	0.030	−0.017	−0.058	0.073	0.003	0.17
	3.16	−4.16	1.10	1.43	−0.56	−1.45	1.82	0.03	
KO	−0.605	−0.055	0.039	0.029	−0.079	0.057	0.019	0.090	0.06
	−0.33	−3.32	1.46	1.65	−2.79	1.35	0.62	1.59	
SG	2.346	−0.057	0.003	0.041	−0.087	0.051	0.057	0.159	0.15
	2.19	−2.80	0.10	1.72	−1.26	0.71	0.59	1.53	
BR	0.862	−0.027	0.012	0.016	−0.095	0.049	0.022	−0.023	0.06
	0.80	−2.84	1.04	1.73	−3.89	1.51	0.88	−0.33	
CL	1.109	−0.035	0.007	0.025	−0.034	0.025	0.002	−0.006	0.08
	1.48	−2.95	0.52	2.37	−2.11	1.23	0.12	−0.07	

Notes: The values in the first row are the estimated coefficients and in the second row are the *t*-statistics.

5.2. GARCH(1,1)-X Method

The estimated results reported in Tables 5 and 6 omit the terms of $\Delta\eta\_(t-1)$ and $\Delta z\_(t-1)$, implyingthe ignorance of EPU innovations on conditional variance. The system Equations (7) and (8) address this issue, and the estimated results using GED-GARCH(1,1)-M are reported in Tables 7 and 8. Several important findings are now summarized. First, in examining the coefficient of AR(1), autocorrelations are not significant in the G7 markets. However, autocorrelations for four markets in the Pacific-Asian group, including Australia, China, South Korea and Singapore, are significant. Viewed from this perspective, the G7 markets appear to behave more consistently with market efficiency than other markets do.

Second, the coefficients for the news variables at the current period, η_t and z_t, are all negative and statistically significant; the exception is the U.S. market where the coefficient of global news is insignificant. This evidence, which shows current news variables are significant, does not go against market efficiency. However, in checking the lagged news, either one of $\eta_{t-1}, \eta_{t-2}, z_{t-1}, z_{t-2}$ or combinations of these lagged variables, we find the null should be rejected, indicating a lack of market efficiency. However, the patterns among the G7 markets (except for CA in the η_{t-1}; JP and US in z_{t-1}) appear to be more consistent as lagged one-period news are all positive and significant. This pattern reflects a market phenomenon, which shows that although the news has a negative effect on stock returns in the current period, the markets do rebound in the subsequent two periods. This pattern is also shown in the PALA markets, although the effect is not as uniform as it is in the G7 markets. Thus, the evidence in general supports the uncertainty premium hypothesis.

Third, the coefficients in the variance equation indicate that the GARCH(1,1) model in general is appropriate although some variations are found across different markets. Interestingly, testing results indicate that both $\Delta\eta_{t-1}$ and Δz_{t-1} firmly contribute to explain variations in the variance, as evidenced by positive and significant coefficients for each market. The only exception is the Chinese market where no evidence exists to support the proposition that the variance in Chinese market volatility can be significantly predicated by EPU innovation or by its historical pattern. We further test the joint significance of all the lagged news variables in the system by setting the null as $\eta_{t-1} = \eta_{t-2} = z_{t-1} = z_{t-2} = 0$. The joint tests from the $\chi(4)$ indicate that the null is strongly rejected. Likewise, the joint test for $\Delta\eta_{t-1} = \Delta z_{t-1} = 0$ in the conditional variance by $\chi(2)$ also indicates the rejection of the null (except in the case in China); this evidence goes against the studies by Li (2017); Lopez de Carvalho (2017) and Chen et al. (2017), who fail to include the lagged EPU innovations in their models for predicting the conditional variance. The testing results thus conclude that the null hypothesis that stock returns are independent of lagged EPU innovations is rejected.

Table 7. Regression estimates of the G7 stock returns on domestic EPU and global EPU with GED-GARCH(1,1)-M procedure: January 1997–June 2016.

Markets	α	η_t	η_{t-1}	η_{t-2}	z_t	z_{t-1}	z_{t-2}	ρ_1	ω	ε^2_{t-1}	σ^2_{t-1}	$\Delta\eta_{t-1}$	Δz_{t-1}	$\chi(4)$	$\chi(2)$	$\bar{R}^2$
CA	1.887	−0.038	0.012	0.017	−0.088	0.068	0.014	−0.006	17.410	0.116	0.343	0.241	0.514	1093.00	25.20	0.10
	2.37	−3.70	0.85	1.68	−4.10	2.24	0.57	−0.08	2.73	1.60	1.93	4.71	3.17	[0.03]	[0.00]	
FR	0.377	−0.025	0.020	0.003	−0.086	0.056	0.011	0.014	0.269	0.017	0.963	0.080	0.320	16.33	34.49	0.13
	0.65	−4.48	2.23	0.33	−4.07	2.22	0.47	0.20	1.13	0.99	40.10	2.07	5.32	[0.00]	[0.00]	
GM	−0.175	−0.066	0.047	0.022	−0.135	0.076	0.016	−0.054	19.578	0.186	0.178	0.170	0.547	60.83	34.80	0.15
	−0.19	−8.97	3.62	1.95	−5.82	2.58	0.73	−0.69	5.11	1.72	1.69	2.61	4.09	[0.00]	[0.00]	
IT	−0.024	−0.054	0.034	0.021	−0.081	0.080	−0.011	−0.021	1.641	0.159	0.788	0.153	0.293	42.26	16.71	0.14
	−0.02	−5.33	2.81	1.90	−7.16	4.05	−0.63	−0.27	1.69	2.72	11.23	2.66	2.55	[0.00]	[0.00]	
JP	1.654	−0.100	0.051	0.034	−0.038	0.022	0.037	−0.104	1.365	0.115	0.827	0.245	0.002	52.34	9.81	0.16
	1.74	−6.63	2.38	2.36	−2.65	1.01	1.97	−1.49	2.38	3.96	4.54	2.81	0.01	[0.00]	[0.00]	
UK	−1.211	−0.015	0.022	0.001	−0.106	0.067	−0.003	−0.091	4.946	0.220	0.472	−0.040	0.166	55.39	6.96	0.12
	−3.23	−3.98	4.70	0.16	−6.78	2.99	−0.15	−1.33	2.64	2.11	2.50	−1.47	2.47	[0.00]	[0.03]	
US	−0.348	−0.036	0.001	0.039	−0.029	0.024	0.032	−0.097	1.537	0.046	0.868	0.317	−0.097	51.76	59.55	0.07
	−0.40	−4.86	4.90	5.64	−1.30	0.96	1.24	−1.15	2.32	1.20	16.00	7.32	−1.20	[0.00]	[0.00]	

Notes: The dependent variable is stock return. The values in the first row are the estimated coefficients and in the second row are the *t*-statistics. The η_t is the domestic EPU at time *t*, and z_t is the global EPU at time *t*. $\chi(4)$ is the chi-squared distribution for testing joint significance of lagged news in the mean equation. That is, $\eta_{t-1} = \eta_{t-2} = z_{t-1} = z_{t-2} = 0$. $\chi(2)$ is the chi-squared distribution for testing joint significance of $\Delta\eta_{t-1} = \Delta z_{t-1} = 0$ in the variance equation.

Table 8. Regression estimates of stock returns on domestic EPU and global EPU with GED-GARCH(1,1)-M procedure: Asian-Pacific and Latin American markets: January 1997–June 2016.

Markets	α	η_t	η_{t-1}	η_{t-2}	z_t	z_{t-1}	z_{t-2}	ρ_1	ω	ε^2_{t-1}	σ^2_{t-1}	$\Delta\eta_{t-1}$	Δz_{t-1}	$\chi(4)$	$\chi(2)$	$\bar{R}^2$
AU	2.052	−0.024	−0.021	0.033	−0.028	−0.018	0.039	−0.168	0.345	0.110	−0.195	0.145	0.032	18.41	7.85	0.13
	4.24	−3.05	−1.82	3.76	−1.96	−1.010	2.71	−2.28	0.12	1.008	−0.55	2.80	0.42	[0.00]	[0.02]	
CN	1.039	−0.027	0.005	0.018	−0.070	0.021	−0.008	0.021	62.381	1.617	0.749	−1.231	−1.748	192.73	0.16	0.03
	4.65	−16.40	2.74	9.31	−13.06	11.80	−2.21	2.01	0.36	0.53	1.57	−0.29	−0.15	[0.00]	[0.93]	
HK	1.563	−0.042	0.009	0.025	−0.052	0.016	0.019	0.102	1.849	0.078	0.861	0.001	0.345	12.77	9.27	0.10
	1.62	−5.04	1.23	3.06	−2.47	0.52	0.79	1.05	2.32	1.44	13.98	0.02	2.43	[0.01]	[0.01]	
IN	2.593	−0.057	0.014	0.027	0.039	−0.091	0.034	0.044	3.870	0.153	0.761	0.236	0.269	37.69	7.98	0.13
	2.23	−3.96	0.71	1.60	1.67	−4.43	2.16	0.40	2.12	1.50	6.08	1.76	1.62	[0.00]	[0.02]	
KO	2.566	−0.071	0.054	0.002	−0.056	0.049	0.052	0.040	14.088	0.350	0.548	0.514	0.057	19.22	25.69	0.01
	1.59	−5.60	3.06	0.10	−1.83	1.00	1.61	20.50	3.97	4.03	9.23	5.01	0.16	[0.00]	[0.00]	
SG	1.791	−0.033	−0.010	0.028	0.015	−0.035	0.064	0.271	5.797	0.478	0.426	0.330	−0.192	25.54	28.43	0.10
	1.29	−3.17	−0.48	2.87	0.32	−0.59	1.19	2.15	3.92	3.66	6.25	5.18	−0.83	[0.00]	[0.00]	
BR	−1.477	−0.020	0.017	0.015	−0.089	0.066	0.024	0.022	19.723	0.497	0.348	0.211	0.545	14.40	10.49	0.02
	−1.86	−1.82	1.26	1.89	−2.87	1.71	0.89	0.21	2.49	4.82	2.47	3.17	2.00	[0.01]	[0.01]	
CL	2.294	−0.036	−0.001	0.023	−0.039	0.060	−0.022	0.006	9.511	0.221	0.426	0.055	0.533	12.89	26.19	0.04
	1.93	−3.93	−0.11	1.67	−3.86	2.55	−1.55	0.05	2.93	1.80	2.47	1.40	4.50	[0.02]	[0.00]	

Notes: The dependent variable is stock return. The values in the first row are the estimated coefficients and in the second row are the *t*-statistics. The η_t is the domestic EPU at time *t*, and z_t is the global EPU at time *t*. $\chi(4)$ is the chi-squared distribution for testing joint significance of lagged news in the mean equation. That is, $\eta_{t-1} = \eta_{t-2} = z_{t-1} = z_{t-2} = 0$. $\chi(2)$ is the chi-squared distribution for testing joint significance of $\Delta\eta_{t-1} = \Delta z_{t-1} = 0$ in the variance equation.

6. Conclusions

This paper examines EMH and tests the news impact on stock returns by employing monthly data for 15 international equity markets. A simple way to test market efficiency is by examining the dependency of return series. By focusing on the univariate correlation analysis of stock returns, the statistics suggest that the null for the absence of correlations up to 12 months is rejected for 13 out of 15 markets; the exceptions are the U.S. and Canada. However, tests of the absence of autocorrelations of absolute values of stock returns are uniformly rejected for all markets under investigation.

We also test whether the news variables have significant effects on the stock returns. By using EPU indices as news variables, this study concludes that stock returns are negatively correlated with EPU in the current period, but are positively correlated in the following two periods, and the estimated coefficients are statistically significant in the majority of cases. This finding reflects a pattern of behavior among investors whose fears about the market, following bad news and the accompanying uncertainty, prompt them to sell off their stocks. This sell-off results in a fall in prices. However, rational traders may take advantage of declining prices and place orders, causing a bounce back in prices in the following two months. This phenomenon produces positive relations between stock returns and lagged news; this group of investors will receive uncertainty premiums, regardless of whether the news originates from a local market or the global market.

In placing the EPU innovations in the variance equation, the evidence consistently shows a predictive power in projecting stock volatility, not only using local news but also global lagged news. The only exception to this finding is the Chinese market, where we are unable to find a significant effect of EPU innovation in predicting variance. In sum, the evidence drawn from this study concretely shows that the news is significant in predicting future stock returns, which allows us to reject the EMH.

Since this study focuses on the time series dynamics to examine the EMH, the impact of accounting information on stock prices has been excluded from this study, but will be considered in future study by factoring in the quality of financial reporting along the line of Ohlson (1995); Glezakos et al. (2012) and Jianu et al. (2014).

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Appendix A

Table A1. Summary of notations of variables.

Variable	Description	Source
$p_t = ln(P_t)$	P_t is the market stock index for each country.	Datastream
$R_{m,t}$	Market stock returns, which is obtained by taking the natural log-difference of stock price index times 100.	Datastream
$\phi_{m,t-1}$	Market information set up to time $t-1$.	
σ_t^2	Variance of stock returns generated from the GARCH(1,1)-M process	
ρ_s	Autocorrelation coefficient with s period lag.	
η_{t-i}	Economic policy uncertainty index at time $t-i$ from Baker et al. (2016). This variable was transformed by taking the natural logarithm.	Baker et al. (2016) *
$\Delta\eta_{t-1}$	EPU innovation measured by natural log-difference of the EPU index.	
z_{t-i}	Global economic policy uncertainty index at time $t-i$ from Davis (2016). This variable was transformed by taking the natural logarithm.	Davis (2016) *

Table A1. *Cont.*

Variable	Description	Source
Δz_{t-1}	Global EPU innovation measured by the natural log-difference of GEPU index.	
ε_t	Random error term.	
Ω_{t-1}	Information set conditional on time $t-1$ in the empirical test.	
CED $(\cdot)$	Generalized error distribution.	
G7	Group 7 industrial markets	
APLA	Asian-Pacific and Latin American (APLA) markets	

* http://www.policyuncertainty.com Website information has been updated to the current. Source: 'Measuring Economic Policy Uncertainty' by Scott Baker, Nicholas Bloom and Steven J. Davis at www.PolicyUncertainty.com.

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Influence of Real Exchange Rate on the Finance-Growth Nexus in the West African Region

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Abstract: This study examines the moderating effects of the real exchange rate and its volatility on the finance-growth nexus in the West African region. It also determines the marginal effects of financial development on economic growth at various levels of the real exchange rates and its volatility. The findings show that financial development has a long-term positive impact on economic growth, but this impact is weakened by real exchange rate and its volatility. The marginal effects of financial development on economic growth vary with the levels of the real exchange rate and its volatility. The higher the real exchange rate and its volatility, the less finance spurs growth. We also provide evidence of this scenario in individual specific countries in the region. The implication of this study is that the development of the financial sector would not provide the desirable economic benefits except it is accompanied by a reduction and stability in the real exchange rates. Based on the findings, the study makes some policy recommendations.

Keywords: real exchange rate; volatility; financial development; economic growth

JEL Classification: G20; F31; O47

1. Introduction

Some empirical studies have emphasized the fundamental role of institutional quality, level of financial development, per capita income and inflation in moderating the impact of financial development on economic growth in developed and developing countries (e.g., Arcand et al. 2015; Ehigiamusoe et al. 2018; Law et al. 2018; Law and Singh 2014). However, the role of the real exchange rate or its volatility on the finance-growth nexus has not been thoroughly explored. The economic benefits of financial development could vary with the level of the real exchange rate. This is because real exchange rate has the capacity to influence economic growth. For instance, some studies reported that real exchange rate has a positive impact on economic growth (e.g., Razmi et al. 2012; Rodrik 2008; Tarawalie 2010), whereas other studies documented a negative linkage (e.g., Bleaney and Greenaway 2001; Conrad and Jagessar 2018; Elbadawi et al. 2012) or insignificant relationship (e.g., Tang 2015). Moreover, Aghion et al. (2009) showed that real exchange rate volatility has a negative impact on productivity growth, while Vieira et al. (2013) revealed that high real exchange rate volatility has a negative impact on economic growth, albeit the impact of low volatility is positive. However, Comunale (2017) noted that exchange rate volatility does not have any robust effect on GDP growth.

Besides its direct effect on economic growth, studies have shown that real exchange rate and financial development could have a dynamic relationship. Lin and Ye (2011) posited that financial development has a significant effect on the choice of exchange rate regime, whereas Katusiime (2018) reported that exchange rate has a significant effect on the growth of private sector credit. Thus, countries with less developed financial markets are more likely to adopt a fixed exchange rate, while countries with higher levels of financial development are more likely to adopt a flexible system, which in turn determines the exchange rate. Moreover, Fujiwara and Teranishi (2011) reported that financial market friction replicates persistent, volatile and realistic hump-shaped responses of the real exchange rates. They concluded that financial market development is a strategic component to understand real exchange rate dynamics. Specifically, Tang and Yao (2018) showed that financial structure, which reflects the proportion of direct financing and indirect financing, plays a crucial role in the relationship between exchange rates and stock prices.

Furthermore, Jayashankar and Rath (2017) argued that there is a significant relationship among the stock market, foreign exchange market and money market in emerging economies to the extent that positive or negative shocks that affect one market could be quickly transmitted to another market via contagious effect. However, they concluded that the empirical connection among these markets is insignificant at lower scales, but robust at higher scales. Moreover, it had been argued that financial development has the capacity to alleviate the adverse effects of the real exchange rate and its volatility on productivity growth. Uncertainty in the real exchange rate worsens the negative effect of domestic credit market constraints (see Aghion et al. 2009). Particularly, Elbadawi et al. (2012) showed that financial development has the capacity to alleviate the negative effects of the real exchange rate overvaluation on economic growth.

Therefore, the specific objective of this paper is to examine the effects of the real exchange rate and its volatility on the finance-growth nexus in the West Africa region. Fundamentally, it seeks to determine the marginal effects of financial development on economic growth at various levels of the real exchange rate and its volatility. In this regard, this paper differs from previous studies and makes a significant contribution to the existing literature. Unlike Levine et al. (2000) that focused mainly on the finance-growth nexus in some selected developed and developing countries, our paper focuses on the finance-growth nexus in developing economies (i.e., West African region). In addition, we augment the finance-growth nexus with real exchange rate (or its volatility) as well as the interaction term between financial development and real exchange rate (or its volatility). This enables us to determine whether the finance-growth nexus varies with the level of the real exchange rate (or its volatility), an issue that was not explored in Levine et al. (2000). To the best of our knowledge, the only paper that used an interaction term between real exchange rate and financial development is Aghion et al. (2009), but they focused on whether the effects of the real exchange rate on productivity growth vary with the level of financial development in some selected countries. However, our paper focuses on whether the impact of financial development on economic growth varies with the level of the real exchange rate (or its volatility) in the West African region. Moreover, we determine the marginal effects of financial development on economic growth at various levels of the real exchange rate (or its volatility), an issue that was not explored in Aghion et al. (2009). This is fundamental because the marginal effect enables us to determine the changes in economic growth caused by simultaneous changes in both financial development and real exchange rate (or its volatility), which is essential for policy formulation (see Brambor et al. 2006; Law et al. 2018; Ehigiamusoe et al. 2018).

Hence, the motivation of this paper is that previous studies have neglected the moderating role of the real exchange rate or its volatility on the finance-growth nexus. Although some studies have shown that financial development has a positive impact on economic growth in the West African region (see Ehigiamusoe and Lean 2018; Ratsimalahelo and Barry 2010), it remains unclear whether this impact varies with the level of the real exchange rate or its volatility. Moreover, most past studies on real exchange rate and its volatility focused mainly on their direct effects on economic growth (see Elbadawi et al. 2012; Iyke 2018; Rodrik 2008; Vieira et al. 2013), while their indirect effects via the financial sector have not been thoroughly explored. To capture the indirect effects, we employ multiplicative interaction model where we interact real exchange rate (or its volatility) with financial development. Brambor et al. (2006) recommended the use of multiplicative interaction model whenever there is a conditional hypothesis (when the relationship between two variables depends on the value of another variable).

The scope of this study is limited to the West African region because several West African countries have employed financial sectors reforms and policies to stimulate greater depth and breadth of the financial markets, create better access to financial resources, and provide efficient supervisory and regulatory frameworks. In recent decades, there have been privatization of commercial banks, liberalization of interest rates, recapitalization of financial institutions and technological innovations aimed at repositioning the sector with a view to enhancing economic growth. The recent reforms notwithstanding, the financial system in the West African region is still largely bank-based, small and undiversified compared to the financial systems in advanced and emerging economies. For instance, during the 1980–2014 period, the average level of financial development (measured by credit to the private sector relative to GDP) in the region was 15.43% compared to 29.85%, 36.32%, 86.06% and 124.28% in South Asia, Middle East and North African region, European Union and high income countries, respectively.

Secondly, in the past three decades, many West African countries have attained significant improvements in their economic growth compared to the 1960s and 1970s. The region has experienced average annual GDP growth of 5 percent, which is higher than the average GDP growth rate in several advanced and emerging economies (see IMF 2014). Therefore, the financial sector could probably be one of the sectors that contribute to this impressive growth.

Moreover, this paper is further motivated by the high and volatile real exchange rate in the West African region. For instance, the real exchange rate has plummeted significantly in the past three decades averaging 1639.9 in 2015 compared to 41.3 in 1980. On a country-by-county basis, the real exchange rate deteriorated from 9.7 to 99.3 in Cape Verde; from 83.5 to 597.8 in Benin; from 124.5 to 600 in Mali; and from 78.7 to 7834 in Sierra Leone in 1980 and 2015, respectively. In addition, most of these countries experienced substantial volatility in their real exchange rates during the period. Hence, this study seeks to provide insights into the influence of the real exchange rate on the finance-growth nexus in the West African region, an issue that has not received adequate attention in the extant literature.

Finally, since West Africa is the largest region in Sub-Sahara Africa in terms of population, it is fundamental to study this region since anything that adversely affects it could have negative effects on the African continent or the larger international community. Hence, the findings on West African countries could be invaluable to other developing or emerging economies that want to accelerate economic growth via financial sector development and the real exchange rate.

Besides this introduction, the remaining parts of the paper are divided into four sections. The methodology is contained in Section 2, while the empirical results are presented in Section 3. The discussion and policy implications of the findings are presented in Section 4, while Section 5 concludes the study with some policy recommendations.

2. Data and Methodology

2.1. Data Description

The study uses annual data[1] of West African countries for the 1980–2014 period. The countries include Benin, Burkina Faso, Cape Verde, Cote D' Ivoire, Gambia, Ghana, Liberia, Guinea, Guinea Bissau, Mali, Mauritania, Niger, Nigeria, Sierra Leone, Senegal and Togo. The estimation period is limited because of the unavailability of data for some West African countries prior to this period. The data on economic growth, credit to the private sector, government consumption expenditure and trade openness were sourced from the World Development Indicators (2016) of the World Bank, while the data for the inflation rate were obtained from the World Economic Outlook (2015) of the International Monetary Fund. In addition, the data for the liquid liabilities were sourced from

[1] We attempt to use different frequency data such as quarterly or monthly data to check the robustness of our annual data; unfortunately, the quarterly or monthly data for all variables in our model are unavailable for the sample period. When the quarterly or monthly data become readily available in the future, further research could utilize them for comparison.

the Economic Data (2016) of the Federal Reserve Bank of St Louis, USA, while the data on human capital were taken from the Human Development Reports (2015) of the United Nations Development Programme. Data on the real exchange rate were computed from an official nominal exchange rate and consumer price index drawn from World Development Indicators (2016), while real exchange rate volatility was computed as the standard deviation of the 5-year moving average of the logarithm of the real exchange rate.

Figure 1 shows the trend analysis of average GDP per capita, financial development indicators and the real exchange rate of the West African region during the 1980–2014 period. It is obvious that financial development indicators were low and experienced no remarkable increase during the period. Although the level of GDP was high relative to the levels of both financial development and real exchange rate, but there was only a marginal increase in the level of GDP during the period. Conversely, the graph shows a significant increase in the real exchange rate in the West African region during the period. These remarkable changes in the real exchange rate could have both direct and indirect effects on economic growth via the financial sector.

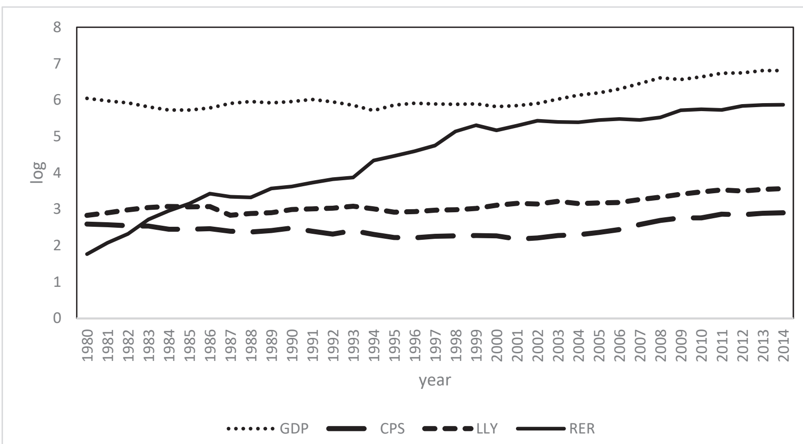

Figure 1. Trends analysis of GDP, financial development and real exchange rate in the West African region.

2.2. Model Specification

This study employs the finance-growth model in extant literature (e.g., Levine et al. 2000; Beck et al. 2000) as the baseline model to examine the impact of financial development on economic growth in the West African region given as follows:

$$Y_{it} = \alpha_1 FD_{it} + \delta' Z_{it} + \eta_i + \mu_t + \varepsilon_{it} \tag{1}$$

where Y = real GDP per capita, FD = financial development (proxy by credit to the private sector relative to GDP, and alternatively by liquid liabilities relative to GDP), Z = a set of control variables (namely government consumption expenditure relative to GDP, trade openness relative to GDP, human capital, and inflation rate), η_i = unobserved country-specific effect; μ_t = time specific-effect, and $\varepsilon_{i,t}$ = independent and identically distributed error term. All the variables except inflation are transformed into natural logarithm before analysis.

Moreover, we augment the finance-growth model with real exchange rate (or its volatility) as well as the interaction term between financial development and real exchange rate or its volatility (see Aghion et al. 2009) given as follows:

$$Y_{it} = \alpha_1 FD_{it} + \alpha_2 RER_{it} + \alpha_3 (FD_{it} * RER_{it}) + \delta' Z_{it} + \eta_i + \mu_t + \varepsilon_{it} \tag{2}$$

where RER = real exchange rate[2] (alternatively as real exchange rate volatility), and $FD * RER$ = interaction term between financial development and real exchange rate (alternatively as real exchange rate volatility).

The interaction term enables us to ascertain whether the growth effect of financial development varies with the levels of the real exchange rate or its volatility. Hence, the study seeks to test the hypothesis that financial development has a larger impact on economic growth in the environment of lower real exchange rate or its volatility compared to the environment of high real exchange rate or its volatility. The interaction term between the two variables captures the marginal effects via the partial derivatives of the economic growth equation (Equation (2)) with respect to financial development given as follows:

$$\frac{\partial Y_{it}}{\partial FD_{it}} = \alpha_1 + \alpha_3 RER_{it} \tag{3}$$

Our conditional hypothesis focuses on the sign of the coefficients of α_1 and α_3. If $\alpha_1 > 0$ and $\alpha_3 > 0$, it implies that financial development has a positive impact on economic growth, and real exchange rate favourably influences that positive impact. If $\alpha_1 > 0$ and $\alpha_3 < 0$, it suggests that financial development has a positive impact on economic growth, and real exchange rate adversely influences that positive impact. If $\alpha_1 < 0$ and $\alpha_3 > 0$, it denotes that financial development has a negative impact on economic growth, and real exchange rate mitigates that negative impact. If $\alpha_1 < 0$ and $\alpha_3 < 0$, it implies that financial development has a negative impact on economic growth, and real exchange rate aggravates that negative impact. However, if the entire marginal effect ($\alpha_1 + \alpha_3 RER$) is positive, it implies that more financial development and real exchange rate or its volatility enhance economic growth, but the opposite holds if the marginal effect is negative. To determine the statistical significance of the marginal effects, Brambor et al. (2006) suggested that the corresponding standard errors and t-statistics should be computed for inferences.

To compute the corresponding t-statistics of the marginal effects, we first employ the following formula to compute the variance from the coefficient covariance matrix:

$$\sigma^2_{\frac{\partial Y}{\partial FD}} = \mathrm{var}(\hat{\alpha}_1) + RER^2 \mathrm{var}(\hat{\alpha}_3) + 2RER\mathrm{cov}(\hat{\alpha}_1 \hat{\alpha}_3) \tag{4}$$

The square root of the variance gives the standard error, and the marginal effect divided by the standard error gives the t-statistics. A large t-statistic suggests that the marginal effect is statistically significant.

2.3. Justification of the Variables in the Model

The model follows the finance-growth nexus but augmented with real exchange rate or its volatility. The dependent variable is economic growth (proxy by real GDP per capita) following some previous studies (e.g., Demetriades and Law 2006; Ehigiamusoe et al. 2018; Gries et al. 2009; Kar et al. 2011; Law et al. 2018). This study uses the preferred and commonly used proxy of financial development in the finance literature, namely domestic credit to the private sector as a ratio of GDP[3]

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2 The real exchange rate between West Africa currencies and the United States dollar is the product of the nominal exchange rate (the units of West Africa currencies given up for one United States dollar) and the ratio of consumer price index between West Africa and United States. The core equation is RER = eP*/P, where e = the nominal West Africa currencies − US dollar exchange rate, P* = the consumer price index in West Africa, and P = the consumer price index in the United States.

3 We thank the anonymous reviewer for this comment. We are aware that, at a low level of financial development (proxy by credit to the private sector relative to GDP), an increase in credit to the private sector could suggest a higher financial development and probably greater economic growth. However, at a high level of financial development, an increase in credit to the private sector (e.g., from 150% to 200% of GDP) may not indicate a positive development in the financial sector, rather it might probably suggest that the financial sector could undermine economic growth (see Arcand et al. 2015; Law and Singh 2014; Samargandi et al. 2015; Law et al. 2018). Specifically, Arcand et al. (2015) showed that the impact of financial development on economic growth turns negative when financial development (proxy by credit to the private sector) reaches 100% of GDP. However, our study focuses on developing economies of the West African region with a

(see Arcand et al. 2015; Beck et al. 2000; Demetriades and Law 2006; Ehigiamusoe and Lean 2018; Ehigiamusoe et al. 2018; King and Levine 1993; Law and Singh 2014; Law et al. 2018; Levine et al. 2000; Rioja and Valev 2004; Samargandi et al. 2015). It measures the credits issued by the banking institutions to the private sector and excludes credits issued to governments, its agencies, public enterprises as well as credits issued by the central bank (Beck et al. 2000; Levine et al. 2000). In order to check the robustness of the results, liquid liabilities relative to GDP is used as alternative proxy of financial development (see Hassan et al. 2011; Loayza and Ranciere 2006). Liquid liabilities are commonly referred to as M3/GDP. It is a measure of financial depth and the overall size of the financial intermediary sector[4]. It is the addition of currency, demand and interest-bearing liabilities of both banks and non-bank financial institutions. It consists of broad money supply (M2) plus commercial paper, travelers' checks, foreign currency time deposits and shares of mutual funds or market funds held by residents as a ratio of GDP (see World Development Indicators 2016). It is a better measure of financial depth because M2 may be a poor proxy of financial development in countries with underdeveloped financial system. M3/GDP is more concerned with the capacity of the financial system to provide transaction services rather than the capacity to channel funds from savers to borrowers (see Khan and Senhadji 2003).

First, theoretical literature on the finance-growth nexus posited that financial development accelerates economic growth by enhancing the sources of growth such as capital accumulation and productivity growth (see King and Levine 1993; Levine and Zervos 1998; Beck et al. 2000; Rioja and Valev 2004). Specifically, Levine and Zervos (1998) noted that a financial system is considered as developed when it can efficiently and effectively perform the resource mobilization and allocation functions aimed at promoting capital accumulation, productivity improvement and, ultimately, economic growth. Beck et al. (2000) reported that financial development has a positive impact on productivity growth and physical capital growth, which feeds through to economic growth (albeit the impact of the latter is tenuous). Rioja and Valev (2004) also revealed that financial development has a positive impact on economic growth; and the channel is primarily through capital accumulation in developing countries but mainly through productivity growth in more developed countries. The capital accumulation channel suggests that an efficient financial system mobilizes savings and allocates resources to domestic and foreign capital investments thereby boosting capital accumulation. Through saving mobilization, the financial sector overcomes the indivisibilities' problems. Conversely, the productivity channel stresses the importance of innovative financial technologies, which decrease the problem of information asymmetry that hinders efficient allocation of financial resources and investment project monitoring (see King and Levine 1993). This channel suggests that a well-developed financial system provides efficient credit facilities and other financial services that promote the adoption of modern technology to boost knowledge- and technology-intensive industries.

Second, theoretical literature has also underscored the influence of the real exchange rate on economic growth. Accordingly, an increase in the real exchange rate could have a negative effect on economic growth, while a decrease in the real exchange rate could have a positive effect (Habib et al. 2017). This present study employs the level of the real exchange rate in line with extant literature (e.g., Gala 2008; Habib et al. 2017; Rautava 2004; Tang 2015), and real exchange rate volatility that is consistent with previous studies (e.g., Aghion et al. 2009; Bleaney and Greenaway 2001; Rapetti et al. 2012; Vieira et al. 2013). The level of the real exchange rate has the capacity to reduce both capital accumulation and productivity growth, thereby weakening the channels through which financial development enhances economic growth. It also affects saving, investment, private

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relatively low level of financial development as indicated in Table 1. It shows that the average credit to the private sector relative to GDP was 15.4%, while liquid liabilities relative to GDP were 25.6% during the 1980–2014 period. Therefore, financial system development in the West African region has not reached the level of excessive financial development, which could undermine economic growth in the region.

4 Although credit to the private sector relative to GDP and liquid liabilities relative to GDP are the two most commonly used proxies of financial development in the literature, but unavailability of data on other proxies (e.g., stock market indicators, commercial-central bank assets, etc.) in the West African region limited our choice of proxies.

consumption and trade balance. For instance, a high and volatile real exchange rate has the potential to diminish international trade, weaken macroeconomic stability, distort price transparency and inhibit international financial integration (see Bleaney and Greenaway 2001; Razmi et al. 2012; Rodriguez 2017). Thus, real shocks and financial shocks are related, since the latter are significantly amplified in countries with high exchange rate fluctuations. In turn, exchange rate fluctuation is the outcome of both real and financial aggregate shocks. It affects the growth performance of credit-constrained firms.

Third, extant literature has posited that financial development and real exchange rate have a dynamic relationship. For instance, Aghion et al. (2009) posited that the growth interaction between financial development and real exchange rate stems from the fact that an increase in exchange rate causes a reduction in the firms' current earnings, their ability to borrow in order to survive liquidity shocks, and long-term investments in innovation. They argued that although a decline in the real exchange rate has the opposite effect, but the existence of credit constraint suggests that the positive effects which a decline in the real exchange rate have on innovation may not be adequately compensated for by the negative effect of an increase in the real exchange rate. In other words, a greater anticipation of exchange rate fluctuation has the capacity to discourage investments in R&D, which ultimately decreases the level of financial development and economic growth. Hence, a high exchange rate fluctuation could dampen the positive impact of financial development on economic growth, especially in countries with a low level of financial development. From the foregoing discussion, therefore, this study seeks to test the hypothesis that financial development has a larger impact on economic growth in an environment of a lower real exchange rate (or its volatility) compared to an environment of a high real exchange rate (or its volatility).

The set of control variables included in the models is government consumption expenditure relative to GDP (used as an indicator of government policy), trade openness relative to GDP (captures the degree of a country's openness), human capital (proxy by average years of schooling), which accounts for the effect of human capital accumulation on growth, and inflation rate (captures macroeconomic instability). These control variables are generally used in finance literature (see Beck et al. 2000; Levine et al. 2000). They are expected to be positively related to economic growth except inflation rate.

2.4. Estimation Techniques

The estimation techniques employed in this study are the Mean Group (MG) proposed by Pesaran and Smith (1995), and the Pooled Mean Group (PMG) proposed by Pesaran et al. (1999). The latter estimator assumes homogeneous long-term coefficients across countries but allows for variations in the short-term coefficients, speed of adjustment and error variances. However, the MG estimator allows the long-term and short-term coefficients, the speed of adjustment and the error variances to differ across countries. After estimation, the study conducts the Hausman test of homogeneity of long-term coefficients to determine the appropriate model between MG and PMG estimators. The MG and PMG estimators are chosen for this study for three reasons: (i) the MG and PMG estimators can be applied irrespective of the order of integration of the variables in the model because they are based on Autoregressive Distributed Lag (ARDL) models. In this study, some of the variables in the model are integrated in order zero [I (0)], while some variables are integrated in order one [I (1)]. (ii) The MG and PMG estimators provide both short-term and long-term estimation results. By distinguishing between short-term and long-term impacts, these estimators provide viable options for policy making. (iii) While the PMG estimator accounts for heterogeneity in short-term coefficients, the MG estimator accounts for heterogeneity in both short-term and long-term coefficients.

To complement the MG and PMG estimators, this study also employs an Instrumental Variable (IV) approach based on Two Stage Least Squares (TSLS), which is capable of controlling for possible endogeneity. The instruments used are the legal origin of the countries as well as the initial values of financial development, inflation rate, government expenditure, trade openness and human capital (see Asongu 2014; La Porta et al. 1997; Levine et al. 2000; Rousseau and Wachtel 2002). To ensure that the IV approach satisfies the order condition for identification, we perform the tests for endogeneity and over-identifying restrictions. The former shows whether the dependent variable is endogenous in the original model, whereas the latter indicates whether the instruments are uncorrelated with the error process.

Additionally, this study also utilizes the Seemingly Unrelated Regression (SUR) estimator proposed by Zellner (1962) on the disaggregated data to examine the influence of the real exchange rate or its volatility on the finance-growth nexus for individual country. SUR estimator enables us to account for possible cross-sectional dependence. Pesaran (2006) revealed that parameters estimates could be substantially biased, and their sizes could be distorted if cross-sectional dependence is ignored. The SUR estimator is a generalization of a linear regression model, which comprises many regression equations with each having its own dependent and independent variables. Each of the regression equations is a valid linear regression that could be estimated separately, but the regression equations are assumed to be correlated with respect to the error terms (see Bittencourt 2011; Ehigiamusoe et al. 2018). After estimating the equations, the study examines the statistical significance of the Lagrange Multiplier (LM) test in order to determine the presence of cross-sectional dependence among the countries in the panel and the suitability of the SUR estimator.

3. Empirical Results

3.1. Preliminary Data Analysis

3.1.1. Summary of Descriptive Statistics and Correlations

Table 1 presents a summary of the descriptive statistics and correlations of West African region for the 1980–2014 period. It is shown that average real GDP per capita, credit to the private sector relative to GDP and liquid liabilities relative to GDP were USD566.73, 15.43% and 25.64%, respectively. It also indicates that the respective average real exchange rate and its volatility were 1144.3 and 61.67 during the period. There are wide variations among the variables as indicated by the standard deviations, which are highest in the real exchange rate, its volatility and GDP. The lower panel in Table 1 shows the correlation analysis, as financial development indicators and the control variables are positively correlated with GDP per capita, while real exchange rate, its volatility and inflation rate are negatively related to GDP per capita. Moreover, real exchange rate and its volatility are negatively related to financial development.

Table 1. Summary of descriptive statistics and correlations.

Variables	Y	CPS	LLY	GOV	TOP	HCA	INF	RER	RERV
Minimum	64.810	0.802	0.416	3.542	6.320	0.400	−35.525	0.001	0.535
Mean	566.729	15.432	25.642	14.807	68.979	2.602	11.858	1144.32	61.667
Maximum	3766.11	65.278	83.026	54.515	321.63	7.004	178.70	88103.8	3939.1
Standard Dev.	527.875	10.774	12.759	5.926	34.172	1.481	19.030	5281.9	412.87
CPS	0.630 ***								
LLY	0.692 ***	0.696 ***							
GOV	0.112 **	0.390 ***	0.172 ***						
TOP	0.112 **	0.217 ***	0.244 ***	0.145 ***					
HCA	0.370 ***	0.200 ***	0.275 ***	−0.200 ***	0.301 ***				
INF	−0.187 ***	−0.295 ***	−0.267 ***	−0.295 ***	−0.036	0.074			
RER	−0.066 **	−0.172 ***	−0.132 ***	−0.156 ***	−0.124 ***	−0.058	0.054		
RERV	−0.078 **	−0.059	−0.046	−0.054	0.129 ***	−0.097 **	0.105 **	−0.031	

Notes: *** and ** indicates statistically significant at 1% and 5%, respectively. Y = real GDP per capita, CPS = credit to the private sector relative to GDP, LLY = liquid liabilities relative to GDP, GOV = government consumption expenditure relative to GDP, TOP = trade openness relative to GDP, HCA = human capital, INF = inflation rate, RER = real exchange rate, RERV = real exchange rate volatility.

3.1.2. Panel Unit Root Tests

We conduct unit root tests using the traditional panel data unit root tests (that assume homogeneity or account for heterogeneity) developed by Im et al. (2003); Levin et al. (2002) and Maddala and Wu (1999) as well as the Pesaran (2007) panel data unit root test that accounts for cross-sectional dependence. The results reported in Table 2 show that all the variables in the model are I(0) except GDP per capita, credit to the private sector, liquid liabilities and human capital, which are I(1). This implies that the variables in the model are a mixture of I(0) and I(1) processes, and the appropriate technique would be the ARDL approach.

Table 2. Panel unit root tests.

Variables	ADF–Fisher	PP–Fisher	LLC	IPS	Pesaran
Y	12.068	9.606	2.203	3.183	−1.457 *
CPS	27.357	27.059	−1.109	−0.059	−0.541
LLY	33.193	31.748	0.317	0.215	−2.662 **
RER	48.882 **	92.522 ***	−4.376 ***	−2.224 **	−2.549 **
RERV	55.457 ***	44.719 *	−2.788 ***	−3.102 ***	−0.793
GOV	78.280 ***	84.061 ***	−2.533 ***	−1.361 *	−3.235 ***
TOP	54.206 ***	55.684 ***	−1.511 *	−2.265 **	−1.496 *
HCA	9.365	11.915	−0.553	5.817	4.443
INF	122.431 ***	174.348 ***	−7.999 ***	−7.612 ***	−6.787 ***
ΔY	179.439 ***	276.720 ***	−9.498 ***	−11.005 ***	−10.704 ***
ΔCPS	180.387 ***	363.000 ***	−10.724 ***	−10.873 ***	−9.191 ***
ΔLLY	184.236 ***	286.182 ***	−11.242 ***	−11.267 ***	−9.709 ***
ΔRER	169.106 ***	257.976 ***	−8.619 ***	−10.494 ***	−8.912 ***
ΔRERV	122.787 ***	250.541 ***	−8.368 ***	−7.903 ***	−8.647 ***
ΔGOV	228.511 ***	403.824 ***	−12.234 ***	−13.619 ***	−10.520 ***
ΔTOP	213.345 ***	366.959 ***	−10.752 ***	−12.801 ***	−9.818 ***
ΔHCA	149.526 ***	306.169 ***	−3.248 ***	−8.169 ***	−2.831 ***
ΔINF	350.181 ***	507.739 ***	−16.868 ***	−19.922 ***	−16.381 ***

Notes: ***, ** and * indicates statistically significant at 1%, 5% and 10%, respectively, and a rejection of null hypothesis of unit root. Δ = first differenced notation, ADF-Fisher = Augmented Dickey Fuller-Fisher test, LLC = Levin et al. (2002), IPS = Im et al. (2003), Pesaran = Pesaran (2007) test. Y = real GDP per capita, CPS = credit to the private sector relative to GDP, LLY = liquid liabilities relative to GDP, RER = real exchange rate, RERV = real exchange rate volatility, GOV = government consumption expenditure relative to GDP, TOP = trade openness relative to GDP, HCA = human capital, INF = inflation rate.

3.2. Estimation Results

3.2.1. Panel Estimation Results

The results of the impact of financial development, real exchange rate and their interaction term on economic growth are reported in Table 3. Column 1 is the baseline model without interaction term, and it shows that financial development has a positive and significant long-term impact on economic growth, suggesting that variations in financial development can explain variations in economic growth in the West African region. In the short term, however, the impact of financial development on economic growth is not statistically significant at conventional level. In Column 2, the interaction term between financial development and real exchange rate is included in the model, and we find that the interaction term enters with a negative coefficient, in both the long term and short term, while the coefficient of financial development remains positive. This suggests that real exchange rate has an adverse effect on economic growth through the financial sector. In essence, the positive sign of the coefficient of financial development and the negative sign of the coefficient of interaction term suggest that the positive impact of financial development on economic growth is adversely influenced by real exchange rate. In Column 3, the linear real exchange rate is included in the model, and the results reveal that both the linear real exchange rate and the interaction term enter with negative coefficients in both the short term and long term, while the coefficient of financial development remains positive (albeit statistically insignificant at conventional level). Thus, the inclusion of both the linear real exchange rate and the interaction term in the model weakens the positive impact of financial development on economic growth.

Table 3. Pooled Mean Group (PMG) estimation results.

Variables	(1)	(2)	(3)	(4)	(5)
Long-term coefficients					
CPS	0.213 *** (0.047)	0.615 *** (0.183)	0.189 (0.436)	0.423 *** (0.049)	0.570 *** (0.055)
RER			−0.026 (0.261)		
CPS*RER		−0.049 (0.035)	−0.031 (0.070)		
RERV					0.079 (0.022)
CPS*RERV				−0.001 (0.001)	−0.022 ** (0.009)
GOV	0.296 *** (0.107)	−0.099 (0.144)	−0.131 (0.191)	0.244 ** (0.123)	0.212 ** (0.116)
TOP	0.447 *** (0.118)	0.653 *** (0.155)	0.538 *** (0.206)	0.829 *** (0.131)	0.671 *** (0.116)
HCA	0.586 *** (0.195)	−0.164 (0.279)	−0.267 (0.393)	0.357 ** (0.192)	0.664 *** (0.219)
INF	−0.003 (0.002)	0.089 *** (0.018)	0.144 *** (0.039)	0.003 (0.003)	−0.002 (0.003)
Convergence coefficient	−0.224 *** (0.035)	−0.090 *** (0.019)	−0.062 *** (0.013)	−0.228 *** (0.043)	−0.227 *** (0.056)
Short-term coefficients					
ΔCPS	−0.086 (0.048)	0.644 *** (0.234)	0.694 (0.482)	−0.061 (0.048)	−0.094 ** (0.049)
ΔRER			−0.082 (0.189)		
ΔCPS*RER		−0.154 *** (0.030)	−0.161 ** (0.069)		
RERV					−0.021 (0.026)
ΔCPS*RERV				−0.001 (0.001)	0.007 (0.009)
ΔGOV	0.037 (0.049)	0.017 (0.049)	0.018 (0.044)	0.055 (0.076)	0.088 (0.073)
ΔTOP	−0.301 *** (0.073)	−0.184 *** (0.063)	−0.139 ** (0.067)	−0.304 *** (0.083)	−0.283 *** (0.087)
ΔHCA	−0.283 *** (0.108)	−0.237 *** (0.079)	−0.265 *** (0.098)	−0.344 ** (0.147)	−0.439 *** (0.122)
ΔINF	−0.001 (0.001)	−0.001 (0.001)	−0.002 (0.001)	−0.002 (0.001)	−0.002 (0.002)
Time trend	0.005 *** (0.001)	0.006 *** (0.001)	0.004 *** (0.001)	0.003 ** (0.002)	0.002 (0.002)
Constant	−0.829 (0.573)	−1.854 *** (0.529)	−1.506 *** (0.376)	−0.905 (0.656)	−0.339 (0.740)
Hausman test	3.47	5.90	10.41	5.20	2.07
Log Likelihood	473.64	625.73	648.89	467.007	498.619
Marginal effects					
Minimum		1.332	0.642	0.422	0.558
Mean		0.397 ***	0.051	0.361	−0.787
Maximum		0.057	−0.164	−3.516	−86.089

Notes: ***, ** and * indicate statistically significant at 1%, 5% and 10%, respectively. Standard errors are in parenthesis. Dependent variable = economic growth; CPS = credit to the private sector relative to GDP, RER = real exchange rate, CPS*RER = interaction term between credit to the private sector and real exchange rate, RERV = real exchange rate volatility, CPS*RERV = interaction term between credit to the private sector and real exchange rate volatility, GOV = government consumption expenditure relative to GDP, TOP = trade openness relative to GDP, HCA = human capital, INF = inflation rate.

In Columns 4 and 5, we replace real exchange rate with real exchange rate volatility. This is necessary because volatility in the real exchange rate could have effect on various dimensions of the economy, one of which is the finance-growth nexus. Hence, we measure real exchange rate volatility as the standard deviation of the 5-year moving average of the logarithm of the real exchange rate (see Aghion et al. 2009; Serenis and Tsounis 2013; Sharifi-Renani and Mirfatah 2012), The results presented in Columns 4 and 5 indicate that the coefficient of the real exchange rate volatility is negative implying that volatility in the real exchange rate is repugnant to economic growth through the financial sector. This suggests that the impact of financial development on economic growth varies with the level of the real exchange rate volatility, the higher the level of volatility, the lower the impact of finance on growth.

In all the models, the convergence coefficients are negative and statistically significant, which suggest the presence of cointegration relationship between economic growth and the independent variables. It shows the speed of adjustment from short-term disequilibrium to long-term equilibrium. The Hausman tests of homogeneity indicate that the PMG models are the appropriate models[5]. In selecting the lag orders for the models, the study uses the unrestricted models based on Schwarz Information Criteria (SIC) subject to a maximum lag of 2.

The lower panel of Table 3 shows the computed marginal effects of financial development on economic growth at various levels of the real exchange rate and its volatility using Equation (2) and the estimated long-term coefficients. We find that the marginal effects diminish with higher real exchange rate and higher volatility. We also compute the corresponding standard errors and t-statistics to determine the statistical significance of the marginal effects. Thus, real exchange rate and its volatility have diminishing effects on the impact of financial development on economic growth in the West African region.

As for the control variables, there is evidence of positive growth-effect from government consumption expenditure, trade openness and human capital, which are consistent with economic theory. The endogenous growth model posited that access to global markets via international trade makes an open economy more likely to grow rapidly and efficiently than a closed economy. It also stressed the importance of human capital accumulation in the process of economic growth. Finally, the effect of inflation rate on economic growth is mixed. Theoretical and empirical literature contended that inflation rate begins to have a negative impact on economic growth when it exceeds a certain threshold level (see Rousseau and Wachtel 2002).

3.2.2. Robustness Checks

This study conducts some checks to ascertain the robustness of the regression results. First, we use alternative estimation techniques, namely an Instrumental Variable (IV) approach based on Two Stage Least Squares (TSLS) to control for possible endogeneity. The results reported in Table 4 are consistent with the PMG results, with financial development positively related to economic growth, whereas the interaction term is negatively related. It also shows that the marginal effects of financial development on economic growth diminish as real exchange rate and its volatility increase.

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[5] Hence, the results of the MG model are not presented to conserve space but available upon request.

Table 4. Robustness checks using Instrumental Variables (IV) regressions.

Variables	(1)	(2)	(3)	(4)	(5)
CPS	0.339 ***	0.289 ***	0.311 **	0.502 ***	0.481 ***
	(0.058)	(0.067)	(0.133)	(0.077)	(0.077)
RER			0.033		
			(0.032)		
CPS*RER		−0.006	−0.002		
		(0.005)	(0.018)		
RERV					−0.002
					(0.003)
CPS*RERV				−0.001	−0.001
				(0.001)	(0.001)
GOV	−0.148 *	−0.119	−0.087	−0.232 *	−0.258 *
	(0.089)	(0.092)	(0.093)	(0.126)	(0.139)
TOP	−0.078	−0.072	−0.105	−0.085	−0.168
	(0.072)	(0.072)	(0.094)	(0.115)	(0.102)
HCA	0.453 ***	0.476 ***	0.518 ***	0.359 ***	0.422 ***
	(0.035)	(0.036)	(0.037)	(0.067)	(0.056)
INF	−0.006 ***	−0.005 ***	−0.005 **	−0.005 **	−0.006 **
	(0.002)	(0.001)	(0.001)	(0.002)	(0.003)
Time Trend	−0.001 ***	−0.001 ***	−0.001 ***	−0.001 ***	−0.001 ***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Constant	5.963 ***	5.899 ***	5.834 ***	5.941 ***	6.341 ***
	(0.300)	(0.306)	(0.188)	(0.511)	(0.528)
F-test	1.02	7.08 ***	1.87 *	6.502 ***	5.536 ***
Eigenvalue stat.	51.62 ***	52.28 ***	64.69 ***	50.647 ***	49.332 ***
Marginal effects					
Minimum		0.377 ***	0.340	0.501 ***	0.480 ***
Mean		0.262 ***	0.302 ***	0.440 ***	0.419 ***
Maximum		0.221 ***	0.288	−3.437 ***	−3.458

Notes: ***, ** and * indicates statistically significant at 1%, 5% and 10%, respectively. Heteroscedasticity–corrected standard errors are in parenthesis. The instruments used are the legal origins of the countries as well as the initial values of financial development, government expenditure, trade openness, human capita and inflation rate. Dependent variable = economic growth; CPS = credit to the private sector relative to GDP, RER = real exchange rate, CPS*RER = interaction term between credit to the private sector and real exchange rate, RERV = real exchange rate volatility, LLY*RERV = interaction term between liquid liabilities and real exchange rate volatility, GOV = government consumption expenditure relative to GDP, TOP = trade openness relative to GDP, HCA = human capital, INF = inflation rate.

Second, we use an alternative proxy of financial development (namely, liquid liabilities relative to GDP) and redo the analysis. The results presented in Table 5 also provided evidence that real exchange rate volatility is deleterious to the finance-growth nexus in the West African region. It also shows that the inclusion of the real exchange rate and the interaction term in the model diminishes the positive impact of financial development on economic growth.

Table 5. Robustness checks using alternative proxy of financial development (liquid liabilities relative to GDP).

Variables	(1)	(2)	(3)	(4)	(5)
Long-term coefficients					
LLY	0.566 *** (0.087)	0.236 (0.259)	−1.735 *** (0.567)	0.631 *** (0.081)	0.564 *** (0.082)
RER			−1.090 *** (0.271)		
LLY*RER		0.071 (0.060)	0.395 (0.102)		
RERV					−0.009 (0.016)
LLY*RERV				−0.001 * (0.001)	0.003 (0.005)
GOV	0.144 (0.106)	−0.273 (0.184)	−0.356 ** (0.149)	0.286 ** (0.135)	0.229 ** (0.137)
TOP	0.464 *** (0.117)	0.427 *** (0.194)	0.470 *** (0.155)	0.658 *** (0.146)	0.789 *** (0.155)
HCA	0.688 *** (0.209)	0.319 (0.384)	0.460 (0.307)	0.627 ** (0.257)	0.606 ** (0.248)
INF	−0.004 (0.002)	0.115 ** (0.026)	0.081 *** (0.017)	0.003 (0.003)	−0.006 ** (0.003)
Convergence coefficient	−0.199 *** (0.037)	−0.068 *** (0.016)	−0.093 *** (0.019)	−0.205 *** (0.039)	−0.197 *** (0.040)
Short-term coefficients					
ΔLLY	−0.288 *** (0.037)	0.431 ** (0.227)	−0.237 (0.780)	−0.241 *** (0.076)	−0.236 *** (0.086)
ΔRER			−0.312 (0.428)		
ΔLLY*RER		−0.135 *** (0.028)	−0.034 (0.132)		
ΔRERV					−0.126 (0.107)
ΔLLY*RERV				−0.002 (0.001)	0.038 (0.035)
ΔGOV	0.085 (0.057)	0.043 (0.049)	0.051 (0.049)	0.025 (0.076)	0.042 (0.078)
ΔTOP	−0.331 *** (0.075)	−0.183 *** (0.071)	−0.199 *** (0.068)	−0.229 ** (0.091)	−0.251 *** (0.090)
ΔHCA	−0.288 *** (0.084)	−0.305 *** (0.088)	−0.295 ** (0.072)	−0.358 ** (0.145)	−0.327 *** (0.116)
ΔINF	−0.002 (0.002)	−0.001 (0.001)	−0.001 (0.001)	−0.002 (0.002)	−0.002 (0.002)
Time trend	0.003 (0.002)	0.003 *** (0.001)	0.003 *** (0.001)	0.002 (0.002)	0.002 (0.002)
Constant	−0.686 (0.723)	−0.865 (0.445)	−0.164 (0.449)	−0.817 (0.859)	−0.491 (0.823)
Hausman test	4.80	5.47	3.70	5.30	3.83
Log Likelihood	491.06	631.62	653.93	472.231	493.481

Notes: ***, ** and * indicate statistically significant at 1%, 5% and 10%, respectively. Standard errors in parenthesis. Dependent variable = economic growth; LLY = liquid liabilities relative to GDP, RER = real exchange rate, LLY*RER = interaction term between liquid liabilities and real exchange rate, RERV = real exchange rate volatility, LLY*RERV = interaction term between liquid liabilities and real exchange rate volatility, GOV = government consumption expenditure relative to GDP, TOP = trade openness relative to GDP, HCA = human capital, INF = inflation rate.

Thirdly, in order to account for structural breaks in the series, we conduct a structural break test using the test developed by Bai and Perron (2003), and found significant structural breaks in some countries. To account for the breaks, we include dummy variables that take the value of 1 from the years of the breaks and 0 otherwise in the model (see Wallack 2003), and redo the analysis.

The estimation results[6] are similar to the earlier results in terms of the sign and significant of the coefficients (albeit the magnitude somewhat differ).

3.2.3. SUR Estimation Results for Individual Country

Tables 6 and 7 show the SUR estimation results of the influence of the real exchange rate and its volatility on the finance-growth nexus in West African countries using disaggregated data. This is necessary to control for cross sectional dependence among the countries in the panel. In essence, the LM test statistic confirms the existence of cross-sectional dependence among the countries in the panel and the suitability of SUR estimator. In Table 6, the interaction term between financial development and real exchange rate enters with a negative coefficient in 12 countries suggesting that the impact of financial development on economic growth is adversely influenced by real exchange rate in these countries[7] (Benin, Burkina Faso, Cape Verde, Cote D'Ivoire, Gambia, Guinea, Mali, Mauritania, Niger, Senegal, Sierra Leone and Togo). The computed marginal effects diminish as real exchange rates increase in these countries. However, there is evidence that the real exchange rate is harmful to the finance-growth nexus in four countries (Ghana, Guinea Bissau, Liberia and Nigeria).

Similarly, Table 7 reveals that the interaction term between financial development and real exchange rate volatility enters with a negative coefficient in 13 countries (Benin, Burkina Faso, Cape Verde, Cote D'Ivoire, Ghana, Guinea, Liberia, Mauritania, Niger, Nigeria, Senegal, Sierra Leone and Togo), implying that real exchange rate volatility reduces the impact of financial development on economic growth. The computed marginal effects are lower at higher levels of volatility relative to lower levels in these West African countries.

[6] The results are not reported to conserve space, but available upon request.

[7] The results of the SUR model with the linear real exchange rate are not reported to conserve space, but available upon request. The results are similar to the ones presented in Table 6, as the interaction term enters with a negative coefficient in 12 countries.

Table 6. Seemingly Unrelated Regression (SUR) estimation results of interaction term between financial development and real exchange rate.

Country	CPS	CPS*RER	GOV	TOP	HCA	INF	Constant	R^2	Marginal Effects		
									Minimum	Mean	Maximum
Benin	0.346 ** (0.148)	−0.017 (0.022)	−0.166 (0.122)	0.233 * (0.129)	0.585 *** (0.050)	−0.004 (0.003)	4.629 *** (0.605)	0.809	0.259	0.242	0.234
Burkina Faso	0.771 *** (0.183)	−0.001 (0.028)	0.505 *** (0.110)	0.525 *** (0.135)	−1.475 (1.979)	0.001 (0.004)	0.747 (0.659)	0.790	0.766	0.765	0.764
Cape Verde	1.790 *** (0.289)	−0.296 *** (0.063)	0.515 (0.464)	0.319 (0.230)	0.246 (0.574)	−0.022 *** (0.007)	2.774 (1.835)	0.905	0.718	0.520	0.364
Cote d'Ivoire	0.588 *** (0.103)	−0.088 *** (0.023)	−0.018 (0.117)	0.463 *** (0.116)	0.403 *** (0.065)	−0.002 (0.003)	4.281 *** (0.687)	0.659	0.152	0.067	0.010
Gambia	−0.245 *** (0.041)	−0.046 *** (0.012)	0.029 (0.055)	−0.583 *** (0.083)	0.262 ** (0.106)	−0.009 *** (0.001)	9.342 *** (0.316)	0.871	−0.191	−0.332	−0.422
Ghana	0.122(0.139)	0.051 *** (0.014)	0.454 *** (0.147)	−0.554 ** (0.117)	1.128 ** (0.518)	−0.002 (0.001)	5.534 *** (0.726)	0.751	−0.624	−0.101	0.173
Guinea	0.306 *** (0.109)	−0.023 *** (0.008)	0.089 (0.074)	−0.129 (0.109)	0.558 *** (0.190)	−0.003 *** (0.001)	5.954 *** (0.429)	0.187	0.238	0.154	0.092
Guinea-Bissau	−0.329 *** (0.108)	0.051 *** (0.019)	−0.141 (0.115)	−0.086 (0.225)	1.486 (1.392)	−0.005 *** (0.002)	5.319 *** (1.566)	0.494	−0.231	−0.069	0.007
Liberia	0.088 (0.116)	0.178 *** (0.019)	−0.262 * (0.146)	0.197 ** (0.099)	−2.811 *** (0.337)	−0.018 (0.017)	7.065 *** (0.628)	0.657	0.010	0.451	0.917
Mali	0.637 *** (0.146)	−0.096 *** (0.019)	−0.065 (0.075)	−0.339 *** (0.101)	0.701 *** (0.032)	−0.002 (0.002)	7.255 *** (0.476)	0.913	0.124	0.052	0.004
Mauritania	−0.766 *** (0.177)	−0.012 (0.018)	−0.196 *** (0.049)	0.081 (0.073)	0.808 *** (0.204)	−0.001 (0.005)	8.653 *** (0.682)	0.825	−0.806	−0.820	−0.835
Niger	0.842 *** (0.143)	−0.101 *** (0.025)	0.008 (0.113)	0.487 *** (0.098)	0.150 *** (0.056)	−0.003 (0.002)	3.187 *** (0.548)	0.789	0.312	0.228	0.175
Nigeria	−0.018 (0.241)	0.026 ** (0.012)	0.342 (0.225)	−0.501 ** (0.256)	8.809 *** (3.268)	−0.012 *** (0.004)	−6.583 (5.959)	0.591	−0.151	0.013	0.121
Senegal	1.333 *** (0.230)	−0.099 *** (0.030)	−1.394 *** (0.307)	−0.341 ** (0.147)	0.585 *** (0.116)	0.001 (0.003)	8.739 *** (0.892)	0.663	0.822	0.732	0.676
Sierra Leone	0.626 *** (0.122)	−0.025 ** (0.013)	0.146 (0.239)	−0.301 ** (0.136)	0.717 *** (0.229)	−0.001 (0.001)	5.492 *** (0.632)	0.676	0.625	0.431	0.341
Togo	0.697 *** (0.147)	−0.067 *** (0.022)	−0.179 (0.140)	0.140 (0.106)	0.421 *** (0.081)	−0.001 (0.002)	4.304 *** (0.453)	0.634	0.360	0.300	0.258
LM Test	466.287 ***										

Notes: ***, ** and * indicate statistically significant at 1%, 5% and 10%, respectively. Standard errors in parenthesis. Dependent variable = economic growth; CPS = credit to the private sector relative to GDP, CPS*RER = interaction term between credit to the private sector and real exchange rate, GOV = government consumption expenditure relative to GDP, TOP = trade openness relative to GDP, HCA = human capital, INF = inflation rate.

Table 7. SUR estimation results of interaction term between financial development and real exchange rate volatility.

Country	CPS	CPS*RERV	RERV	GOV	TOP	HCA	INF	Constant	R^2	Marginal Effects		
										Minimum	Mean	Maximum
Benin	0.426 *** (0.069)	−0.072 *** (0.016)	0.164 *** (0.037)	0.049 (0.126)	0.134 (0.092)	0.678 *** (0.052)	−0.008 *** (0.002)	3.919 *** (0.384)	0.922	0.362	0.179	−0.432
Burkina Faso	1.145 *** (0.139)	−0.152 *** (0.029)	0.327 *** (0.073)	−0.145 (0.192)	0.336 *** (0.106)	−3.656 *** (1.312)	0.001 (0.003)	3.151 *** (0.686)	0.885	1.025	0.736	−0.077
Cape Verde	0.529 *** (0.072)	−0.101 *** (0.027)	0.208 *** (0.068)	−0.212 (0.315)	0.455 ** (0.207)	0.655 (0.581)	−0.002 (0.008)	3.666 ** (1.507)	0.746	0.424	0.333	0.144
Cote d'Ivoire	0.481 ** (0.190)	−0.025 (0.087)	0.079 (0.238)	−0.042 (0.132)	0.583 *** (0.193)	0.457 *** (0.113)	−0.008 ** (0.004)	2.552 ** (1.188)	0.772	0.462	0.418	0.278
Gambia	−0.132 * (0.072)	0.001 ** (0.001)	−0.001 *** (0.001)	0.269 *** (0.074)	−0.222 * (0.128)	−0.142 (0.103)	−0.017 *** (0.003)	7.087 *** (0.552)	0.900	−0.131	0.548	3.807
Ghana	0.586 *** (0.138)	−0.009 (0.010)	0.029 (0.028)	0.659 *** (0.147)	−1.354 *** (0.156)	1.904 *** (0.411)	−0.002 (0.002)	5.747 *** (0.716)	0.896	0.573	0.378	−0.463
Guinea	0.216 * (0.121)	−0.039 (0.025)	0.054 (0.035)	0.131 (0.088)	−0.309 *** (0.113)	0.383 ** (0.197)	0.002 (0.002)	6.538 *** (0.409)	0.219	0.172	−0.100	−0.597
Guinea-Bissau	0.059 (0.056)	0.003 (0.004)	−0.016 (0.011)	0.695 *** (0.176)	−0.016 (0.205)	3.449 *** (1.335)	0.001 (0.002)	1.171 (1.566)	0.484	0.060	0.085	0.165
Liberia	−0.164 (0.236)	−0.002 ** (0.001)	0.003 ** (0.001)	0.247 (0.269)	−0.001 (0.231)	0.492 (0.563)	−0.059 ** (0.029)	5.137 *** (1.119)	0.241	−0.165	−0.447	−1.669
Mali	0.249 (0.182)	0.002 (0.037)	0.007 (0.095)	−0.007 (0.175)	−0.803 *** (0.186)	0.568 *** (0.070)	−0.002 (0.004)	8.372 *** (0.861)	0.852	0.250	0.254	0.264
Mauritania	−0.906 ** (0.474)	−0.069 (0.296)	0.144 (0.985)	−0.398 *** (0.071)	0.384 *** (0.094)	0.272 (0.184)	−0.006 (0.005)	8.918 *** (1.722)	0.871	−0.942	−1.067	−1.241
Niger	0.427 *** (0.059)	−0.021 (0.018)	0.049 ** (0.026)	0.219 ** (0.109)	0.221 ** (0.104)	0.242 *** (0.086)	−0.007 ** (0.003)	3.225 *** (0.522)	0.863	0.410	0.368	0.236
Nigeria	−0.079 (0.262)	−0.004 ** (0.002)	0.007 (0.005)	0.607 ** (0.303)	−0.092 (0.264)	14.96 *** (3.156)	−0.006 (0.042)	−18.35 *** (5.631)	0.606	−0.081	−0.429	−1.931
Senegal	0.726 *** (0.130)	−0.025 (0.038)	0.081 (0.105)	0.409 * (0.229)	0.689 *** (0.191)	0.392 *** (0.102)	−0.007 ** (0.003)	−0.135 (1.054)	0.823	0.711	0.660	0.516
Sierra Leone	0.468 *** (0.157)	−0.016 * (0.009)	0.011 (0.011)	−0.132 (0.232)	−0.069 (0.132)	0.753 *** (0.205)	−0.001 (0.001)	5.216 *** (0.625)	0.767	0.404	0.223	−0.281
Togo	0.601 *** (0.136)	−0.139 * (0.081)	0.393 * (0.232)	−0.018 (0.130)	0.195 ** (0.103)	0.202 * (0.111)	−0.002 (0.003)	3.112 *** (0.535)	0.707	0.476	0.211	−0.679
LM Test	358.366 ***											

Notes: ***, ** and * indicate statistically significant at 1%, 5% and 10%, respectively. Standard errors in parenthesis. Dependent variable = economic growth; CPS = credit to the private sector relative to GDP, CPS*RERV = interaction term between credit to the private sector and real exchange rate volatility, RERV = real exchange rate volatility, GOV = government consumption expenditure relative to GDP, TOP = trade openness relative to GDP, HCA = human capital, INF = inflation rate.

4. Discussion and Policy Implications

The findings of this study are summarized as follows: first, financial development enhances economic growth in the West African region. This implies that variations in financial development can explain variations in economic growth in the region. This is consistent with empirical literature, which opined that financial development enhances economic growth in developing countries by accelerating the sources of growth such as capital accumulation and productivity growth (see Ehigiamusoe and Lean 2018; Ehigiamusoe et al. 2018; Karimo and Ogbonna 2017; Ratsimalahelo and Barry 2010; Rioja and Valev 2004; Sanogo and Moussa 2017). This suggests that the financial system in the West African region is capable of mobilizing savings and allocating resources to domestic and foreign capital investments, which boost capital accumulation. In recent times, the financial system in many West African countries have embarked on innovative financial technologies which decrease the problem of information asymmetry (which hinders efficient allocation of financial resources and investment project monitoring), thereby facilitating economic growth.

Second, the findings on the link between real exchange rate and economic growth are consistent with Aghion et al. (2009), Elbadawi et al. (2012) and Vieira et al. (2013) who reported a negative impact of the real exchange rate on economic growth. Specifically, Aghion et al. (2009) reported that real exchange rate volatility has deleterious effects on economic variables such as productivity growth, investment and private consumption. They argued that uncertainty in the real exchange rate worsens the negative effect of domestic credit market constraints on investments. Jayashankar and Rath (2017) also posited that the relationship between the foreign exchange market and money market in emerging economies could make positive or negative shocks that affect one market to be quickly transmitted to another market via the contagious effect.

Apart from its direct adverse effect on economic growth, this study also reveals that real exchange rate weakens the impact of financial development on economic growth in the West African region. The level of the real exchange rate has the capacity to reduce both capital accumulation and productivity growth, thereby weakening the channels through which financial development enhances economic growth. It also affects saving, investment, private consumption and trade balance (see Razmi et al. 2012; Rodriguez 2017).

Similarly, this study shows that real exchange rate volatility has a deleterious effect on the impact of financial development on economic growth in the West African region. This is consistent with the theoretical literature which contended that high and volatile real exchange rate has the potential to diminish international trade, weaken macroeconomic stability, distort price transparency and inhibit international financial integration (see Bleaney and Greenaway 2001; Katusiime 2019; Razmi et al. 2012). Thus, real shocks and financial shocks are related, since the latter are significantly amplified in countries with high exchange rate fluctuations. In turn, exchange rate fluctuation is the outcome of both real and financial aggregate shocks. It affects the growth performance of credit-constrained firms.

Unlike previous studies, this present study shows that the impact of financial development on economic growth varies with the level of the real exchange rate and its volatility. In other words, besides their direct effects, real exchange rate and its volatility have indirect effects on economic growth through the financial sector. This study represents a novel idea by showing the marginal effects of financial development on economic growth at various levels of the real exchange rate (or its volatility), an issue that was not explored in previous literature. This is fundamental because the marginal effect enables us to determine the changes in economic growth caused by simultaneous changes in both financial development and real exchange rate (or its volatility), which is essential for policy formulation.

The implication of this study is that high real exchange rate and high volatility adversely affect the finance-growth nexus in the West African region. Hence, a reduction or stability in the real exchange rate is fundamental for financial development to enhance economic growth in West African countries. This suggests that the existing policies on real exchange rate have not been able to reduce the variable to the level that it would have beneficial effects on the finance-growth nexus. Hence, West African countries need to re-evaluate the policies as well as formulate the necessary fiscal and monetary policies that would ensure reduction in the real exchange rate.

5. Conclusions

This paper focuses on the influence of the real exchange rate and its volatility on the finance-growth nexus using both panel and disaggregated data of West African countries. It employs different econometric techniques such as MG, PMG, IV and SUR estimators[8]. The study reveals that financial development has a positive impact on economic growth, but the impact is weakened by the real exchange rate and its volatility. Thus, the marginal effects of financial development on economic growth computed at lower levels of the real exchange rate or its volatility are larger than the marginal effects computed at higher levels. The higher the real exchange rate and its volatility, the less that finance spurs growth.

The implication of this study is that high real exchange rate and high volatility adversely affect the finance-growth nexus in the West African region. Hence, a reduction or stability in the real exchange rate is fundamental for financial development to enhance economic growth in West African countries. This study has succeeded in revealing the impact of the real exchange rate and its volatility on the finance-growth nexus within panel and disaggregated data framework. Therefore, future study may complement this study by examining the threshold levels of the real exchange rate and its volatility beyond which the marginal effects of financial development on economic growth turn negative. Apart from the level and volatility of the real exchange rate, future research could also investigate the influence of the real exchange rate misalignment, currency overvaluation (undervaluation) or real exchange rate regimes on the finance-growth nexus.

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Put–Call Ratio Volume vs. Open Interest in Predicting Market Return: A Frequency Domain Rolling Causality Analysis

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Abstract: This study examined the efficacy of the Put–Call Ratio (PCR), a widely used information ratio measured in terms of volume and open interest, in predicting market return at different time scale. Volume PCR was found to be an efficient predictor of the market return in a short period of 2.5 days and open interest PCR in a long period of 12 days. Thus, traders and portfolio managers should use the appropriate PCR depending upon the time horizon of their trade and investment. The results are robust even after controlling for the information generated from the futures market.

Keywords: Put–Call Ratio; volume; open interest; frequency-domain roiling causality

1. Introduction

Options are a conduit of carrying information into the market, which subsequently leads to stock price changes Grossman (1988). Because informed traders prefer to trade in options market for leverage and low transaction cost Black (1975) and Easley et al. (1998)[1], trading activities of options market measured in terms of volume and open interest are informative to predict the future price of their respective underlying assets. Both options volume and open interest have been used in addition to other factors in modeling early warning system for market crisis Li et al. (2015). Further, as per Jena and Dash (2014), trading volume and open interest represent the strength and potential of price change of the underlying asset, respectively. In addition, traders and technical analysts use open interest data to study the behavior of the underlying asset and design appropriate options strategies. Fodor et al. (2011) found individual call and put open interest have the power to predict future stock return. Most often PCR remains in the news as one of the important and parsimonious information variables used by traders to predict the market return[2]. This ratio is a contrarian indicator of the market by looking at build up options. That means, if there is excessive fall or rise in the market, PCR will move

1 Informational role of derivative markets was discussed by Back (1993), Biais and Hillion (1994), Brennan and Cao (1996) and John et al. (2000) and others who further enriched the linkage among trade, price and private information in derivative market. In addition, few empirical studies support the informational role of derivative markets (e.g., Du et al. (2018), Ryu (2015), Cao and Ye (2016) and Chordia et al. (2018)).

2 https://economictimes.indiatimes.com/markets/stocks/news/rising-nifty-put-call-ratio-bringssolace-for-bulls-no-big-fall-likely/articleshow/60456238.cmshttps://economictimes.indiatimes.com/markets/stocks/news/spike-in-put-call-ratio-shows-niftymay-correct-1-or-more-in-a-single-session/articleshow/59484386.cmshttps://economictimes.indiatimes.com/markets/stocks/news/rising-put-call-ratio-falling-volatilitysupporting-the-bulls/articleshow/60727912.cms

towards an extreme value based on which the traders can take a contrarian call. Thus, the direction of the market can be determined from the options market by using this most popular indicator, i.e., PCR, which is estimated as follows on a given day for both the measures of trading activity such trading volume and open interest.

PCR (OI) = open interest of put options on a given day/open interest of call options on the same given day

PCR (VOL) = volume of put options on a given day/volume of call options on the same given day

The objective of our study was to discern the efficacy of PCR (OI) and PCR VOL) in predicting the market return. However, is the predictability power of PCR stable across different time scales? Therefore, to answer this question, we investigated the strength and direction of causality at different frequencies using the novel frequency domain causality methodology of Breitung and Candelon (2006) in a rolling framework.

However, few academic studies are found in the literature related to this ratio. Billingsley and Chance (1988) found volume PCR as an effective forecasting tool in predicting the direction of the market. Blau and Brough (2015) in the US market found that current daily PCR of stock options is negatively related to next day's return, thus, as a contrarian trading strategy, PCR has the power of return predictability. Pan and Poteshman (2006) stated that the PCR constructed from buyer initiated volume (signed volume) contains information about future stock prices. Economically, stocks with low PCR are outperforming their higher counterpart stocks by 40 basis points and 1% on the next day and one week, respectively. However, this relative predictability of the PCR is short-lived Pan and Poteshman (2006). Therefore, in our study, we investigated whether the predictability of this ratio is consistent at a different frequencies over a period of time. Unlike Pan and Poteshman (2006), Blau et al. (2014) used unsigned trading volume in their study and investigated the relative information content of PCR and Option to Stock (O/S) ratio. They found that the nature of the information content of PCRs is fleeting at different frequencies. In our study, we tested this fleeting property of PCR at different frequencies in a time-varying framework.

Although information content of option ratios was studied by Roll et al. (2010) and Johnson and So (2012), they both used Option to Stock (O/S) volume ratio[3]. Further, in the literature, only PCR based on volume is studied, ignoring open interest, which is an important trading activity variable. Thus, in our study, in addition to volume PCR, we studied the efficacy of PCR open interest ratio in predicting the future market return. Thus far, existing literature provides one-shot statistic in the time domain in predicting the market return, thereby ignoring the causality dynamics at different frequencies. Thus, we applied Breitung and Candelon's (2006) frequency domain causality for this comparative study of predictability of PCR in both the short and long run. Since in sample frequency domain causality is not robust to structural changes[4] Batten et al. (2017) and Bouri et al. (2017), we estimated out of sample rolling frequency domain causality using a fixed window size of 250 days of observations.

Our contribution to the literature of the derivative market in general and options market, in particular, is threefold.

First, horizon heterogeneity requires information regarding the market at different time periods for trading and investment at different time horizon. We investigated the predictability of option ratios at different frequencies, thereby providing a robust measure for trading and investment at different time horizon for the investors. Second, in addition to volume PCR, we took PCR based on open interest, it being one of the important measures of investors' activity in the derivative market that is currently missing in the literature. Finally, we studied the robustness of our results at the different time periods as well as in the presence of the futures market.

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[3] Other studies on markets include those by Roll et al. (2009) and Chang et al. (2009).

[4] We estimated the Bai and Perron (2003) test and the results show five breakpoints in both the cases, i.e., volume PCR and market return, and open interest PCR and market return. The results are available on request.

We found that open interest PCR is an efficient predictor of market return in the long period of 12 days and volume PCR in the short period of 2.5 days. The results are robust after controlling for the information generated in the futures market.

The rest this paper is outlined as follows. Section 2 describes the data and methodology used in the study. The empirical results are presented and discussed in Section 3. Section 4 concludes the paper.

2. Data and Methodology

Daily volume and open interest data were collected for the Nifty Index[5] call and put option from the official website of National Stock Exchange of India (NSE)[6] from 1 June 2001 to 16 May 2013. The daily volume and open interest were aggregated across expiry and moneyness for both call and put options and taken for further calculation of daily PCR, the information variable for our study, by following Blau et al. (2014) and Bandopadhyaya and Jones (2008). Put–Call volume (open interest) ratio is the total volume (open interest) of put divided by total volume of call for the day. Log (P_t/P_{t-1}) was taken as market return, where P_t and P_{t-1} are closing price of the Nifty index at t and $t-1$, respectively. To control for the information originating from futures trading, we took the trading volume of the NIFTY index futures as a control variable. The descriptive statistics of the variables are presented in Table 1.

Table 1. Descriptive statistics of volume put–call ratio (PCRTO), open interest put–call ratio (PCROI), market return (RET) and log Nifty index futures volume (LFTO).

	PCROI	PCRTO	RET	LFTO
Mean	1.124	0.904	0.001	12.790
Median	1.140	0.911	0.001	13.473
Maximum	3.049	2.773	0.162	14.944
Minimum	0.210	0.136	−0.163	6.862
Std. Dev.	0.414	0.264	0.019	1.703
Skewness	0.155	0.370	−0.136	−1.420
Kurtosis	3.177	4.969	12.447	3.840
Jarque–Bera	11.491	399.741	8065.200	791.801
Probability	0.003 ***	0.000 ***	0.000 ***	0.000 ***
Observations	2168	2168	2167	2168
Augmented Dickey–Fuller test	−7.892	−7.682	−46.776	−3.314
statistic (p-values)	(0.000 ***)	(0.000 ***)	(0.000 ***)	(0.014 **)

*** and ** represent significance at 1% and 5% levels, respectively.

An average PCROI (PCRTO) greater than one (less than one) indicates a positive (negative) market sentiment. This justifies the PCROI taken in this study in addition to PCRTO. All the series were stationary. Moreover, since all the series were non-normal and fat-tailed, it further justified our methodology.

For the purpose of estimation, we used the frequency domain Granger causality (GC) test by following Bouri et al. (2017) as the widely utilized GC test (Granger 1969) is the one-shot measure of GC, which is assumed to be constant over time and frequency. Hosoya (1991) suggested that the causal influence may change across frequencies; nonetheless, they pointed out estimation difficulties owing to nonlinearities of the data to measure GC, which was made possible by Breitung and Candelon (2006)[7] by imposing linear restrictions on the autoregressive parameters in a VAR model and thus allowing

5 The bellwether index of National Stock Exchange of India (NSE) represents 65% of the total market capitalization and 12 sectors of the economy.

6 www.nseindia.com.

7 Yamada and Yanfeng (2014) through theoretical evaluation tested the usefulness of the methodology even at a frequency close to zero.

for the estimation of the frequency domain approach to causality at different frequency bands. Several studies have used this approach (for example, Tiwari et al. 2014, 2015 and references therein), therefore we provide a small introduction to the approach.

Let us present an equation of a stationary VAR framework of two series x_t and y_t as follows:

$$x_t = a_1 x_{t-1} + \ldots + a_p x_{t-p} + \beta_1 y_{t-1} + \ldots + \beta_p y_{t-p} + \varepsilon_t \quad (1)$$

The null hypothesis that y_t does not Granger-cause x_t at frequency (ω) in Equation (1) is tested by,

$$H_0 : R(\omega)\beta = 0 \quad (2)$$

where β is the vector of the coefficients of y_t i.e., $\beta = [\beta_1, \beta_1, \ldots \beta_p]$ and

$$R(\omega) = \begin{bmatrix} \cos(\omega)\cos(2\omega)\ldots\cos(p\omega) \\ \sin(\omega)\sin(2\omega)\ldots\sin(p\omega) \end{bmatrix} \quad (3)$$

According to the Breitung and Candelon (2006), an ordinary F statistic for Equation (2) can be used to test the hull hypothesis at any frequency interval (i.e., $\omega \in (0, \pi)$) as it is approximately distributed as $F(2, T-2p)$. Further, for the purpose of interpretations in time framework, the frequency parameter ω (omega) can be used to obtain the time period of the causality in days (T) by using formula T = $2\pi/\omega$.

3. Empirical Analysis

First, we estimated the VAR granger causality[8] (both unconditional and conditional on index futures volume) for the purpose of comparisons with the results of causality estimated at the frequency domain. The results are presented in Table 2.

Table 2. VAR Granger causality.

	Unconditional Chi-sq. Test Statistic (*p*-Values)	Conditional Chi-sq. Test Statistic (*p*-Values)
PCR TO $\neq>$ RET	3.548 (0.470)	5.887 (0.207)
NIFTY RET $\neq>$ PCR TO	23.403 (0.000 ***)	26.213 (0.000 ***)
PCR OI $\neq>$ RET	9.326 (0.009 ***)	15.999 (0.000 ***)
NIFTY RET $\neq>$ PCR OI	27.469 (0.000 ***)	36.878 (0.000 ***)

*** indicates significance at 1% level. $\neq>$ refers to "does not granger cause".

No causality was observed from PCRTO to market return. PCROI Granger causes market return. However, this one-shot measure of GC may not hold across frequencies owing to nonlinearities of the data Hosoya (1991). This further justifies the application of Breitung and Candelon's (2006) methodology and the results are discussed in the following section.

Figure 1 presents the frequency domain causality from put–call ratio volume (PCRTO) and open interest (PCROI) to market return[9]. The blue solid line shows the Granger causality from PCRTO to market return, which is insignificant throughout at both 5% and 10% levels. That means volume PCR does not have predictive power of market return, which is against the popular belief of being a sentiment indicator Open interest put–call ratio (PCROI) significantly (at 5% level) Granger causes market return in long run at a frequency band 0.51 corresponding to 12 days and above. At the 10%

[8] We are thankful to the anonymous referees for this suggestion.
[9] The descriptive statistics of the F-statics of the frequency domain causality results are presented in Appendix A Table A1.

level of significance, it leads the market return between a frequency bands of 0.93–0.51 corresponding to 6–12 days. It implies that open interest PCR is a better predictor of market return than its volume counterpart in the long run. None of these ratios can predict in the short run.

Figures 2 and 3 present the rolling frequency domain causality from PCR volume and open interest to market return. Notably, short term causalities were estimated at frequency of 2.5 corresponding to 2–3 days, as presented in Figure 3, and long-term causality at frequency of 0.50 corresponding to 12–13 days is estimated, aas presented in Figure 2.

The long-term rolling causality in Figure 2 is consistent with the results reported in the in-sample analysis. The predictability of open interest PCR dominates its volume counterparts, as indicated by the dominant and significant peak of its frequency curve from June 2003 to June 2006 and from December 2010 to February 2012. One thing that stands out is that, during the 2008 financial crisis and after the 2012 European sovereign debt crisis, none of the indicators is significant in predicting the market return. Thus, the traders should carefully use these ratios during market crisis.

However, over a short period of 2.5 days, the reported rolling causality in Figure 3 volume PCR dominates its open interest counterpart, which is in stark contrast to the in-sample result. Another interesting thing that stands out from the figures is that, in the short term, volume PCR is a good predictor of market return. Moreover, it is a good predictor during the 2008 financial crisis, as evident from the higher amplitude volume PCR frequency curve, which is significant at 5% level. However, open interest PCR in the short run dominates for a brief period from April 2011 to November 2011[10]. Our results supplement the findings of Pan and Poteshman (2006) and Blau et al. (2014) that the volume PCR is short lived and fleeting, respectively.

[10] We also estimated conditional frequency domain rolling causality analysis after controlling for the futures market activities. The results are quite similar and available upon request.

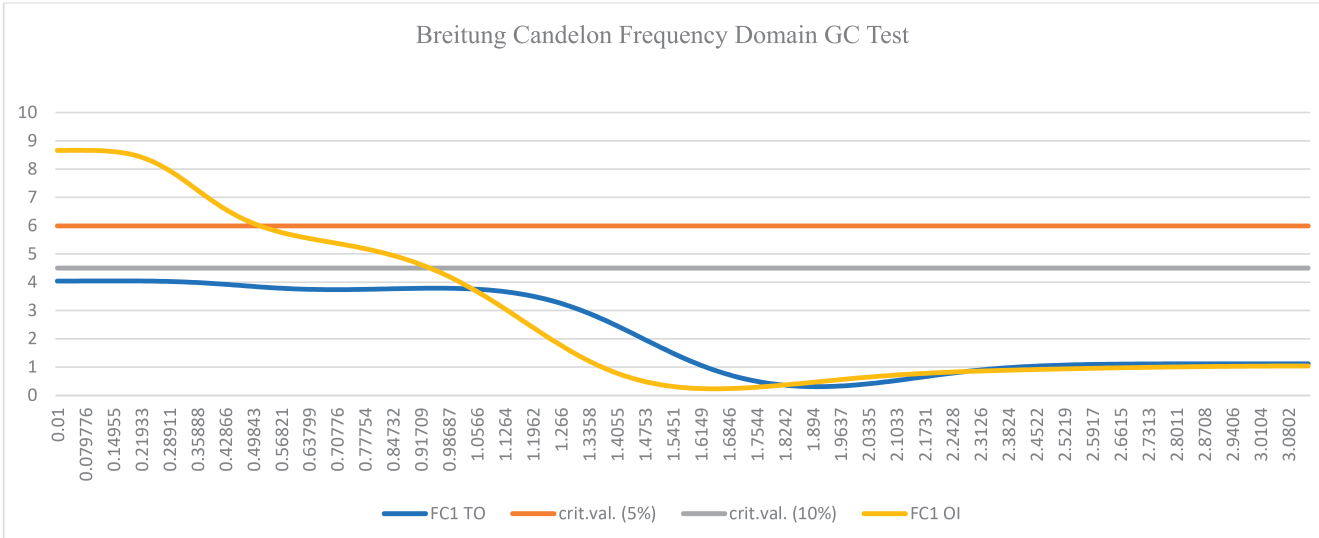

Figure 1. Full sample period frequency domain causality from volume put–call ratio (PCRTO) to market return is represented by blue solid line (FC1 TO) and the yellow solid line (FC1 OI) shows from open interest put–call ratio (PCROI) to market return. The frequencies (omega, ω) are on x-axis, and F-statistics testing the null hypothesis of no Granger causality are on y-axis. The horizontal red solid line and grey solid line indicate the 5% and 10% critical values, respectively.

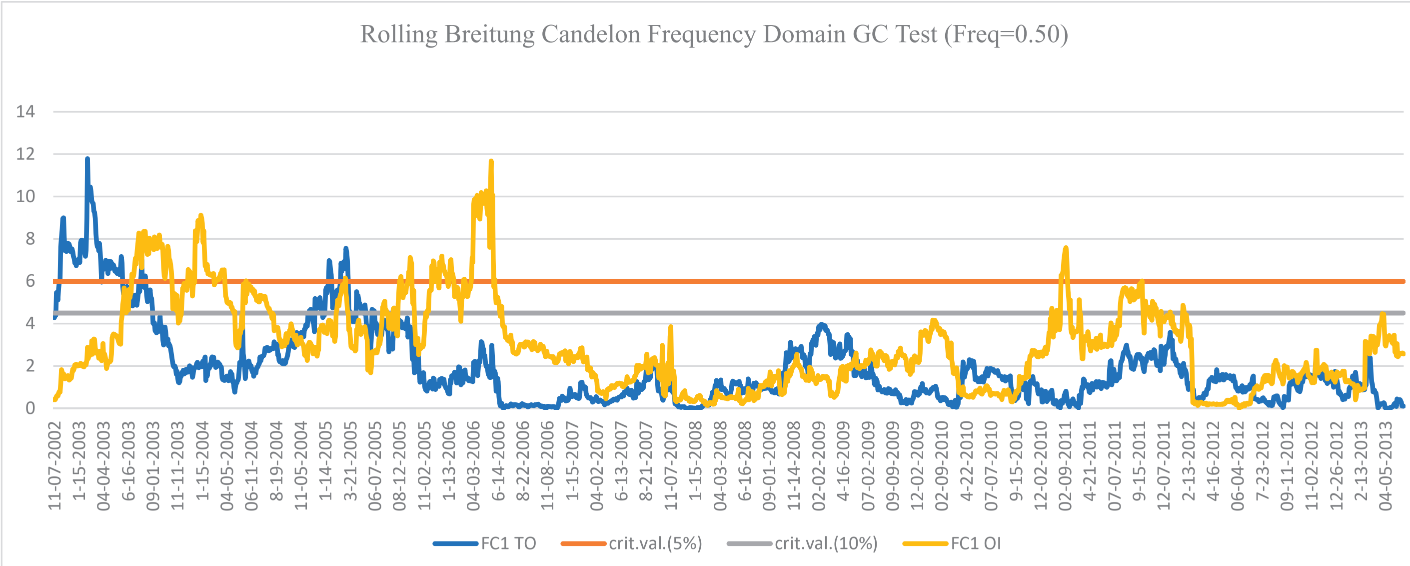

Figure 2. Long-run (ω = 0.50 or 12 days) rolling window frequency domain causality. The x-axis represents the date and y-axis shows the F-statistics testing the null hypothesis of no Granger causality from volume Put–call ratio (FC1 TO) and open interest Put–call ratio (FC1 OI) to market return. The horizontal red solid line and grey solid line indicate the 5% and 10% critical values, respectively. The blue solid line (FC1 TO) and yellow solid line (FC1 OI) show long run causality from volume PCR and open interest put ratio, respectively, to market return.

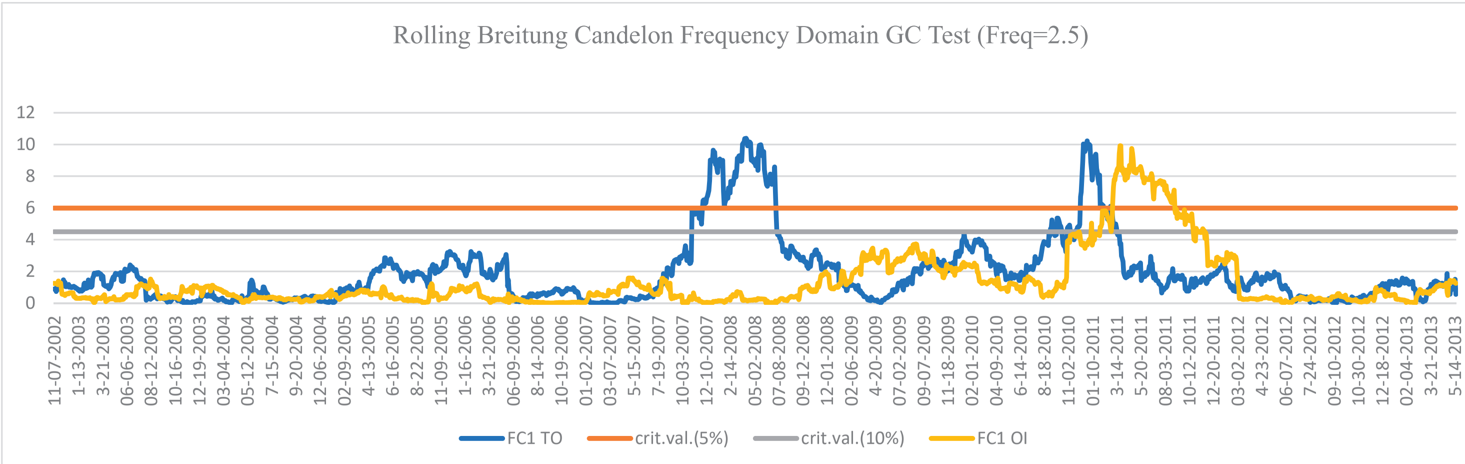

Figure 3. Short-run (ω = 2.5 or 2.5 days) rolling window frequency domain causality. The x-axis represents the date and y-axis shows the F-statistics testing the null hypothesis of no Granger causality from volume Put–call ratio (FC1 TO) and open interest Put–call ratio (FC1 OI) to market return. The horizontal red solid line and grey solid line indicate the 5% and 10% critical values, respectively. The blue solid line (FC1 TO) and yellow solid line (FC1 OI) show short run causality from volume PCR and open interest put ratio, respectively, to market return.

4. Conclusions

Extending the prior research relating to informational role of derivative market in general and option market in particular, this study examined the informational efficiency of volume and open interest PCR in predicting the market return and its implication for traders and portfolio managers. First, we studied the efficiency of the PCR at different frequencies and the results were tested in an out of sample forecasting exercises in a rolling frequency domain causality framework. The Granger causality from PCR to market return varies across the frequencies. Long-run causality was observed from open interest PCR to market return corresponding to time period of 12 days. In the short run, corresponding to 2.5 days, volume PCR Granger causes market return. Thus, traders and portfolio managers should use the appropriate PCR at the different time period in predicting a market return for trading and investment. In addition, unlike in the long run, the short-run volume PCR holds the predictability of market return during crisis period. Further, our findings are robust even after controlling for the information generated from futures market. In the future, this study could be extended to effectiveness of PCR ratios across maturity and moneyness of the index options as well as stock options.

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Conflicts of Interest: The authors declare no conflict of interest.

Appendix A

Table A1. Descriptive statistics of the F-statics of the frequency domain causality.

	In Sample		Out of Sample (Freq. 0.5)		Out of Sample (Freq. 2.5)	
	FC1 TO	FC1 OI	FC1 TO	FC1 OI	FC1 TO	FC1 OI
Mean	2.195	2.785	1.953	2.955	1.942	1.323
Median	1.332	1.026	1.359	2.571	1.350	0.565
Standard Deviation	1.441	2.772	1.888	2.112	2.157	1.849
Kurtosis	−1.783	−0.620	3.032	0.621	4.114	5.483
Skewness	0.140	0.929	1.719	0.948	2.050	2.380
Minimum	0.308	0.232	0.002	0.009	0.000	0.001
Maximum	4.046	8.662	11.784	11.674	10.391	9.919
No of Obs.	314	314	1917	1917	1917	1917

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Article

The Impact of Financial Constraints on the Convertible Bond Announcement Returns

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Abstract: As of now, very few research studies have examined the effects of financial constraints on the short- and long-term performances of companies after their announcement of convertible bonds. Due to asymmetric information, previous studies consider issuance of convertible bonds as negative news. As a result, the short- and long-term performances of companies generally decline after their convertible bond announcement. This study argues that when companies have investment plans, they are expected to have higher future cash flows. They will become increasingly more valuable regardless of the fact that they raise funds through the issue of convertible bonds (due to financial constraints), positively affecting the performance of companies. The results indicate that financial constraints have no effect on short-term performance, but did have a significantly positive impact on the long-term performance of companies after their issuance of convertible bonds.

Keywords: convertible bond; financial constraints; stock performance

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1. Motivation

The previous literature has pointed out that financial constraints significantly influence companies. Fazzari et al. (1988), Kaplan and Zingales (1997), and Cleary (1999) proved that financial constraints affect the investment decisions of a company. Hoshi et al. (1991), Fohlin (1998), and Houston and James (2001) stated that the relationship between companies and banks affects the degree of financial constraints. Fazzari et al. (1988), Hoshi et al. (1991), Hubbard et al. (1995), and Cleary (1999) assumed that dividend payout ratio also affects the degree of financial constraints. Chen and Wang (2012) suggested that companies with financial constraints have poor stock repurchase performance of treasury stock because they face a high financial risk.

Convertible bonds, with the dual characteristics of stocks and bonds, help alleviate the problem of information and agency costs caused by the external financing of companies. However, numerous studies have specified that the release and announcement of convertible bonds generate unfavorable messages, which in turn, have a negative effect on stock prices, causing issuing firms to receive negative stock performance (e.g., Dann and Mikkelson 1984; Mikkelson and Partch 1986; Stein 1992; Wolfe et al. 1999; Hillion and Vermaelen 2004; Ammann et al. 2006; Duca et al. 2012). For example, Duca et al. (2012) showed that convertible offerings announced between 1984 and 1999 induced average abnormal stock returns of −1.69%, and convertible announcement effects over the periods from 2000–2008 are more than twice as negative (−4.59%) in US convertible debt. However, Kim and Han (2019) indicated that convertible bond issues have significantly positive cumulative abnormal returns around the announcement in Korea. In particular, issuing firms that state capital expenditure as the use of proceeds have significantly higher cumulative abnormal returns compared to firms that state other purposes.

Among past literature, very few studies have been done examining the effects of financial constraints on the short- and long-term performance of companies after their announcement of issuing convertible bonds. The results of these limited research studies show that the bond issue announcement has a negative effect on the performance of companies. Theoretically, a company's performance is reflected in its stock price movement—a company that has better performance implies better returns and dividends, which in turn will be reflected in its stock price. The aim of this study is to investigate the relationship between the announcement of issuing convertible bonds and the stock price performance of a company with financial constraints.

Additionally, Luo (2011) argues that in comparison with companies without financial constraints, companies with financial constraints would more effectively use the limited capital that they raise in the future. The result indicates that the executives of the companies with financial constraints are relatively effective in terms of managing capital spending. Therefore, this study argues that companies with financial constraints tend to raise their funds by issuing convertible bonds that have a positive influence on innovation and investment activities, which in turn are expected to cause higher future cash flows and increases in asset value. Thus, the objective of this study is to also investigate the effects of financial constraints on the short- and long-term performances of companies after their announcement of convertible bond issuance.

The remainder of this paper is arranged as follows. Section 2 describes the data and model, Section 3 introduces the empirical variables, and Section 4 presents the empirical results. Findings are summarized in Section 5.

2. The Model

This study adopts the pooled ordinary least squares regression approach to investigate the relationship between the financial constraint and firm stock performance of convertible bond issuance.[1] The specifications of the model are as follows:

$$\begin{aligned} CAR(\tau_1, \tau_2) = \beta_0 + \beta_1 HFC_{i,t} + \beta_2 SIZE_{i,t} + \beta_3 MB_{i,t} + \beta_4 FCFratio_{i,t} \\ +\beta_5 STDAR_{i,t} + \beta_6 LEV_{i,t} + \beta_7 Rm\_Rf_{i,t} + \varepsilon_{i,t} \end{aligned} \tag{1}$$

where subscripts i and t indicate a sampled company and current period, respectively. In this study, the cumulative abnormal returns (*CAR*) was considered as the dependent variable, and the financial constraint indicator (*HFC*) was set as the independent variable. If *CAR* is influenced by financial constraint, the coefficient β_1 will be statistically significant. β_1 is expected to be positive. This implies that companies with financial constraints tend to raise their funds by issuing convertible bonds that have a positive influence on innovation and investment activities, which in turn are expected to have higher future cash flows and increases in asset value.

Following the works of Marsh (1982), McConnell and Muscarella (1985), Jensen (1986), Lakonishok and Vermaelen (1990), Pilotte (1992), Spiess and Affleck-Graves (1995), and Pettengill et al. (2002), this study adopted company size (*SIZE*), market net value ratio (*MB*), free cash flow ratio (*FCFratio*), information asymmetry (*STDAR*), debt ratio (*LEV*), and market trend (*RmRf*). *SIZE* refers to the natural logarithm of a firm's market value. *MB* refers to the ratio of market value of a company to its net worth. *FCFratio* refers to the ratio of free cash flow to total assets. *STDAR* is the residual standard deviation of the daily rate of return, measured according to market mode. *LEV* is the ratio of total debt to total assets. *RmRf* is the difference between the monthly return on Weighted Stock Index and risk-free rate.

1 Panel data regression was run with fixed effect in addition to pooled ordinary least regression approach. This yielded favorable results which support our claim, that companies with high financial constraints have higher long-term performance after issuing convertible bonds.

Moreover, using the heteroscedasticity consistent estimator introduced by White (1980), this study adjusted the standard error of the estimated parameters and modified the heterogeneity variation. Considering the date of announcement and the completeness of the variables, there were a total of 418 TAIEX-listed and OTC-listed companies issuing convertible bonds in Taiwan collected from Taiwan Economics Journal covering the period from 2005 to 2009.

3. Empirical Variables

3.1. Financial Constraint

Adopting the Financial Constraint Index (*FCindex*), formulated by Kaplan and Zingales (1997)[2], this study divided the samples into two groups: high financial constraints *HFC* and low financial constraints *LFC*. *HFC* was set to1 if the *FCindex* of a sample company was higher than the mean value of the industry; otherwise, it was 0. The *FCindex* estimated by Kaplan and Zingales (1997) is denoted as

$$\begin{aligned} FCindex = \underset{(0.23)}{-1.002} \times \left(\frac{Cashflow}{K}\right) + \underset{(0.08)}{0.283} \times Q + \underset{(0.45)}{3.139} \times \left(\frac{Dedt}{K}\right) \\ \underset{(6.10)}{-39.368} \times \left(\frac{Dividends}{K}\right) - \underset{(0.29)}{1.315} \times \left(\frac{Cash}{K}\right) \end{aligned} \tag{2}$$

where K refers to the total assets; *Cashflow* represents the net profit after the tax subtracted by the abnormal item and depreciation; Q is the proxy variable of Tobin'Q, that is, the sum of the market value of equity and the book value of debt divided by the book value of the asset; *Debt* is the total debt; *Dividends* refers to the total cash dividends paid by the enterprise; *Cash* is the cash and cash equivalents; and the figures in brackets below the coefficients in Equation (2) are the standard deviations.

3.2. Performance Index

The market model was used to measure the short- and long-term performances after the announcement of convertible bonds. OLS was adopted to establish the regression model of individual securities on the market portfolio.

$$R_{i,t} = \alpha_i + \beta_i R_{m,t} + \varepsilon_{i,t} \tag{3}$$

where $R_{i,t}$ is the rate of return of the stock of company i in day (month) t; $R_{m,t}$ is the rate of return of the market portfolio in day (month) t regarding the daily (monthly) rate of return of the Taiwan weighted stock index; α and β are regression coefficients; and ε is the error term.

The date (month) of the announcement of the convertible bonds was regarded as the event day (month); 30 days after the announcement was set as the short-term event period; and 60 months after the announcement was regarded as the long-term event period. The period from 31 days to 210 days before the announcement was considered the short-term estimating period and the period from 12 months to 60 months was regarded as the long-term estimating period. A total of 180 days and 49 months comprised the observation period.

Abnormal returns (ARs) was calculated with the actual return in event period minus the expected return estimated by the market model. Mean ARs refers to the mean value of the ARs of all sample companies. The short-term (long-term) cumulative abnormal returns *SCAR0_t* (*LCAR0_t*) denote the accumulated AR by company i from the day (month) of announcement of convertible bonds, 0, to day (month) t. The cumulative mean ARs represent the cumulative value of the mean ARs from the day (month) of announcement of convertible bonds 0 to day (month).

2 The index measuring the degree of companies' financial constraints were widely used, including by Lamont et al. (2001), Baker et al. (2003), Chen et al. (2007), and Hennessy et al. (2007). In following Whited and Wu (2006), the WW index was included to measure whether a company has financial constraints. The result is consistent with the empirical results.

4. Empirical Analysis

4.1. Industrial Distribution of Sample Companies and Events

Table 1 shows the sample companies, events of the announcement of convertible bonds, and industrial distribution. The table particularly indicates 418 sample companies and 643 events of announcements of convertible bonds.

Table 1. Sample companies, events of the announcement of convertible bonds, and industrial distribution.

Industry	Number of Companies	%	Number of Events	%
Food	4	0.96%	4	0.62%
Plastic	4	0.96%	7	1.09%
Textile	9	2.15%	15	2.33%
Electric Machinery	18	4.31%	25	3.89%
Electric and Cable	6	1.44%	8	1.24%
Biotechnology	23	5.50%	32	4.98%
Glass and Ceramic	1	0.24%	2	0.31%
Paper and Pulp	5	1.20%	7	1.09%
Iron and Steel	15	3.59%	28	4.35%
Rubber	4	0.96%	5	0.78%
Automobile	2	0.48%	5	0.78%
Electronics	267	63.88%	408	63.45%
Building Material and Construction	23	5.50%	37	5.75%
Shipping and Transportation	5	1.20%	13	2.02%
Tourism	2	0.48%	2	0.31%
Trading and Consumers' Goods	6	1.44%	11	1.71%
Oil, Gas, and Electricity	4	0.96%	5	0.78%
others	20	4.78%	29	4.51%
Total	418	100.00%	643	100.00%

4.2. Analysis on the Difference in Short- and Long-Term Performances after the Announcement of Convertible Bonds between High and Low Financial Constraints

Table 2 demonstrates that the announcements of convertible bonds by low- and high-financial constraint companies negatively affect their short- and long-term performances. However, the negative effect of high-financial constraint companies is lower than that of low-financial constraint companies. For long-term performance, the cumulative AR, *LCAR0_36* of high-financial constraint companies is −25.53%, whereas that of low-financial constraint companies is −46.97%. The difference between the high and low financial constraints is 21.44%, with a significance level of 5%. The cumulative ARs *LCAR0_24*, (*LCAR0_48*), and (*LCAR0_60*) have the same empirical result. These findings suggest that the companies with high financial constraints have higher long-term performance than those with low financial constraints.

Table 2. The effects of announcement of convertible bonds by low- and high-financial constraint companies on their short- and long-term performances.

Panel A Short-Term Cumulative Abnormal Returns [1]				
Performance	**High Financial Constraints**	**Low Financial Constraints**	**Difference**	***p*-Value**
SCAR0_5	−1.10	−0.65	−0.46	0.3639
SCAR0_10	−1.29	−1.56	0.27	0.6796
SCAR0_15	−1.27	−1.65	0.38	0.6358
SCAR0_20	−1.77	−2.35	0.58	0.5399
SCAR0_25	−2.15	−2.21	0.06	0.9616
SCAR0_30	−2.06	−2.62	0.56	0.6502

Table 2. *Cont.*

Panel B Long-Term Cumulative Abnormal Returns [2]				
Performance	High Financial Constraints	Low Financial Constraints	Difference	*p*-Value
LCAR0_12	−12.68	−19.08	6.40	0.1951
LCAR0_24	−21.35	−35.21	13.86 *	0.0656
LCAR0_36	−25.53	−46.97	21.44 **	0.0347
LCAR0_48	−38.09	−62.73	24.64 *	0.0546
LCAR0_60	−47.85	−78.79	30.94 **	0.0425

Note: * significant at 10% level; ** significant at 5% level. [1] The short-term performance including the cumulative AR from 0 to 5 days (*SCAR0_5*), from 0 to 10 days (*SCAR0_10*), from 0 to 15 days (*SCAR0_15*), from 0 to 20 days (*SCAR0_20*), from 0 to 25 days (*SCAR0_25*), and from 0 to 30 days (*SCAR0_30*). [2] The long-term performance, including the cumulative AR from 0 to 12 months (*LCAR0_12*), from 0 to 24 months (*LCAR0_24*), from 0 to 36 months (*LCAR0_36*), from 0 to 48 months (*LCAR0_48*), and from 0 to 60 months (*LCAR0_60*).

4.3. Short-Term Performance from High and Low Financial Constraints

Table 3 illustrates that the short-term cumulative AR of high-financial constraint companies is negative. The cumulative ARs *SCAR0_5*, *SCAR0_10*, *SCAR0_20*, and *SCAR0_30* are −1.20%, −1.38%, −1.96%, and −2.31%, respectively, with statistical significance. The companies with low financial constraints have the same empirical results. These findings are consistent with the negative AR after the announcement of convertible bonds obtained by Dann and Mikkelson (1984), Stein (1992), Wolfe et al. (1999), Hillion and Vermaelen (2004), Ammann et al. (2006), and Duca et al. (2012).

Table 3. Short-term performances of high and low financial constraints.

Performance	High Financial Constraints		Low Financial Constraints	
SCAR0_t	Rate of Return	*t*-Value	Rate of Return	*t*-Value
SCAR0_0	−0.09	−0.64	−0.25 *	−1.65
SCAR0_1	−0.43 **	−2.10	−0.36	−1.55
SCAR0_2	−0.73 ***	−2.92	−0.60 **	−2.15
SCAR0_3	−0.78 ***	−2.62	−0.66 **	−2.04
SCAR0_4	−0.89 ***	−2.60	−0.53 *	−1.53
SCAR0_5	−1.20 ***	−3.34	−0.65 *	−1.71
SCAR0_6	−1.49 ***	−3.92	−0.96 **	−2.40
SCAR0_7	−1.55 ***	−3.76	−1.12 ***	−2.69
SCAR0_8	−1.60 ***	−3.81	−1.24 ***	−2.83
SCAR0_9	−1.67 ***	−3.77	−1.41 ***	−3.02
SCAR0_10	−1.38 ***	−3.05	−1.63 ***	−3.33
SCAR0_11	−1.24 **	−2.56	−1.44 ***	−2.72
SCAR0_12	−1.24 **	−2.46	−1.64 ***	−2.91
SCAR0_13	−1.34 **	−2.54	−1.61 ***	−2.77
SCAR0_14	−1.31 **	−2.35	−1.67 ***	−2.87
SCAR0_15	−1.43 **	−2.53	−1.57 **	−2.57
SCAR0_16	−1.50 ***	−2.66	−1.56 **	−2.41
SCAR0_17	−1.80 ***	−3.06	−1.64 **	−2.51
SCAR0_18	−1.90 ***	−3.08	−1.90 ***	−2.88
SCAR0_19	−1.93 ***	−3.03	−2.06 ***	−3.02
SCAR0_20	−1.96 ***	−2.97	−2.28 ***	−3.20
SCAR0_21	−1.90 ***	−2.80	−2.32 ***	−3.17
SCAR0_22	−2.04 ***	−2.93	−2.22 ***	−2.99
SCAR0_23	−2.23 ***	−3.06	−2.23 ***	−2.95
SCAR0_24	−2.27 ***	−3.07	−2.16 ***	−2.83
SCAR0_25	−2.42 ***	−3.24	−2.20 ***	−2.80
SCAR0_26	−2.24 ***	−2.90	−2.06 ***	−2.60
SCAR0_27	−2.28 ***	−2.90	−2.20 ***	−2.71
SCAR0_28	−2.24 ***	−2.79	−2.31 ***	−2.72
SCAR0_29	−2.17 ***	−2.64	−2.51 ***	−2.96
SCAR0_30	−2.31 ***	−2.76	−2.69 ***	−3.07

Note: * significant at 10% level; ** significant at 5% level; *** significant at 1% level.

4.4. Long-Term Performance from High and Low Financial Constraints

Table 4 shows that the cumulative ARs of the companies with high and low financial constraints are negative. However, the comparative analysis indicates that the cumulative ARs of the companies with high financial constraints, namely *LCAR0_10*, *LCAR0_20*, *LCAR0_30*, *LCAR0_40*, *LCAR0_50*, and *LCAR0_60*, are −9.72%, −21.03%, −23.83%, −31.99%, −43.00%, and −49.84%, respectively. For the same set of cumulative ARs, the companies with low financial constraints have −13.26%, −28.57%, −39.68%, −49.46%, −65.08%, and −78.66%. In summary, the cumulative AR of high-financial constraint companies is higher than that of low-financial constraint companies, with an increasing difference.

Table 4. Long-term performances of high and low financial constraints.

Performance	High Financial Constraints		Low Financial Constraints		Performance	High Financial Constraints		Low Financial Constraints	
SCAR0_t	**Return**	***t*-Value**	**Return**	***t*-Value**	***LCAR0_t***	**Return**	***t*-Value**	**Return**	***t*-Value**
LCAR0_0	−1.39 **	−2.02	−1.66 **	−1.87	*LCAR0_31*	−24.38 ***	−3.88	−40.01 ***	−5.68
LCAR0_1	−1.59	−1.42	−2.49 **	−2.02	*LCAR0_32*	−24.84 ***	−3.87	−40.38 ***	−5.59
LCAR0_2	−3.28 **	−2.31	−3.32 **	−2.04	*LCAR0_33*	−25.09 ***	−3.85	−40.94 ***	−5.50
LCAR0_3	−3.66 **	−2.12	−4.05 *	−2.19	*LCAR0_34*	−25.71 ***	−3.86	−41.43 ***	−5.41
LCAR0_4	−4.55 **	−2.30	−4.12 **	−1.91	*LCAR0_35*	−25.57 ***	−3.74	−42.06 ***	−5.42
LCAR0_5	−4.99 **	−2.25	−5.33 **	−2.20	*LCAR0_36*	−26.54 ***	−3.79	−44.48 ***	−5.60
LCAR0_6	−5.66 **	−2.37	−7.34 ***	−2.83	*LCAR0_37*	−28.51 ***	−3.98	−46.34 ***	−5.69
LCAR0_7	−7.57 ***	−2.88	−9.49 ***	−3.54	*LCAR0_38*	−28.88 ***	−3.95	−47.34 ***	−5.64
LCAR0_8	−8.38 ***	−2.95	−10.23 ***	−3.49	*LCAR0_39*	−30.58 ***	−4.13	−48.85 ***	−5.66
LCAR0_9	−8.99 ***	−3.00	−11.99 ***	−3.84	*LCAR0_40*	−31.99 ***	−4.26	−49.46 ***	−5.61
LCAR0_10	−9.72 ***	−2.94	−13.26 ***	−4.03	*LCAR0_41*	−32.89 ***	−4.29	−50.94 ***	−5.67
LCAR0_11	−10.57 ***	−3.11	−16.49 ***	−4.98	*LCAR0_42*	−34.89 ***	−4.46	−52.21 ***	−5.73
LCAR0_12	−13.68 ***	−3.72	−17.83 ***	−5.00	*LCAR0_43*	−35.89 ***	−4.53	−52.69 ***	−5.74
LCAR0_13	−16.02 ***	−4.24	−19.04 ***	−5.13	*LCAR0_44*	−36.87 ***	−4.52	−54.61 ***	−5.84
LCAR0_14	−16.86 ***	−4.31	−21.37 ***	−5.38	*LCAR0_45*	−36.77 ***	−4.44	−55.44 ***	−5.81
LCAR0_15	−18.35 ***	−4.54	−22.78 ***	−5.37	*LCAR0_46*	−37.53 ***	−4.5	−57.24 ***	−5.87
LCAR0_16	−20.61 ***	−4.95	−24.84 ***	−5.67	*LCAR0_47*	−37.31 ***	−4.44	−59.54 ***	−5.94
LCAR0_17	−20.96 ***	−4.86	−25.23 ***	−5.54	*LCAR0_48*	−40.10 ***	−4.68	−60.64 ***	−5.92
LCAR0_18	−21.84 ***	−4.92	−26.14 ***	−5.56	*LCAR0_49*	−42.24 ***	−4.85	−63.98 ***	−6.17
LCAR0_19	−21.15 ***	−4.60	−26.43 ***	−5.43	*LCAR0_50*	−43.00 ***	−4.87	−65.08 ***	−6.16
LCAR0_20	−21.03 ***	−4.49	−28.57 ***	−5.59	*LCAR0_51*	−44.90 ***	−5.00	−66.14 ***	−6.15
LCAR0_21	−21.74 ***	−4.54	−30.19 ***	−5.60	*LCAR0_52*	−45.75 ***	−5.03	−67.73 ***	−6.22
LCAR0_22	−22.26 ***	−4.49	−30.98 ***	−5.50	*LCAR0_53*	−46.54 ***	−5.05	−69.73 ***	−6.33
LCAR0_23	−22.79 ***	−4.44	−33.12 ***	−5.89	*LCAR0_54*	−46.19 ***	−4.93	−71.03 ***	−6.27
LCAR0_24	−22.65 ***	−4.32	−33.42 ***	−5.74	*LCAR0_55*	−47.39 ***	−4.96	−72.71 ***	−6.29
LCAR0_25	−23.35 ***	−4.32	−34.08 ***	−5.72	*LCAR0_56*	−47.46 ***	−4.91	−73.11 ***	−6.26
LCAR0_26	−23.34 ***	−4.17	−35.07 ***	−5.80	*LCAR0_57*	−48.07 ***	−4.96	−73.82 ***	−6.21
LCAR0_27	−23.93 ***	−4.10	−36.49 ***	−5.95	*LCAR0_58*	−48.65 ***	−4.97	−74.48 ***	−6.19
LCAR0_28	−24.84 ***	−4.14	−38.68 ***	−6.15	*LCAR0_59*	−48.94 ***	−4.96	−75.88 ***	−6.23
LCAR0_29	−25.04 ***	−4.08	−37.96 ***	−5.83	*LCAR0_60*	−49.84 ***	−4.98	−78.66 ***	−6.31
LCAR0_30	−23.83 ***	−3.84	−39.68 ***	−5.91					

Note: * significant at 10% level; ** significant at 5% level; *** significant at 1% level.

4.5. Effect of Financial Constraints on Short-Term Performance after the Announcement of Convertible Bonds

The results of the regression analysis in Table 5 imply that the regression coefficients of the effects of financial constraints (*HFC*) on the cumulative ARs *SCAR0_5*, *SCAR0_10*, *SCAR0_15*, *SCAR0_20*, *SCAR0_25*, and *SCAR0_30* are −0.0064, 0.0034, 0.0020, 0.0100, 0.0074, and 0.0100, respectively, without statistical significance. This finding shows that financial constraints insignificantly affect the short-term performance of companies after their announcement of convertible bonds.

Table 5. Effects of financial constraints on the short-term performances of companies after their issuance of convertible bonds.

Independent Variable \ *Performance*	*SCAR0_5*	*SCAR0_10*	*SCAR0_15*	*SCAR0_20*	*SCAR0_25*	*SCAR0_30*
Intercept	0.0188	−0.0211	−0.0106	−0.0065	−0.0253	−0.0157
	(0.0179)	(0.0244)	(0.0300)	(0.0349)	(0.0393)	(0.0446)
HFC	−0.0064	0.0034	0.0020	0.0100	0.0074	0.0100
	(0.0064)	(0.0079)	(0.0097)	(0.0113)	(0.0131)	(0.0142)
SIZE	−0.0029	0.0015	−0.0005	−0.0004	0.0031	0.0017
	(0.0020)	(0.0027)	(0.0034)	(0.0040)	(0.0044)	(0.0050)
MB	−0.0014	−0.0033	−0.0009	−0.0008	−0.0011	−0.0035
	(0.0019)	(0.0028)	(0.0035)	(0.0043)	(0.0049)	(0.0056)
FCFratio	0.0237	0.0248	0.0303	0.0371	0.0196	0.0343
	(0.0152)	(0.0225)	(0.0303)	(0.0296)	(0.0386)	(0.0372)
STDAR	0.0161	0.0001	0.0208	0.0225	0.0119	−0.0378
	(0.0280)	(0.0486)	(0.0620)	(0.0673)	(0.0746)	(0.0986)
LEV	0.0008	−0.0105	−0.0095	−0.0491	−0.0688	−0.0583
	(0.0244)	(0.0318)	(0.0386)	(0.0439)	(0.0516)	(0.0586)
RmRf	0.0071	0.0714	0.1458 **	0.1244 *	0.1761 **	0.2784 ***
	(0.0398)	(0.0515)	(0.0638)	(0.0713)	(0.0826)	(0.0950)
Adj.R^2	0.0115	0.0096	0.0136	0.0113	0.0133	0.0225
F-value	0.4344	0.5657	0.311	0.4433	0.3262	0.0569

Note: * significant at 10% level; ** significant at 5% level; *** significant at 1% level.

4.6. Effect of Financial Constraints on Long-Term Performance after the Announcement of Convertible Bonds

Table 6 shows that the regression coefficients of the effects of financial constraints (*HFC*) on the cumulative ARs *LCAR0_12*, *LCAR0_24*, *LCAR0_36*, *LCAR0_48*, and *LCAR0_60* are 0.1199, 0.2043, 0.2587, 0.2378, and 0.3127, respectively, with statistical significance. This observation suggests that financial constraints positively affect the long-term cumulative AR of companies, thus the companies with high financial constraints have higher long-term performance after they issue convertible bonds.[3]

Table 6. Effects of financial constraints on the long-term performances of companies after their issuance of convertible bonds.

Independent Variable \ *Performance*	*LCAR0_12*	*LCAR0_24*	*LCAR0_36*	*LCAR0_48*	*LCAR0_60*
Intercept	0.1850	0.2522	0.6774 **	0.7336 *	0.9665 **
	(0.1777)	(0.2498)	(0.3276)	(0.3994)	(0.4852)
HFC	0.1199 **	0.2043 **	0.2587 **	0.2378 *	0.3127 *
	(0.0571)	(0.0877)	(0.1133)	(0.1415)	(0.1681)
SIZE	−0.0015	0.0118	−0.0332	−0.0455	−0.0685
	(0.0219)	(0.0292)	(0.0379)	(0.0471)	(0.0562)
MB	−0.0663 *	−0.1439 ***	−0.1839 ***	−0.2376 ***	−0.3031 ***
	(0.0363)	(0.0387)	(0.0471)	(0.0621)	(0.0747)
FCFratio	0.4405 **	0.4677 *	0.6997 **	0.7404 *	0.8466 *
	(0.1791)	(0.2558)	(0.3144)	(0.3864)	(0.4332)
STDAR	−2.4905 ***	−5.0979 ***	−7.1942 ***	−8.6716 ***	−9.6888 ***
	(0.6469)	(0.8699)	(1.2583)	(1.6700)	(2.0607)
LEV	−0.4961 **	−0.7041 **	−0.7173 *	−0.5391	−0.6762
	(0.2105)	(0.3011)	(0.4190)	(0.5418)	(0.6353)
RmRf	−0.0640	−0.5177	−0.3523	−0.3101	−0.4929
	(0.4306)	(0.5495)	(0.6946)	(0.8714)	(1.0643)
Adj.R^2	0.1136	0.1982	0.2278	0.225	0.2304
F-value	8.18 ***	15.78 ***	18.84 ***	18.54 ***	19.12 ***

Note: * significant at 10% level; ** significant at 5% level; *** significant at 1% level.

[3] Panel data regression was run with fixed effect in addition to pooled ordinary least regression approach. This yielded favorable results which support our claim that companies with high financial constraints have higher long-term performance after issuing convertible bonds.

5. Conclusions

The previous literature posits that convertible bonds negatively affect stock performance. They argue that investors believe that stock prices are overvalued and that companies have high risk because of the existence of information asymmetry. Therefore, stock performance becomes poor after the announcement of convertible bonds. By arguing that companies under financial constraint will cautiously and efficiently use their funds. This study investigates the effects of financial constraints on short- and long-term performances of companies after their announcement of convertible bonds. The empirical results demonstrate that financial constraints do not have any significant short-term effects, but they do have significant positive long-term effects on the performances of companies. In addition, high financial constraints have higher long-term cumulative AR than those with low financial constraints.

Past literature have shown that the companies' convertible bond announcement negatively affect their stock prices. However, the result of our study shows the opposite. Thus, investors are recommended to choose companies with high financial constraints if they are considering investing in those that are going to issue convertible bonds, which is beneficial with regards to planning investment strategies.

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An Experiment on Autoregressive and Threshold Autoregressive Models with Non-Gaussian Error with Application to Realized Volatility

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Abstract: This article explores the fitting of Autoregressive (AR) and Threshold AR (TAR) models with a non-Gaussian error structure. This is motivated by the problem of finding a possible probabilistic model for the realized volatility. A Gamma random error is proposed to cater for the non-negativity of the realized volatility. With many good properties, such as consistency even for non-Gaussian errors, the maximum likelihood estimate is applied. Furthermore, a non-gradient numerical Nelder–Mead method for optimization and a penalty method, introduced for the non-negative constraint imposed by the Gamma distribution, are used. In the simulation experiments, the proposed fitting method found the true model with a rather insignificant bias and mean square error (MSE), given the true AR or TAR model. The AR and TAR models with Gamma random error are then tested on empirical realized volatility data of 30 stocks, where one third of the cases are fitted quite well, suggesting that the model may have potential as a supplement for current Gaussian random error models with proper adaptation.

Keywords: Autoregressive Model; non-Gaussian error; realized volatility; Threshold Autoregressive Model

1. Introduction

As the financial market and investment instruments grow more sophisticated, the need for the proper risk management of financial activities and the modeling of financial volatility has become more crucial. As there is no unique and unambiguous definition for volatility, observable quantities (such as daily high-lows or intra-day price changes) are used to approximate the quantity, thus dividing volatility modeling techniques into two sub-groups: Parametric and non-parametric (Anderson et al. 2002; Zheng et al. 2014). The first group are the traditional parametric latent volatility models, such as the Generalized Autoregressive Conditional Heteroscedastic (GARCH) model or the Stochastic Variance (SV) model. However, these parametric models have become increasingly restrictive in use, due to growing complexity. As mentioned in McAleer and Medeiros (2008), as the traditional standard latent volatility models cannot adequately describe the slowly decreasing auto-correlations of squared returns and as the usage of Gaussian standardized error has been criticized by many, the Realized Volatility (RV) model, as an alternative non-parametric method, has received increasing attention. In its simplest form, the RV model can be simply defined as

$$RV_t = \sum_{i=0}^{n_t} r_{t,i}^2, \tag{1}$$

where RV_t denotes the realized volatility at day t, $r_{t,i}$ denotes the ith intra-period return at day t, and n_t is the number of high frequency data observed. It has been shown that the RV model more accurately measures the 'true volatility' than daily squared returns (Anderson et al. 1999; Kambouroudis et al. 2016) and it is among the best for modeling the volatilities of the U.S. and E.U. stock indices (Kambouroudis et al. 2016). It is also a good measure for market risk, due to its ability to show clustering and fat-tail behavior for price fluctuations (Zheng et al. 2014).

A lot of work has been done towards constructing the realized volatility; see McAleer and Medeiros (2008) for a review. The focus of this article is to consider possible probabilistic models, given RV_t; particularly if it is possible to model it with a non-Gaussian random error structure. As models based on the Wishart distribution have been proposed for multi-variate realized volatility (Golosnoy et al. 2012) and multi-variate stochastic volatility (Gouriéroux et al. 2009), and as the Wishart distribution is the multi-variate analog of the chi-square distribution (which is a member of the Gamma distribution family), a Gamma random error structure in the univariate case has become of interest. Thus, traditional Autoregressive (AR) and Threshold-type non-linear AR (TAR) models with Gamma random error are explored. This article can be regarded as an extension of Li and McLeod (1988).

2. Materials and Methods

This section aims to provide the specification for the proposed model and the fitting methodology. It will also briefly touch on the materials and methods for conducting the empirical data analysis.

2.1. Model Specification

Time-series models with non-Gaussian error were previously considered, in some detail, by Li and McLeod (1988), and earlier in Lawrance and Lewis (1980) and Ledolter (1979). In this article, specifically, the AR and TAR models are further explored. The AR(p) model is defined as follows:

$$RV_t = \sum_{i=1}^{p} \varphi_i * RV_{t-i} + \varepsilon_t\,, \tag{2}$$

where ε_t is the random error, assumed to follow a Gamma distribution; thus, $\varepsilon_t \sim \Gamma(\alpha, \beta)$, where the density function is defined as

$$f(x) = \frac{1}{\Gamma(\alpha) * \beta^{\alpha}} * x^{\alpha-1} * e^{-\frac{x}{\beta}}\,. \tag{3}$$

It should be noted that it is assumed that there is no drift term in the AR model; yet, the drift term could be easily incorporated into the model. The TAR(p) model, similar to that introduced in Tong (1978) but with a modification in the random error term, is defined as follows:

$$\begin{aligned} RV_t &= \sum_{i=1}^{p} \varphi_{1,i} * RV_{t-i} + \varepsilon_{1,t} \qquad if\ RV_{t-d} \le T\,, \\ RV_t &= \sum_{i=1}^{p} \varphi_{2,i} * RV_{t-i} + \varepsilon_{2,t} \qquad if\ RV_{t-d} > T\,, \end{aligned} \tag{4}$$

where $d \ge 1$ is the lag of the model and T is the threshold, such that the model is divided into two regimes, according to the observations at d time periods earlier. The pivot element RV_{t-d} determines which regime RV_t falls into, with RV_t falling into the first regime if RV_{t-d} is less than or equal to the threshold and into the second regime, otherwise. Each regime follows an AR(p) model, as defined above, with different AR and Gamma parameters.

2.2. Model Estimation

The fitting of the AR(p) model is introduced in this part, followed by the extension of the procedure to the fitting of the TAR(p) model. Both procedures are fitted with the maximum likelihood procedure, as it has been shown that the maximum likelihood estimators (MLE) are consistent for Gamma random error (Li and McLeod 1988).

The MLE for AR(p) model are derived by $l(\hat{\alpha}, \hat{\beta}, \hat{\varphi}) = argmin(-l)$, where l denotes the log-likelihood function, in the form of

$$l(\alpha, \beta, \varphi) = -n * ln(\Gamma(\alpha)) - n * \alpha * ln(\beta) + (\alpha - 1) * \sum_{t=1}^{n} ln(\varepsilon_t) - \frac{\sum_{t=1}^{n} \varepsilon_t}{\beta}, \tag{5}$$

where

$$\varepsilon_t = RV_t - \sum_{i=1}^{p} \varphi_i * RV_{t-i} \tag{6}$$

is the random error.

To further reduce the dimension of estimation, a profile likelihood method is used. The Gamma parameters α and β are replaced by the MLE of α and β, using the result of Wilk et al. (1962) and the approximation $\frac{dln(\gamma(\alpha))}{d\alpha} \approx ln(\alpha - \frac{1}{2})$. Thus, the final estimates of α and β are as follows:

$$\hat{\alpha} = \frac{A}{2 * (A - G)} \qquad and \qquad \hat{\beta} = \frac{A}{\hat{\alpha}}, \tag{7}$$

where A stands for the arithmetic mean of the random error and G is the geometric mean. Thus, the estimation of the model is achieved by estimating $\hat{\varphi} = argmin(-\hat{l})$, where

$$\hat{l}(\varphi) = -n * ln(\Gamma(\hat{\alpha})) - n * \hat{\alpha} * ln(\hat{\beta}) + (\hat{\alpha} - 1) * \sum_{t=1}^{n} ln(\varepsilon_t) - \frac{\sum_{t=1}^{n} \varepsilon_t}{\hat{\beta}}, \tag{8}$$

where $\hat{\alpha}$ and $\hat{\beta}$ are estimated by Equation (7) and, by Equation (6), thus depend on φ .

The Nelder–Mead method, which is a non-gradient optimization method, is proposed to optimize the negative log-likelihood function. Although such a procedure is heuristic and may converge to non-stationary points, its performance is much more stable than traditional gradient methods, such as the Hessian matrix method, which may not be easily calculated (even numerically) given the dependency of the log-likelihood function and as φ is quite complicated.

Additionally, before simply applying the method and carrying out the optimization, it should be noticed that, as the random error ε_t is assumed to be Gamma, it is required to be greater than zero, which is also evident from the term $ln(\varepsilon_t)$ in the expression of the log-likelihood function. To reflect this non-negativity constraint, a penalty method is applied and the log-likelihood function becomes:

$$\hat{l} = (-n * ln(\Gamma(\hat{\alpha})) - n * \hat{\alpha} * ln(\hat{\beta}) + (\hat{\alpha} - 1) * \sum_{t=1}^{n} ln(\varepsilon_t) - \frac{\sum_{t=1}^{n} \varepsilon_t}{\hat{\beta}}) * I_{all\ \varepsilon_t \geq 0} - M * I_{some\ \varepsilon_t < 0}, \tag{9}$$

where M is some large-enough number.

As the Nelder–Mead method is a heuristic search method, the choice of initial point may greatly affect the result and, thus, the estimation process takes various initial points and returns the result that yields a best fit, using the AIC or BIC . Furthermore, a candidate set of AR order p is given and the procedure searches for the best AR order within the set, again by AIC and BIC. Specifically, in the scope of the simulation study in this report, the initial points for φ are set uniformly within [0,1] and the initial points for T are set within $[\mu - n * \sigma, \mu + n * \sigma]$, where μ the sample mean of the RV, σ is the sample variance, and n is a pre-determined number to control the range, here set as 0.5. The step size of φ is set to be 0.25 and that of T to be 0.05σ. For empirical data analysis, values of φ in the ranges [0,0.5] and [0.5,1] are tested, with step size 0.125, and the results showed that the outcome from [0,0.5] almost always dominated that from [0.5,1] and, thus, the range [0,0.5] and step size 0.125 were used for φ.

The fitting of the TAR(p) model is essentially the same, except that the random errors are classified into two different regimes. Thus, the log-likelihood function is expressed as:

$$\begin{aligned}\hat{l} = (&-n_1 * ln(\Gamma(\hat{\alpha_1})) - n_1 * \hat{\alpha_1} * ln(\hat{\beta_1}) + (\hat{\alpha_1} - 1) * \sum_{t=1}^{n_1} ln(\varepsilon_{1,t}) - \frac{\sum_{t=1}^{n_1} \varepsilon_{1,t}}{\hat{\beta}_1} \\ &-n_2 * ln(\Gamma(\hat{\alpha_2})) - n_2 * \hat{\alpha_2} * ln(\hat{\beta_2}) + (\hat{\alpha_2} - 1) * \sum_{t=1}^{n_2} ln(\varepsilon_{2,t}) - \frac{\sum_{t=1}^{n_2} \varepsilon_{2,t}}{\hat{\beta}_2}) \\ &* I_{all\ \varepsilon_{1,t},\varepsilon_{2,t} \geq 0} - M * I_{some\ \varepsilon_{1,t},\varepsilon_{2,t} < 0}\,,\end{aligned} \tag{10}$$

where $\varepsilon_{1,t}$ are the random errors corresponding to the observations in the first regime, n_1 is the number of observations in the first regime, and $\varepsilon_{2,t}$ and n_2 the corresponding counterparts in the second regime, respectively.

A final concern regarding the model estimation would be that, for the first few observations, the AR model may not be properly initiated, as there are no earlier observations. Therefore, the sample estimates are essentially estimated by a sample, with the first few observations serving only as the independent variable, but not the dependent variable; that is,

$$RV_{t+n} = \sum_{i=1}^{p} \varphi_i * RV_{t+n-i} + \varepsilon_{t+n}\,, \tag{11}$$

with n being the truncated size. Additionally, as the AIC and BIC are typically applied on the same sample with the same sample size, to allow for the comparison between models of different AR order and lag, a common truncation of size 10 is applied in the scope of this study, as the AR order and lag investigated did not exceed this reasonably.

As with the process of fitting the AR(p) model, the fitting for TAR(p) searches for the best model of AR order p and lag d, where p and d are given in the pre-determined candidate set and the threshold T.

2.3. Empirical Data Analysis Preparation

The data used in this paper were the consolidated realized volatility data from Shen et al. (2018), which are the realized volatilities for 30 stocks traded on the New York Stock Exchange (NYSE).

Graphs of PACF and the corresponding naive 95% confidence bound, proposed by Quenouille (1949), were first examined for the stock data, which showed that the PACF of the stocks were mostly significant within a lag of 5 and demonstrated a somewhat cut-off property; thus suggesting the fitting the AR model was potentially a good starting point. Non-linear threshold type AR models were also considered as a supplement to the AR model.

After considering the practical reasonableness of the model and the computational power available, an AR order up to 5 and lag order up to 3 were considered.

The final model for each stock was determined by both considering the AIC and BIC and the associated Ljung–Box test for each criterion. If the model selected by the two criteria differed with a similar goodness of fit, a simpler model was preferred. Otherwise, the model that gave a better goodness of fit result was preferred.

The data set and R code used for the study are available upon request, from either author.

3. Results

This section aims to briefly describe how the proposed AR and Threshold AR (TAR) models were fitted with a simulation study and some empirical data.

3.1. Simulation Study

A simulation study was conducted, by running the model-fitting process on batches of randomly generated AR or TAR models of observation length 500 and batch size 50 for all the results in this section (i.e., 50 simulated observations of length 500 were considered in each simulation experiment). The completion of each simulation took around half a day on a laptop. The following tables give the results for the bias and mean square error in the simulation study. Tables 1 and 2 give the results for the threshold models and Table 3 gives the result for AR models. The correct estimation of AR order and lag meant that the estimation of both the AR order p and the lag d were in line with the true parameters. The bias and MSE were calculated with the results in the simulations which gave the correct estimation of AR order and lag. The parameter for the true TAR model was selected such that the TAR structure was reasonably demonstrated (i.e., there were not too few observations in any regime).

Table 1. Simulation results for the threshold Autoregressive (TAR) (2) model with $d = 2$.

True Model	α_1	β_1	α_2	β_2	$\varphi_{1,1}$	$\varphi_{1,2}$	$\varphi_{2,1}$	$\varphi_{2,2}$	T
	5	2	5	2	0.5	0.3	0.3	0.2	30
AIC	Proportion of correct estimation of Autoregressive (AR) order and Lag: 44/50								
AIC Bias	0.032	0.023	0.341	−0.022	0.013	−0.007	0.003	−0.004	0.001
AIC MSE	1.245	0.083	2.759	0.123	0.002	0.003	0.002	0.002	0.001
BIC	Proportion of correct estimation of AR order and Lag: 50/50								
BIC Bias	0.015	0.022	0.384	−0.015	0.012	−0.006	0.004	−0.005	0.001
BIC MSE	1.198	0.08	3.887	0.143	0.002	0.003	0.002	0.002	0.001

Table 2. Simulation results for the TAR (1) model with $d = 1$.

True Model	α_1	β_1	α_2	β_2	$\varphi_{1,1}$	$\varphi_{2,1}$	T
	4	2	4	2	0.7	0.3	15
AIC	Proportion of correct estimation of AR order and Lag: 36/50						
AIC Bias	0.34	−0.074	0.068	−0.006	−0.008	0.007	0.019
AIC MSE	0.929	0.086	0.722	0.078	0.003	0.001	0.002
BIC	Proportion of correct estimation of AR order and Lag: 50/50						
BIC Bias	0.199	−0.035	0.016	0.024	−0.002	0.007	0.019
BIC MSE	0.825	0.079	0.711	0.082	0.003	0.001	0.002

Table 3. Simulation results for the AR (2) model.

True Model	α	β	φ_1	φ_2
	5	2	0.6	0.2
AIC	Proportion of correct estimation of AR order and Lag: 7/50			
AIC Bias	0.627275	−0.08103	0.020833	−0.02968
AIC MSE	2.004022	0.087312	0.001747	0.002992
BIC	Proportion of correct estimation of AR order and Lag: 46/50			
BIC Bias	0.137581	−0.02197	0.006732	−0.00646
BIC MSE	0.605966	0.037434	0.001058	0.001104

The estimates of the AR order and lag were generally good, except the AIC criterion for the AR model, as the AIC tends to pick a more complicated model. In fact, the AIC estimated the AR order correctly in 36 out of 50 cases; yet, in most of these cases, it preferred a threshold structure.

The simulation results show that the model could identify the correct AR order p and the lag d with good accuracy in general, the estimate for the threshold T was very consistent; and the results for the AR parameters φ were rather accurate when p and d were estimated correctly. It should be noted that the accuracy here is defined as the probability of identifying the correct AR model order and correct threshold, given that the underlying model was indeed an AR/TAR model.

3.2. Empirical Data Analysis

The realized volatilities of 30 stocks traded on the New York Stock Exchange (NYSE) were tested by the proposed models. Please kindly refer to Appendix A–C for the best model selected by the AIC, BIC, and the final model.

From the results, the AR/TAR model seemed to be a good fit for around 33% of the cases, with almost all of the final models having a threshold structure and a marginally good fit for another 10% of the cases, where the Ljung–Box test was marginally significant. This demonstrates that, overall, the proposed model has the potential to explain a little less than half of the empirical data, in this case, and further investigation, through other data sets or improved fitting algorithms, is worthwhile.

4. Discussion

This section aims to provide a brief discussion as a supplement to the results found above. It is divided into discussions regarding the simulation study and the empirical data, respectively.

4.1. Simulation Study

While, as mentioned before, the bias and MSE were acceptable overall, with consistent estimates for the AR parameter and threshold, it can be noticed that the estimates for Gamma parameters were more volatile. This is possibly due to the profile likelihood methodology adopted for estimation, which increases the complexity in estimating the Gamma parameters.

Additionally, as the simulation study was constructed in such a way that the true model was within the set of candidate models, the BIC would select the true model with probability tending to one and, thus, outperformed the AIC. However, in practice, the true model may not reside within the candidate set, and the AIC may give a better result, yet may also choose a more complicated model (as mentioned above), while the BIC would prefer a simpler model. Therefore, in terms of forecasting MSE, both criteria are considered, in practice, for model selection.

4.2. Empirical Data Analysis

A residual analysis was conducted by looking at the PACF plots for the models with significant goodness of fit test results. It was observed that, in some cases, the PACF still demonstrated a rather clear cut-off at a higher order, suggesting that the AR order of the model could be further increased. Thus, it is suggested that, in this case, it is possible that the model was not a good enough fit, as it did not select a high enough order. This was possible, as the model fitting limited the highest AR order to be less than five, for practical concerns, and as the optimization process was sensitive to the selection of initial points and the initial points were evaluated in a sparser set at higher AR orders, thus resulting in a less-than-ideal fit.

Alternative models with non-Gaussian error provide another perspective of improvement. A Buffered Threshold Autoregressive (BAR) model, as described in Li et al. (2015), has been examined, using a fitting methodology similar to that of the TAR model. However, as the goodness of fit did not improve much, and as it is natural to choose a simpler model given similar goodness of fit, the results of BAR model have not yet been reported. However, other models (such as the Autoregressive Moving-Average model (ARMA)) could still be considered.

5. Conclusions

In this article, the model fitting of a non-Gaussian model on the realized volatility is explored. As the definition of realized volatility requires it to be positive, previous works established a Wishart model (a multi-variate analog of the chi-square distribution) that belongs to the Gamma family;

considering this selection, a univariate Gamma random error is proposed and the AR and TAR models are explored. MLE estimation, based on the AIC and BIC, and with some adjustment, is proposed. A profile likelihood method, which replaces the Gamma parameters with their MLE counterparts, is used to reduce the dimension of the estimation and a non-gradient numerical optimization method is employed, as the calculation of gradient may not be feasible. A penalty method is introduced into the likelihood function, to enforce the non-negative constraint imposed by Gamma random error. The proposed process manages to find the true model with a rather insignificant bias and MSE, when the true model is AR or TAR. Finally, the model is tested on the empirical realized volatility data of 30 stocks and managed to fit one third of the cases quite well, suggesting that the model may have the potential to be further generalized, in order to act as a good supplement for current Gaussian random error models. The lack of fit may be improved by considering higher AR orders or a denser initial point selection for the Nelder–Mead method, which requires more computational time. Other possible directions of improvement include using a better method (instead of AIC or BIC) to reduce the ambiguity in choosing the model and possibly using other AR structures, such as the Heterogeneous Auto-Regressive (HAR) model. Other time-series models with non-Gaussian error may also be considered and the model fitting methodology proposed in this article could possibly be extended to these models without difficulty.

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Abbreviations

The following abbreviations are used in this manuscript:

AR	Autoregressive
AIC	Akaike Information Criterion
BAR	Buffered Threshold Autoregressive
BIC	Bayesian Information Criterion
EU	European Union
GARCH	Generalized Autoregressive Conditional Heteroscedastic
MSE	Mean Square Error
NYSE	New York Stock Exchange
PACF	Partial Auto-Correlation Function
RV	Realized Variance
SV	Stochastic Variance
TAR	Threshold Autoregressive
US	United States

Appendix A

Table A1. Best Model Selected by the AIC.

StockNum	p	d	AIC	Ljung–Box Test	*p*-Value
1	2	2	275.7274	Significant	0.0073
2	2	2	2.2509	Insignificant	0.2034
3	5	3	3.8177	Insignificant	0.0220
4	2	2	246.9670	Insignificant	0.3230
5	5	1	143.1260	Significant	0.0155
6	4	2	−28.6272	Significant	0.0218
7	4	1	−9.54336	Insignificant	0.0716
8	5	1	−21.6088	Insignificant	0.1159
9	5	1	5.7717	Significant	0.0000
10	2	1	144.2935	Insignificant	0.6415
11	2	2	−17.8815	Somewhat Significant	0.0093
12	5	2	4.7316	Significant	0.0012
13	4	1	−81.0311	Somewhat Significant	0.0064
14	2	1	−241.8272	Insignificant	0.4850
15	2	2	157.0407	Significant	0.0000
16	3	1	−180.8073	Significant	0.0000
17	2	1	−127.2748	Somewhat Significant	0.0194
18	1	1	−90.0935	Significant	0.0000
19	5	1	−117.8152	Significant	0.0000
20	3	1	30.9568	Significant	0.0136
21	4	1	−60.7726	Significant	0.0005
22	1	3	−192.5901	Significant	0.0000
23	2	1	−99.0953	Significant	0.0000
24	3	2	−92.6265	Significant	0.0000
25	2	2	68.0884	Insignificant	0.8520
26	1	1	16.6098	Significant	0.0005
27	1	1	44.5472	Insignificant	0.2261
28	2	2	−121.6981	Significant	0.0000
29	2	1	−120.5036	Significant	0.0000
30	1	1	−93.9557	Significant	0.0002

Appendix B

Table A2. Best Model Selected by the BIC.

StockNum	p	d	BIC	Ljung-Box Test	*p*-Value
1	2	2	582.7805	Significant	0.0073
2	2	2	35.8275	Insignificant	0.2304
3	1	1	36.9940	Significant	0.0000
4	2	2	525.2598	Insignificant	0.3203
5	5	0	318.3741	Significant	0.0000
6	1	1	−28.8146	Significant	0.0000
7	1	3	17.7029	Insignificant	0.8858
8	2	0	−11.8445	Significant	0.0060
9	1	1	38.3802	Significant	0.0000
10	2	1	319.9127	Insignificant	0.6415
11	2	2	−4.4373	Somewhat Significant	0.0093
12	1	1	43.3797	Significant	0.0000
13	1	1	−134.143	Significant	0.0000
14	2	1	−452.3287	Insignificant	0.4850
15	2	2	345.4071	Significant	0.0000
16	1	1	−331.1404	Significant	0.0000
17	2	1	−223.2238	Somewhat Significant	0.0194
18	1	1	−155.8226	Significant	0.0000
19	1	3	−192.3672	Significant	0.0000
20	1	1	93.1204	Significant	0.0000
21	1	1	−86.9778	Significant	0.0183
22	1	3	−360.8156	Significant	0.0000
23	2	1	−166.8648	Significant	0.0000
24	1	2	−159.1344	Significant	0.0000
25	2	2	167.5026	Insignificant	0.8520
26	1	1	57.5842	Significant	0.0002
27	1	1	113.4588	Insignificant	0.2261
28	2	2	−212.0704	Significant	0.0000
29	2	1	−209.6814	Significant	0.0000
30	1	1	−163.5470	Significant	0.0002

Appendix C

Table A3. Best Model Selected by considering both AIC and BIC and goodness of fit.

StockNum	p	d	Info Cri *	Ljung-Box Test	*p*-Value
1	2	2	BIC	Significant	0.0073
2	2	2	AIC	Insignificant	0.2304
3	5	3	AIC	Insignificant	0.0220
4	2	2	AIC	Insignificant	0.3203
5	5	0	BIC	Significant	0.0000
6	1	1	BIC	Significant	0.0000
7	1	3	BIC	Insignificant	0.8858
8	5	1	AIC	Insignificant	0.1159
9	1	1	BIC	Significant	0.0000
10	2	1	AIC/BIC	Insignificant	0.6415
11	2	2	AIC/BIC	Somewhat Significant	0.0093
12	1	1	BIC	Significant	0.0000
13	4	1	AIC	Somewhat Significant	0.0064
14	2	1	AIC/BIC	Insignificant	0.4850
15	2	2	AIC/BIC	Significant	0.0000
16	1	1	BIC	Significant	0.0000
17	2	1	AIC/BIC	Somewhat Significant	0.0194
18	1	1	AIC/BIC	Significant	0.0000
19	1	3	BIC	Significant	0.0000
20	1	1	BIC	Significant	0.0000
21	1	1	BIC	Significant	0.0000
22	1	3	AIC/BIC	Significant	0.0000
23	2	1	AIC/BIC	Significant	0.0000
24	1	2	BIC	Significant	0.0000
25	2	2	AIC/BIC	Insignificant	0.8520
26	1	1	AIC/BIC	Significant	0.0005
27	1	1	AIC/BIC	Insignificant	0.2261
28	2	2	AIC/BIC	Significant	0.0000
29	2	1	AIC/BIC	Significant	0.0000
30	1	1	AIC/BIC	Significant	0.0002

* denotes the information criteria by which the fitted model is selected. The goodness of fit is regarded as somewhat significant if, out of the different lags considered in the Ljung–Box Test, which is five in this case, around half (two or three) are insignificant, while the others are only marginally significant.

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Value Premium and Technical Analysis: Evidence from the China Stock Market

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Abstract: We find value premium in the Chinese stock market using a conventional buy-and-hold approach which longs the portfolio with the highest BM ratio and shorts the one with the lowest BM ratio. Based on the finding, we test a new strategy by combining the value premium effect and technical analysis. During the sample period (1995 to 2015), we trade the objective portfolio or risk-free asset according to the moving average timing signals, and we find excess return from such a zero-cost trading strategy. We perform various robustness tests and find that the excess returns remain significantly positive after adjusting for risks (on three factor models) and transaction costs. In general, we find that the combined trading strategy can generate significant positive risk-adjusted returns after the transaction costs.

Keywords: value premium; technical analysis; moving average; China stock market

JEL Classification: G11; G14

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1. Introduction

In this paper, we investigate whether technical analysis can add additional value to investments in the Chinese stock market. In particular, we try to answer the research question of whether technical strategies can enhance conventional value investment (high BM-minus-low BM) in the Chinese market. For this purpose, we propose and examine the performance of a zero-cost strategy that combines technical analysis and value premium investing. The results show that the combined strategy can generate superior performance compared to simple buy-and-hold value investment. The excess profits made from the proposed strategy remain prominent after transaction costs are taken into consideration.

The value premium refers to the excess average return on stocks with high book-to-market (BM) ratios over those with low BM ratios. The positive relationship between BM ratio and average return are first documented in the 1980s (e.g., Rosenberg et al. 1985). Numerous studies have since confirmed the value premium effect using U.S. (Lakonishok et al. 1994; Fama and French 1992, 1996) or global data (Fama and French 1998; Bauman et al. 1998). Two main theories have been proposed to explain why the value premium exists. The first theory links the value premium with the financial distress risk of high BM firms (Fama and French 1992, 1996). The second theory claims that overreacting investors underprice the distressed firms, which leads to higher returns on high BM stocks (Daniel and Titman 1997).

The value premium has also been found to be prevalent in China's financial market. Wang (2004) shows that there is a significant value premium in China using different investment portfolios. Su and Xu (2006) argue that the value premium exists generally in China and has a greater influence on small-size stocks. Xie and Qu (2016) study the period after the non-tradable share reform and find that the significant value premium exists from 2005 to 2012. However, these papers focus on the value premium generated from the conventional buy-and-hold returns on BM portfolios; none of them extend the research scope to the influence of technical analysis on value investing.

Technical analysis, which encompasses trading strategies using past price or volume information to predict future asset prices, has been shown to be a useful tool in the stock market. For example, Brock et al. (1992) and Lo et al. (2000) suggest that technical analysis strategy can add value to investment and is helpful for making better decisions. Zhu and Zhou (2009) explore the usefulness of moving average analysis and propose that technical analysis strategy becomes more remarkable in an incomplete information environment. Han et al. (2013) find that moving average timing strategy outperforms simple buy-and-hold strategy and has a greater effect on portfolios with higher information uncertainty. Wong et al. (2003) show that technical analysis tools such as moving average and relative strength index generate considerable profits in Singapore's market, and Du and Wong (2018) find the simple moving average trading rule significantly outperform the buy-and-hold strategy on the Singapore Straits Times Index.

Menkhoff (2010) uses an international survey with fund managers and finds that technical analysis is prevalently used in the industry, which has a great relation with the belief of fund managers that psychological influences on stock prices are substantial. Han et al. (2016) use the moving average indicator to construct a new equity pricing factor, the trend factor, which can capture three types of trend related anomalies (short-, intermediate-, and long-term trends) and outperform other well-known reversal and momentum related factors. Technical analysis tools can also be used in forecasting market level equity risk premium (Neely et al. 2014).

According to research conducted by Lim and Luo (2012), who examine 14 Asian stock markets, including China's, none of the stock returns follow a martingale difference sequence. This indicates that in the Chinese market, the stock price does not reflect information immediately; therefore, the application of technical analysis should be meaningful and useful in this information-asymmetric environment. A number of studies support this idea. For instance, Wong et al. (2005) find a group of moving average indicators can generate positive excess returns in Chinese stock markets. Wang et al. (2011) find that there is significant predictability of technical analysis in price changes in China.

However, the usefulness of technical analysis is debatable. Shynkevich (2012) find that, using four families of technical indicators, the performance of technical indicators deteriorated substantially in the second half of 2010s due to the improvement of efficiency in the US market. Chen and Li (2006) study the application of technical analysis in China and do not find it to be superior to passive trading strategies, as they conclude that the past price or volume cannot provide extra information in China. Zhu et al. (2015) investigate the profitability of technical trading strategies, including the moving average and trading range break, on the Shanghai Composite Index, and they show that these strategies cannot beat the buy-and-hold strategy if transaction fees are taken into consideration.

Our study is motivated by at least three causes. First, although the value premium generated from buy-and-hold strategy has been proven to be existent in China's stock market, no study has explored whether technical analysis can further enhance the value investment in China. Our paper attempts to fill this gap. Second, a study by Ko et al. (2014) finds that in the Taiwan stock market, a market with no value premium, a combined strategy with value investment and moving average based trading can generate a better average return than the simple buy-and-hold value investment strategy. Because our sample is from a market with a positive value premium, our findings help determine whether the profitability of the combined strategy is independent of the existence of the value premium. Third, the mixed results on the usefulness of technical analysis in the Chinese market give us an incentive to provide additional evidence on this issue that can contribute to the literature on technical analysis-based trading in China.

Zhu and Zhou (2009) provide theoretical support for the rationale of our proposed approach. They utilize an asset allocation perspective to demonstrate that rational risk-averse investors would purposely adopt the moving average strategy combined with fixed wealth allocation rules, which can improve their expected utility substantially. This explains why the moving average strategy is widely used in practice among both institutional and individual investors.

We first construct decile portfolios from the sample according to the BM ratio of shares each year, with portfolio one consisting of stocks with the lowest BM ratios and portfolio ten consisting of the highest BM ratios. We then construct a zero-cost arbitrage portfolio by longing the highest BM portfolio and shorting the smallest BM portfolio at the same time. The return from such a portfolio is called the value premium. We then impose technical analysis on each BM portfolio with 20-day moving average timing signals. Based on the signals, we choose to hold either the stock portfolio or the risk-free asset.

We then form a new trading strategy by integrating the value premium effect and the moving average timing indicator into one. Under this combined strategy, we use the technical analysis based on the conventional buy-and-hold trading portfolio sorted by BM ratio. We further investigate whether the positive excess returns generated by the strategy are risk-driven. We compute the risk-adjusted excess returns by considering the risk from the capital asset pricing model (CAPM), Fama and French's (1993) three-factor and liquidity-augmented four-factor models (Datar et al. 1998; Lam and Tam 2011). Moreover, we try different lag lengths of the moving average, such as 5, 10, 20, 50, 100, and 200 days of lag on the technical analysis portfolios. We also examine whether transactional costs eliminate the risk-adjusted excess returns.

We also perform robustness tests to ensure that the excess returns generated from the new strategy are reliable. First, we investigate the sub-period performance of the strategy by testing the risk-adjusted excess returns of these two sub-periods. Second, we use regression tests to check whether business cycles can affect the excess return. Third, we examine the timing ability of the strategy. Lastly, we perform tests on a subsample containing stocks that can be short sold.

The remainder of this paper is organized as follows. Section 2 describes the sample data and the details of the combined zero-cost trading strategy. Section 3 presents the empirical results. Section 4 discusses the robustness tests. Section 5 concludes the paper.

2. Data and Methodology

2.1. Data

China's two main stock exchanges are the Shanghai and Shenzhen Stock Exchanges. On these two exchanges, two types of shares are listed: A-shares, which are priced and traded in RMB, and B-shares, which are priced in foreign currencies. We obtain stock-level data for all the A-shares from the China Stock Market and Accounting Research (CSMAR) database. We exclude financial companies from our sample because their BM ratios could have very different interpretations from those of companies in other industries. The China stock market was established in 1991, but until 1995, the number of stocks listed was very small. Hence, we examine the trading strategy for the period from 1 July 1995 to 30 June 2015.

Before executing the proposed strategy, we conduct a data-clearing procedure to delete stocks with negative BM ratios and remove stocks with no trading for three consecutive months. We remove 535,685 observations, about 9% of the sample, in this clearing step. We use the daily returns calculated from the stock prices adjusted for capital changes such as dividend payout, share repurchases, and stock splits. We use the daily interest rate for the one-year fixed time deposit as the proxy for the risk-free rate.

2.2. Zero-Cost Trading Strategy

The zero-cost trading strategy is constructed as follows. For the period from 1 July 1995 to 30 June 1996, we compute the end of the 1994 book-to-market (BM) ratios of stocks. We sort the stocks in ascending order by their BM ratios and assign them into decile portfolios. Portfolio 1 consists of stocks with the lowest BM ratios while Portfolio 10 consists of stocks with the highest BM ratios. We repeat this procedure for the next 20 years with annual rebalancing.

We then impose technical analysis on each BM portfolio with moving average timing signals rather than the passive buy-and-hold approach. First, we calculate the moving average (MA) indicator with L days of lag length as

$$A_{j,t,L} = \frac{P_{j,t-(L-1)} + P_{j,t-(L-2)} + \ldots + P_{j,t-1} + P_{j,t}}{L}, \tag{1}$$

where $P_{j,t}$ is the average price for portfolio j on day t, L is the length in days of the moving average window, and $A_{j,t.L}$ is the L-day MA indicator for portfolio j on day t.

The trading strategy is as follows. For each BM portfolio, we either buy or continue to hold the portfolio for today if the past price index $P_{j,t-1}$ is higher than the past MA indicator $A_{j,t-1},_L$ on t−1. Otherwise, we invest in the risk-free asset to protect our capital. We then compute the daily average return, $\widetilde{R}_{j,t,L}$ or $R_{f,t,L}$, for the decile portfolios as below. For comparison, we also compute the return of the traditional buy-and-hold strategy for the deciles.

$$\widetilde{R}_{j,t,L} = \begin{cases} R_{j,t}, & if\ P_{j,t-i} > A_{j,t-1,L}, \\ R_{f,t}, & otherwise, \end{cases} \tag{2}$$

Through comparisons between the returns of the moving average strategy and the traditional buy-and-hold strategy, we can study the differing effects of these two strategies on the BM premium. We expect that the portfolio returns will be higher after the application of technical analysis. Therefore, we compute the difference between the two strategies, $MAP_{j,t,L}$, by subtracting the return of the buy-and-hold strategy, $R_{j,t}$, from the return of the MA timing strategy, $\widetilde{R}_{j,t,L}$. If $MAP_{j,t,L}$ is significantly greater than zero, this indicates that the MA timing strategy outperforms the traditional buy-and-hold strategy.

$$MAP_{j,t,L} = \widetilde{R}_{j,t,L} - R_{j,t}, \quad j = 1, 2, \ldots, 10, \tag{3}$$

After studying the difference between the two strategies, we investigate whether the return difference, if significant, is driven by exposure to alternative risk factors. We perform regressions on $MAP_{j,t,L}$ with three well-known asset pricing models in the literature: the CAPM, Fama, and French three-factor (FF3F), and liquidity augmented four-factor (LIQ4F) models, which are

$$MAP_{j,t,L} = \alpha_{j,L} + \beta_{j,L,MKT}R_{MKT,t} + \varepsilon_{j,t,L}, \quad j = 1, 2, \ldots, 10, \tag{4}$$

$$MAP_{j,t,L} = \alpha_{j,L} + \beta_{j,L,MKT}R_{MKT,t} + \beta_{j,L,SMB}R_{SMB,t} + \beta_{j,L,HML}R_{HML,t} + \varepsilon_{j,t,L}, \quad j = 1, 2, \ldots, 10, \tag{5}$$

$$\begin{gathered} MAP_{j,t,L} = \alpha_{j,L} + \beta_{j,L,MKT}R_{MKT,t} + \beta_{j,L,SMB}R_{SMB,t} + \beta_{j,L,HML}R_{HML,t} + \beta_{j,L,LIQ}R_{LIQ,t} + \varepsilon_{j,t,L}, \\ j = 1, 2, \ldots, 10, \end{gathered} \tag{6}$$

where $R_{MKT,t}$ is market excess returns; $R_{SMB,t}$ is the size factor; $R_{HML,t}$ is the book-to-market factor; $R_{LIQ,t}$ is the liquidity risk factor proxied by turnover ratio; $\varepsilon_{j,t,L}$ is the error term assumed to have a zero mean and to be uncorrelated with all other explanatory variables; and the factor sensitivities or loadings $\beta_{j,L,MKT}$, $\beta_{j,L,SMB}$, $\beta_{j,L,HML}$, and $\beta_{j,L,LIQ}$ are the slope coefficients for the factors, respectively. $\alpha_{j,L}$ is the intercept of the regression.

Our new technical analysis enhanced BM strategy is implemented as follows. We start with the traditional BM strategy, in which we long the highest BM portfolio and short the lowest BM portfolio. Next, we apply the moving average indicator trading strategy to the two extreme BM portfolios. If the previous index price of portfolio 10 is higher (lower) than the previous moving average indicator, it indicates that the portfolio value is about to rise (fall). Therefore, we will long portfolio 10 (risk-free asset). In the same month, if the previous index price of portfolio 1 falls below (rises above) its previous MA indicator, the portfolio value is expected to drop (increase), and we will short portfolio one (risk-free asset). The return of such a trend-following strategy is denoted by $TLS_{MA,t,L}$ and is shown as follows.

$$TLS_{MAP,t,L} = \begin{cases} R_{10,t} - R_{1,t}, & if\ P_{10,t-1} > A_{10,t-1,L}\ and\ P_{1,t-1} < A_{1,t-1,L}; \\ R_{10,t} - R_{f,t}, & if\ P_{10,t-1} > A_{10,t-1,L}\ and\ P_{1,t-1} > A_{1,t-1,L}; \\ R_{f,t} - R_{1,t}, & if\ P_{10,t-1} < A_{10,t-1,L}\ and\ P_{1,t-1} < A_{1,t-1,L}; \\ 0, & otherwise, \end{cases} \tag{7}$$

$$TLS_{MAP,t,L} = \begin{cases} 0, & if\ P_{10,t-1} > A_{10,t-1,L}\ and\ P_{1,t-1} < A_{1,t-1,L}; \\ R_{1,t} - R_{f,t}, & if\ P_{10,t-1} > A_{10,t-1,L}\ and\ P_{1,t-1} > A_{1,t-1,L}; \\ R_{f,t} - R_{10,t}, & if\ P_{10,t-1} < A_{10,t-1,L}\ and\ P_{1,t-1} < A_{1,t-1,L}; \\ R_{1,t} - R_{10,t}, & otherwise, \end{cases} \tag{8}$$

$TLS_{MAP,t,L}$ is the result of subtracting the return of the proposed trading strategy from the return of a traditional BM strategy. It measures the difference between the proposed trading strategy, combining the value premium effect and technical analysis with the simple buy-and-hold strategy.

3. Empirical Findings

3.1. Summary Statistics

Table 1 shows the summary statistics of the returns of the buy-and-hold strategy, $R_{j,t}$, the returns of the 20-day moving average timing strategy, $\widetilde{R}_{j,t,L}$, and the difference between the two, $MAP_{j,t,L}$. The average return of our proposed trading strategy, $TLS_{MA,t,L}$, and the difference between the new strategy and the traditional BM strategy, $TLS_{MAP,t,L}$, are also reported at the bottom.

The average BM ratios for all 10 portfolios are less than one and range from 0.12 (portfolio 1) to 0.85 (portfolio 10), suggesting that the average book values of the sample stocks are smaller than their average market values in the China market. We further investigate the change of sample stocks' BM ratios over time and find that there exist stocks with BM ratios bigger than one after 2008, but the proportion is very small.

In panel A, we present the results for equally-weighted portfolios. For the decile BM portfolios, the simple average returns range from 5.51 basis points to 10.28 basis points (we use "points" to refer to basis points hereafter) and increase monotonically as a whole except for the return of portfolio 8 (9.45 points), which is slightly smaller than that of portfolio 7 (9.46 points). Seven (two) of the average returns are significant at the 5% (1%) level. The average high-minus-low return is 4.77 point with a t-value of 2.07[1], which is significant at the 5% level. This provides preliminary evidence that BM effect exists in China market. The values of the standard deviations are increasing monotonically, which indicates that portfolios with higher average returns tend to have higher standard deviations in China. The standard deviation for the high-minus-low portfolio is about half of the value of the other BM portfolios, which is consistent with the nature of a zero-cost hedging portfolio. The skewness of the portfolios is very small, with most of the values lower than 0.6.

For the 20-day moving average (MA(20)) timing portfolios, we find that the average returns of MA20 portfolios range from 10.73 to 14.40 points and there is no obvious trend in the returns. We find that the average returns of MA timing portfolios are at least double those of the buy-and-hold portfolios. However, we observe that the standard deviations are smaller than those of the BM portfolios, which demonstrates that when we apply MA(20) strategy to the BM portfolios, we receive higher returns but lower total risks, which is a promising result. We check whether these profits (higher returns) are due to risk exposure or not in our later tests.

[1] We report Newey and West (1987) t-statistics in parenthesis to adjust for the possible effects of serial correlation and heteroscedasticity.

Table 1. Descriptive statistics for BM, MA(20), and MAP ranked portfolios.

Rank	BM Ratio	BM Decile Portfolios				MA(20) Timing Portfolios				MAP			
		Ave Ret	Std Dev	Skew	t	Ave Ret	Std Dev	Skew	t	Ave Ret	Std Dev	Skew	t
Panel A: Equally-weighted portfolios													
Low	0.12	5.51	15.97	0.55	1.54	11.88	12.80	1.02	4.15	5.57	8.39	0.52	2.97
2	0.20	5.88	15.58	0.41	1.69	11.06	14.68	0.09	3.37	4.28	8.50	1.74	2.25
3	0.26	6.75	16.05	0.61	1.88	10.73	13.82	0.97	3.47	3.11	7.16	−0.02	1.94
4	0.31	7.82	15.97	0.62	2.19	13.23	12.56	0.55	4.71	4.44	8.12	0.75	2.45
5	0.35	8.06	16.22	0.33	2.22	12.71	13.49	0.39	4.21	3.64	8.28	0.24	1.97
6	0.40	9.39	16.94	0.41	2.48	13.18	13.72	0.94	4.29	2.84	6.46	0.29	1.96
7	0.45	9.46	16.65	0.40	2.54	13.81	13.55	0.61	4.56	3.36	8.25	0.31	1.82
8	0.52	9.45	17.35	0.42	2.43	14.40	16.46	0.90	3.91	3.89	8.64	0.26	2.02
9	0.62	9.78	17.69	0.43	2.47	13.58	14.70	0.76	4.13	2.85	5.51	0.04	2.31
High	0.85	10.28	17.78	0.77	2.59	13.03	15.85	0.79	3.68	1.77	7.15	0.21	1.11
High–Low		4.77	8.32	1.22	2.56	0.86	9.12	2.10	0.42	−4.21	7.22	0.49	−2.61
		(2.07)				(0.40)				(−2.87)			
TLS						16.43	14.92	0.28	4.92	11.23	12.40	0.99	4.05
						(4.85)				(4.12)			
Panel B: Value-weighted portfolios													
Low	0.12	5.78	16.13	0.41	1.60	11.22	13.12	1.02	3.82	4.62	8.88	0.40	2.33
2	0.20	5.44	14.80	0.52	1.64	10.36	14.42	0.12	3.21	4.02	8.84	1.61	2.04
3	0.26	5.34	16.42	0.87	1.45	9.76	14.26	1.14	3.06	3.49	7.29	0.24	2.14
4	0.31	8.78	16.79	0.63	2.34	12.11	12.32	0.46	4.40	2.26	7.30	−0.05	1.38
5	0.35	7.28	17.78	0.58	1.83	11.86	14.03	0.54	3.78	3.55	9.00	0.73	1.76
6	0.40	7.13	18.43	0.01	1.73	12.33	14.06	0.78	3.92	4.19	6.85	0.76	2.73
7	0.45	9.49	16.60	0.41	2.56	13.21	13.42	0.72	4.40	2.74	8.09	0.24	1.51
8	0.52	8.31	17.79	0.58	2.09	13.02	17.48	1.02	3.33	3.61	8.81	0.44	1.83
9	0.62	10.35	19.24	0.84	2.41	13.41	15.59	0.95	3.85	2.12	6.65	0.11	1.42
High	0.85	10.79	18.43	0.85	2.62	13.03	17.01	0.80	3.42	1.24	6.80	0.28	0.82
High–Low		4.78	8.46	0.58	2.53	1.39	10.32	1.44	0.60	−3.87	8.16	0.16	−2.12
		(2.15)				(0.60)				(−2.12)			
TLS						15.34	15.97	0.42	4.30	9.94	12.06	0.87	3.68
						(4.50)				(3.95)			

The sample stocks are sorted in ascending order by their BM ratios and assigned into decile portfolios each year. The equally-weighted and value-weighted portfolio daily returns are then obtained, for which the summary statistics are reported in Panels A and B, respectively. The average returns, standard deviation, skewness, and t-test statistics of these portfolios are reported. MA(20) represents the technical analysis with 20-day moving average timing signals imposed on the BM portfolios. MAP represents the difference between the MA(20) strategy and the buy-and-hold strategy. High–Low represents the return difference between the highest and lowest BM portfolios, the highest MA(20) and lowest MA(20) portfolios, and the highest and lowest MAP, respectively. TLS_{MA} represents the proposed technical analysis enhanced BM strategy. TLS_{MAP} represents the difference between the prosed strategy and the buy-and-hold strategy. Simple t-statistics are reported in column t and Newey and West (1987) t-statistics are reported in the parentheses.

The differences between MA(20) and BM portfolios, MAPs, are all positive and range from 1.77 to 5.57 points. Interestingly, we observe the special pattern that the average MAPs are generally decreasing as portfolio BM ratios increase, which indicates that the moving average technical analysis is more successful for portfolios with lower BM ratios.

For the proposed trading strategy, we can see that the average high-minus-low return of the MA(20) portfolios is very small (0.86 points) and insignificant (t = 0.40), much smaller than that of the BM portfolios (4.77 points). We conjecture that the small and insignificant result is caused by the misuse of the moving average timing signals. The high-minus-low return of MA(20) can be regarded as longing the highest MA(20) and shorting the lowest MA(20) portfolios. Shorting the lowest portfolio means that we will sell the assets when the last trading price $P_{j,t-1}$ is higher than the last 20-day moving average indicator $A_{j,t-1,L}$, whose signal indicates that the price will increase. In other words, we will sell the assets that we think will grow, which is logically wrong. Therefore, we conduct our trading strategy with the correct use of the moving average indicator for the lowest BM portfolio, which we discussed in the methodology section. The $TSL_{MA,t,L}$ is 16.43 points, which is substantially higher than that of the buy-and-hold strategy (4.77 points). The average significant difference between the two strategies ($TSL_{MAP,t,L}$) is 11.23 points, which represents the additional profits from the new TLS strategy, which is 2.36 times the buy-and-hold strategy.

In panel B, we present the performance of the value-weighted portfolios to check the size effect on the result. We find that the magnitude of the portfolio average returns is only slightly bigger than the return of the corresponding equally-weighted portfolios. The simple average return of the buy-and-hold strategy ranges from 5.34 to 10.79 points, with portfolio 10 (3) getting the highest (lowest) average return. In addition, all deciles with the MA(20) strategy have higher returns than the BM portfolios, ranging from 9.76 to 13.03 points. All of the MAP returns are positive and have lower standard deviations. The daily average return of the new trading strategy, $TSL_{MA,t,L}$, is 15.34 points (t = 4.50), which is 221.13% higher than the high-minus-low return of the BM portfolio (4.78 points) but lower than the corresponding equally-weighted portfolios. The difference between MA(20) and buy-and-hold strategies, $TSL_{MAP,t,L}$, is 9.94 points (t = 3.95), which is also slightly lower than that of the corresponding equally-weighted portfolios.

Overall, Table 1 shows that the value premium effect exists in the China stock market and that the moving average technical analysis strategy is useful in producing positive and significant excess returns. In addition, the proposed strategy, $TSL_{MA,t,L}$, clearly outperforms the traditional buy-and-hold BM strategy.

3.2. Risk-Adjusted Performances

The MAP results show that the MA timing strategy outperforms the buy-and-hold strategy. However, we observe that generally, portfolios with higher returns have higher standard deviations, which suggests that their risk (or total risk) levels are different. Therefore, a natural research question is whether the return differences are due to exposure to risks. In this sub-section, we concentrate on the risk-adjusted profitability of MAP and TLS using three asset pricing models: the CAPM, FF3F, and LIQ4F models. We use MAP and $TLS_{MAP,t,L}$ as dependent variables and run time-series regressions against the risk factors. The results are presented in Table 2.

If the portfolio average return, $MAP_{j,t,L}$ is not fully explained by the risk factors, we expect $\alpha_{j,L}$ to be significantly different from zero. Otherwise, it suggests that the positive additional return found in the MA strategy is artificial after taking exposure to well-documented risk factors into consideration.

Table 2. Time-series regressions with the CAPM and LIQ4F models.

Rank	CAPM			LIQ4F Model					
	α	βmkt	Adj. R^2	α	βmkt	βsmb	βhml	βliq	Adj. R^2
Low	8.18	−0.45	0.40	9.08	−0.46	−0.59	0.20	0.15	0.45
	(5.41)	(−18.52)		(6.26)	(−18.38)	(−9.45)	(6.21)	(4.13)	
2	7.13	−0.49	0.42	8.10	−0.49	−0.53	0.15	0.17	0.46
	(4.73)	(−18.38)		(5.59)	(−18.35)	(−8.92)	(5.03)	(4.99)	
3	5.77	−0.46	0.39	6.70	−0.47	−0.51	0.15	0.16	0.42
	(3.75)	(−16.98)		(4.48)	(−16.78)	(−7.97)	(4.84)	(4.36)	
4	7.42	−0.52	0.43	8.53	−0.51	−0.43	0.07	0.19	0.46
	(4.76)	(−18.50)		(5.58)	(−18.30)	(−6.95)	(2.24)	(5.39)	
5	6.69	−0.53	0.44	8.12	−0.52	−0.53	0.05	0.15	0.47
	(4.20)	(−18.79)		(5.33)	(−18.59)	(−8.19)	(1.54)	(4.21)	
6	5.64	−0.49	0.40	7.12	−0.48	−0.44	−0.01	0.19	0.44
	(3.48)	(−17.45)		(4.60)	(−17.56)	(−7.33)	(−0.28)	(5.41)	
7	5.64	−0.49	0.40	8.00	−0.49	−0.47	−0.04	0.18	0.45
	(3.48)	(−17.45)		(5.12)	(−18.31)	(−7.44)	(−1.23)	(5.14)	
8	6.98	−0.54	0.41	8.98	−0.51	−0.43	−0.12	0.19	0.48
	(4.10)	(−18.26)		(5.61)	(−18.34)	(−6.82)	(−3.20)	(5.18)	
9	5.63	−0.49	0.39	7.30	−0.47	−0.37	−0.09	0.18	0.43
	(3.45)	(−17.32)		(4.69)	(−17.41)	(−6.29)	(−2.46)	(5.36)	
High	4.65	−0.50	0.40	6.57	−0.48	−0.40	−0.14	0.15	0.45
	(2.86)	(−17.57)		(4.25)	(−17.92)	(−6.57)	(−3.56)	(4.20)	
High–Low	−3.53	−0.05	0.01	−2.51	−0.02	0.19	−0.33	0.00	0.08
	(−2.49)	(−3.27)		(−1.82)	(−1.24)	(3.71)	(−8.34)	(−0.08)	
TLS_{MAP}	13.24	−0.09	0.01	15.14	−0.04	0.14	−0.46	0.12	0.06
	(5.24)	(−1.88)		(6.08)	(−0.86)	(1.39)	(−7.99)	(1.90)	

The sample stocks are sorted in ascending order by their BM ratios and assigned into decile portfolios each year. The equally-weighted portfolio daily returns are then obtained. MAP is the difference between the MA(20) strategy and the buy-and-hold strategy. The regression models are $MAP_{j,t,L} = \alpha_{j.L} + \beta_{j,L,MKT}R_{MKT,t} + \varepsilon_{j,t,L}$ and $MAP_{j,t,L} = \alpha_{j.L} + \beta_{j,L,MKT}R_{MKT,t} + \beta_{j,L,SMB}R_{SMB,t} + \beta_{j,L,HML}R_{HML,t} + \beta_{j,L,LIQ}R_{LIQ,t} + \varepsilon_{j,t,L}$, where $R_{MKT,t}$ is market excess returns; $R_{SMB,t}$ is the size factor; $R_{HML,t}$ is the book-to-market factor; $R_{LIQ,t}$. is the liquidity risk factor proxied by turnover ratio; $\varepsilon_{j,t,L}$ is an error term assumed to have a zero mean and to be uncorrelated with all other explanatory variables; and the factor sensitivities or loadings, $\beta_{j,L,MKT}$, $\beta_{j,L,SMB}$, $\beta_{j,L,HML}$, and $\beta_{j,L,LIQ}$, are the slope coefficients for the factors, respectively. $\alpha_{j.L}$ is the intercept of the regression. *t*-test statistics are presented in the parentheses.

Table 2 provides the results of the equally-weighted portfolios on the CAPM and LIQ4F models. Because the results of FF3F are similar to those from the LIQ4F model, we do not report them to save space. All of the alphas of the 10 portfolios in the two models are significantly different from zero at the 5% level, which suggests that the profits generated from the timing strategy are not fully captured by these well-known risk factors. The alphas of the CAPM model range from 4.65 to 8.18 points, while the alphas of the LIQ4F model range from 6.57 to 9.08 points.

The betas of the market excess return and size factors are all negative and highly significant, which can partially explain why the alpha becomes larger than the unadjusted return of the MAPs. Half of the coefficients of the HML factor are positive and half are negative. The coefficients of the LIQ factor are all significantly positive.

The alphas of the TSL_{MAP} in the CAPM and LIQ4F models are 13.24 and 15.14 points, respectively, which are larger than the unadjusted TSL_{MAP} (11.23 points). Interestingly, while the adjusted R^2 for most of the deciles in the two models are larger than 40%, the adjusted R^2 for the TSL_{MAP} is extremely low. Overall, the low R^2 and significant alphas indicate that the CAPM and LIQ4F models cannot explain the excess profit from the new BM strategy.

3.3. Components of Strategies

We now establish that the moving average technical analysis can help us obtain better returns than the buy-and-hold strategy. We are curious about how exactly the excess returns are created. To answer this question, we consider the operation of the MA timing strategy. We know that we hold the underlying portfolio when the signal $P_{j,t-1} > A_{j,t-1,L}$ appears and hold the risk-free asset otherwise. Comparing this with the buy-and-hold strategy, a difference appears only when $P_{j,t-1} < A_{j,t-1,L}$.

This difference is between the return generated from the underlying portfolio and the risk-free asset. Therefore, we can express the MAP return in another way:

$$MAP_{j,t,L} = \begin{cases} 0, & if\ P_{j,t-1} > A_{j,t-1,L}; \\ R_{f,t} - R_{j,t}, & otherwise, \end{cases} \tag{9}$$

To examine the difference, we separate the sample into two parts: when $P_{j,t-1} > A_{j,t-1,L}$ (buy signal) and when $P_{j,t-1} \leq A_{j,t-1,L}$ (sell signal). We calculate the proportion of days when R_j is higher (or lower) than R_f for the buying and selling signal states. The results are shown in Table 3.

Table 3. Components of strategies.

Rank	Condition	Position	Equally-Weighted Portfolio	
			$R_p > R_f$	$R_p \leq R_f$
Low	$P_{i,t-1} > A_{i,t-1,L}$	BM portfolio	58.8	41.2
	$P_{i,t-1} \leq A_{i,t-1,L}$	Risk-free asset	47.83	52.17
2	$P_{i,t-1} > A_{i,t-1,L}$	BM portfolio	56.71	43.29
	$P_{i,t-1} \leq A_{i,t-1,L}$	Risk-free asset	49.35	50.65
3	$P_{i,t-1} > A_{i,t-1,L}$	BM portfolio	56.96	43.04
	$P_{i,t-1} \leq A_{i,t-1,L}$	Risk-free asset	46.8	53.2
4	$P_{i,t-1} > A_{i,t-1,L}$	BM portfolio	59.29	40.71
	$P_{i,t-1} \leq A_{i,t-1,L}$	Risk-free asset	48.82	51.18
5	$P_{i,t-1} > A_{i,t-1,L}$	BM portfolio	59.71	40.29
	$P_{i,t-1} \leq A_{i,t-1,L}$	Risk-free asset	47.85	52.15
6	$P_{i,t-1} > A_{i,t-1,L}$	BM portfolio	59.85	40.15
	$P_{i,t-1} \leq A_{i,t-1,L}$	Risk-free asset	46.03	53.97
7	$P_{i,t-1} > A_{i,t-1,L}$	BM portfolio	60.02	39.98
	$P_{i,t-1} \leq A_{i,t-1,L}$	Risk-free asset	48.46	51.54
8	$P_{i,t-1} > A_{i,t-1,L}$	BM portfolio	59.66	40.34
	$P_{i,t-1} \leq A_{i,t-1,L}$	Risk-free asset	49.38	50.62
9	$P_{i,t-1} > A_{i,t-1,L}$	BM portfolio	60.15	39.85
	$P_{i,t-1} \leq A_{i,t-1,L}$	Risk-free asset	48.97	51.03
High	$P_{i,t-1} > A_{i,t-1,L}$	BM portfolio	58.83	41.17
	$P_{i,t-1} \leq A_{i,t-1,L}$	Risk-free asset	49.82	50.18

We separate the MA(20) portfolio sample into two parts. One is when $P_{j,t-1} > A_{j,t-1,L}$ which indicates a buy signal and the other is when $P_{j,t-1} \leq A_{j,t-1,L}$ which suggests a sell signal. We then compare the return of the BM portfolio and the risk-free rate. We calculate the proportion of each situation for buying and selling signal states.

We find that the proportions of the state in which $R_{j,t} > R_{f,t}$ are all bigger than 50%, ranging from 56.71% to 60.15%, when $P_{j,t-1} > A_{j,t-1,L}$. However, this does not affect the MAP. In addition, the proportions of the state in which $R_{j,t} < R_{f,t}$ are also all bigger than 50% when $P_{j,t-1} \leq A_{j,t-1,L}$. The highest is 53.97% in decile 6 and the lowest is 50.18% in decile 10. Although the successful rates are not very high (mostly between 50% and 60%), all of them are bigger than 50%, which leads to better performance by MA strategy when a selling signal emerges. These results show that the MA signal is useful in generating positive excess returns and help explain why the moving average can outperform the buy-and-hold strategy.

3.4. Alternative Lag Lengths

In this sub-section, we investigate how the returns of the MAP and TLS change with the lag lengths. We conduct the moving average timing strategy with 5-day, 10-day, 20-day, 50-day, 100-day, and 200-day timing signals. The results are illustrated in Figure 1.

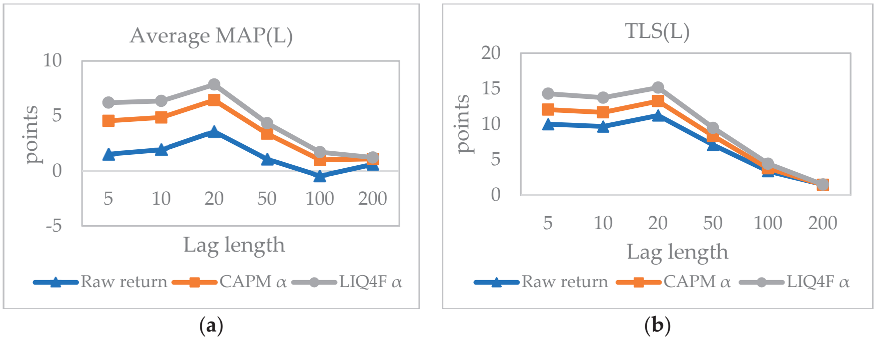

Figure 1. (**a**) For each BM portfolio, the moving average timing strategy is imposed with 5-day, 10-day, 20-day, 50-day, 100-day, and 200-day timing signals. The MAP returns for the decile portfolios are then averaged cross-sectionally. The raw returns of the average MAP, risk-adjusted alphas of CAPM and LIQ4F models are plotted; (**b**) The proposed technical analysis enhanced BM strategy is imposed with 5-day, 10-day, 20-day, 50-day, 100-day, and 200-day timing signals. The raw returns of the average TLS strategy, risk-adjusted alphas of CAPM and LIQ4F models are plotted.

Figure 1a plots the average return of MAPs across the decile portfolios with different lag lengths. The 20-day average MAP return is the highest (in fact, although it is not plotted, the 20-day MAP is the highest for each decile portfolio). The 5-day MAP and 10-day MAP are also significantly positive but are slightly smaller than that of the 20-day signals. The returns with signals that are longer than 20 days start to decline and become progressively smaller, and the results of the 100-day lag even become negative. The CAPM and LIQ4F model-adjusted MAP alphas present similar patterns to that of the unadjusted returns.

The returns of the proposed trading strategy, TLS, are plotted in Figure 1b. Again, the 20-day lag strategy generates the highest raw and risk-adjusted profits. The MA(5) and MA(10) strategies also perform well, as their returns are close to that of MA(20). However, when lags longer than 50 days are used, the strategy return drops sharply, almost reaching zero. We conjecture that this is because the Chinese stock market is highly volatile. A shorter moving average signal can capture the fluctuations in information more accurately than a longer moving average signal. The signals with long lag length may miss important information changes, and so the abnormal return produced by these signals becomes flat and small.

The results seem to suggest that a shorter moving average of up to 50 days can produce significant and meaningful positive returns. However, the 20-day lag signal provides the best result by capturing the most information regarding past prices. To sum up, lag length can influence the performance of the moving average timing strategy, and we need to choose the best one for China's stock market.

3.5. Transaction Operations

In the real market, the utilization of the moving average timing strategy would induce more transaction operations, resulting in higher transaction costs. In this section, we examine the effect of trading costs on the earlier results. Table 4 reports the statistics that address this issue.

The average holding days is the average number of days that we hold the portfolio. Longer average holding days suggest that the trading portfolio is more stable. From Table 4, we can tell that the average holding days becomes longer as the moving average lag length increases. The average holding days of the 5-day MAP is around 4 days, while that of the 20-day MAP is around 10 days. Moreover, the average holding days for 200-day MAP ranges from 130.99 days to 183.08 days. We do not report those of the two zero-cost trading strategies because it is difficult to define the holding period while investors hold two portfolios simultaneously.

Table 4. Transaction operations.

Rank	MAP(5)			MAP(10)			MAP(20)			MAP(50)			MAP(100)			MAP(200)		
	Holding	Freq	BETC	Holding	Freq	BETC	Holding	Freq	BETC	Holding	Freq	BETC	Holding	Freq	BETC	Holding	Freq	BETC
Low	3.80	0.29	38.77	5.56	0.20	41.20	9.35	0.13	83.35	19.37	0.07	81.28	50.06	0.04	−7.51	168.65	0.02	87.36
2	3.81	0.29	8.50	5.76	0.20	17.49	10.34	0.13	64.09	16.06	0.09	−8.96	51.74	0.04	16.88	150.48	0.02	41.78
3	3.92	0.29	11.84	6.34	0.19	15.16	9.90	0.13	47.22	25.57	0.07	24.41	43.17	0.05	−41.89	130.99	0.02	28.16
4	3.87	0.28	13.58	6.14	0.19	23.75	10.54	0.12	76.79	19.94	0.08	8.84	50.81	0.05	−25.54	137.26	0.02	0.30
5	3.95	0.28	8.28	6.16	0.19	18.48	9.59	0.13	58.54	21.51	0.07	33.90	48.25	0.04	−2.14	176.57	0.02	121.70
6	4.07	0.28	3.56	6.26	0.19	10.09	10.95	0.12	48.74	25.31	0.07	45.19	67.41	0.04	−10.50	183.08	0.02	126.02
7	3.92	0.28	4.66	6.40	0.18	28.86	11.45	0.11	61.02	22.11	0.07	22.78	46.50	0.05	−22.12	141.55	0.02	65.13
8	4.07	0.27	16.91	6.63	0.18	13.19	11.04	0.11	69.38	27.90	0.07	78.57	47.64	0.05	−9.26	146.77	0.02	81.68
9	4.00	0.28	4.42	6.37	0.18	22.56	10.80	0.12	48.92	20.48	0.07	33.73	46.56	0.05	−18.22	156.47	0.02	120.17
High	4.01	0.28	−3.00	6.72	0.18	10.80	10.45	0.12	28.91	21.22	0.08	−9.39	48.86	0.06	−60.33	141.45	0.02	52.11
High–Low		0.45			0.32			0.22			0.13			0.09			0.03	
TLS		0.45			0.32			0.22			0.13			0.09			0.03	
Transaction Cost for TLS			7.09			5.24			3.95			2.99			2.68			2.58
MAP for TLS			9.99			9.67			11.23			7.08			3.39			1.51
Return after Transaction Cost			2.91			4.43			7.28			4.08			0.70			−1.08

We calculate the average holding days, trading frequency of MA and TLS portfolios, break-even transaction cost and after transaction cost returns of TLS. The average holding days represent the average number of days during which the portfolio is held before it is sold out. The trading frequency of the portfolios is the fraction of the number of trading days to the number of days in the whole sample period. Break-even transaction cost (BETC) is the fee which is required in each round-trip transaction for the portfolios if the final profit is zero. Transactions Cost for TLS consists commission, transfer fee, stamp tax, and interest fee for stock borrow. MAP for TLS is the return difference between the proposed technical analysis enhanced BM strategy and the traditional buy-and-hold BM strategy.

Next, we calculate the trading frequency of the MAP and TLS portfolios, which is the fraction of the number of trading days of the number of days in the whole period. A shorter (longer) lag length strategy implies that the portfolios will be traded more (less) and that the trading frequency should be higher (smaller). For the 20-day lag length, the trading frequency ranges from 0.11 to 0.13 for the 10 deciles and is 0.22 for the High–Low and TLS strategies. The trading frequency for all of the deciles with lag lengths longer than 20 days is lower than 0.10. Apparently, the MA timing strategies incur higher transaction fees if a shorter lag length is chosen for the MA indicator.

According to the China Securities Regulatory Commission, the Securities Association of China and notices of securities companies, the cost for trading A-shares consists of a commission, transfer fee, and stamp tax. The commission fee should be lower than 30 basis points of the transaction amount and is determined by securities companies in the allowable interval. Because securities companies in China use low price strategies to attract customers, according to the Eastmoney Choice Database, the average commission fee for trading stocks in 2015 is just 5.1 basis points. The amounts of the other two kinds of fees are fixed. The transfer fee for A-shares is 0.2 basis points of the transaction amount, and the stamp tax is 10 basis points only on the sell side. To sum up, we need to pay 20.6 ((5.1 + 0.2)*2 + 10) basis points on average for a round trip of transactions. Following Balduzzi and Lynch (1999), we assume that we pay the transaction fee when we trade BM portfolios but not when we trade the risk-free asset.

Following Han et al. (2013) and Ko et al. (2014), we use break-even transaction costs (BETCs) to evaluate the profit versus cost for the MAP returns. BETC here is the fee that we can afford in each round-trip transaction for the deciles if the final profit is zero. We report the results in Table 4, where we label BETCs with n.a. when the MAP return is negative, as BETCs are meaningless in such a situation. Overall, the BETCs are mostly higher than 20.6 basis points. The MAP(5) and MAP(10) strategies in general have lower BETCs because transaction operations are too frequent, thus incurring higher transaction fees. The BETCs of MAP(20) are higher than 20.6 for all deciles, indicating positive after-cost profitability. The BETCs start to decline after the MAP(20) strategy. This pattern is similar to the results in Figure 1.

In our new proposed zero-cost trading strategy, TLS, we need to borrow stocks when receiving short signals and pay interest for stock borrowing. In China, most interest rates for short-selling are lower than 9% annually, which is 2.4658 points daily (9%/365). To compute the after-cost returns of TLS, in addition to the normal transaction fee, we need to subtract the interest fee. We calculate the interest fee by multiplying the short-selling interest rate by the number of days that we borrow stocks. From Table 4, we can see that transaction costs for TLS decrease monotonically from 7.09 to 2.58 points as the lag length increases. We obtain a positive final return for all of the portfolios except for the MAP(200) strategy. Again, the MAP(20) strategy generates the highest after-transaction-cost TLS returns, which is consistent with the findings in Figure 1. Therefore, MA timing strategy with 20-day lag seems to be the best choice both before and after transaction costs.[2]

4. Robustness Tests

This section presents the tests of the robustness of the MA and TLS trading strategies. First, we examine whether there is a difference in the trading results in the sub-periods before and after the non-tradable stock reform in China. Second, we investigate whether business cycles affect returns. Third, we study the impact of market timing ability on the strategies. Lastly, we use an alternative sample that contains stocks for which short-selling is permitted in China's market.

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[2] In an unablated wealth analysis test, the end wealth of an initial zero-cost investment (long $1 million in highest BM portfolio and short $1 million in lowest BM portfolio) using the TLS(20) strategy is $687 million, while the counterpart from the buy-and-hold strategy is only $10.22 million.

4.1. Sub-Period Analysis

Since China's market underwent non-tradable stock reform in 2005, market conditions, such as market regulations, rules, trading mechanisms, participants, and trading volume, have changed drastically. To investigate the effect of the policy change on our strategy, we conduct tests on sub-periods, dividing our whole sample period at mid-2005 into two periods of nearly equal length. We repeat our analysis and obtain the daily average return data for the two sub-periods, 1 July 1995 to 30 June 2005 and 1 July 2005 to 30 June 2015. To examine the difference between the two subsamples, we conduct a two-sample mean test. First, we check the normality of the two subsamples using the Kolmogorov–Smirnov test, which is suitable for big data like ours. Panel A of Table 5 shows that all of the *p*-values for the sample differences are smaller than 0.01, which indicates that the samples do not follow a normal distribution.

We then conduct the Wilcoxon rank-sum test to check the difference between the two sub-periods after determining that they do not follow a normal distribution. Panel B of Table 5 reports the test results. Most of the *p*-values are smaller than 0.1, ranging from 0.0005 to 0.3607. The *p*-value of the TLS portfolio is 0.0118, which is very small and rejects the null hypothesis. The two sub-samples are significantly different from each other in the TLS strategy.

Next, we run regressions with the CAPM, FF3F, and LIQ4F models to check the robustness of the risk-adjusted returns. Because the results are similar, we only report the LIQ4F model alphas and betas in the sub-periods in Table 5 to save space.

Overall, we find that the two sub-periods' results are similar to those for the whole period. All of the alphas of the deciles are positive, and almost all of them are significant (portfolio 10 is marginally significant at 10%). As in the previous findings, the coefficients of market excess return and SMB are negative. The TLS strategy alphas are large and highly significant for both sub-periods; however, the result for the latter sub-period is better than the former for both the deciles and the TLS. Specifically, the second sub-period alpha of the TLS is 19.32 points, while that of the former period is 11.12. The results suggest that the MA and TLS strategies work better in the most recent period, which has undergone non-tradable share reform to push more non-tradable shares to become tradable shares in the market. As many more shares are traded in the market, the market becomes more efficient, which suggests that technical analysis should become less profitable in the market. However, our results seem to contradict this inference. These results are interesting and need further investigation, which is beyond the scope of our study.

Table 5. Sub-period analysis.

Panel A: Normality Check (Kolmogorov–Smirnov)

Rank	First Sub-Period		Second Sub-Period	
	Statistic D	*p*-Value	Statistic D	*p*-Value
Low	0.2586	<0.0100	0.3258	<0.0100
2	0.2884	<0.0100	0.3415	<0.0100
3	0.2925	<0.0100	0.3346	<0.0100
4	0.2687	<0.0100	0.3349	<0.0100
5	0.2741	<0.0100	0.3203	<0.0100
6	0.2917	<0.0100	0.3289	<0.0100
7	0.285	<0.0100	0.3341	<0.0100
8	0.2857	<0.0100	0.3285	<0.0100
9	0.2863	<0.0100	0.3307	<0.0100
High	0.2883	<0.0100	0.3223	<0.0100
High–Low	0.2286	<0.0100	0.2402	<0.0100
TLS	0.1373	<0.0100	0.1305	<0.0100

Panel B: Wilcoxon Two-Sample Test

Rank	Statistic	Normal Approximation Z	Two-Sided Pr > |Z|
Low	6021507	3.50	0.0005
2	5905501	0.91	0.3607
3	5967378	2.36	0.0184
4	5992645	2.89	0.0038
5	5956286	2.06	0.0399
6	5992566	2.93	0.0034
7	5942272	1.76	0.0781
8	5956512	2.08	0.0375
9	5982790	2.69	0.0071
High	5924624	1.35	0.1766
High–Low	5818216	−1.03	0.3020
TLS	5744009	−2.52	0.0118

Panel C: Time-series regressions with LIQ4F model

Rank	First Sub-Period						Second Sub-Period					
	α	βmkt	βsmb	βhml	βliq	Adj. R^2	α	βmkt	βsmb	βhml	βliq	Adj. R^2
Low	7.24	−0.43	−0.56	0.22	0.14	0.44	10.96	−0.48	−0.53	0.09	0.20	0.46
	(4.01)	(−11.98)	(−6.95)	(5.61)	(2.82)		(4.86)	(−14.38)	(−6.15)	(1.67)	(3.84)	
2	3.95	−0.49	−0.52	0.15	0.11	0.48	12.07	−0.49	−0.43	0.08	0.28	0.45
	(2.13)	(−11.99)	(−6.18)	(3.94)	(2.35)		(5.47)	(−14.29)	(−5.23)	(1.35)	(5.37)	
3	6.07	−0.44	−0.54	0.13	0.08	0.43	7.16	−0.48	−0.38	0.09	0.30	0.42
	(3.43)	(−10.85)	(−6.56)	(3.67)	(1.69)		(2.97)	(−13.11)	(−4.16)	(1.54)	(5.11)	
4	6.92	−0.49	−0.45	0.04	0.11	0.49	10.02	−0.52	−0.33	0.04	0.31	0.45
	(3.81)	(−12.09)	(−5.74)	(1.11)	(2.37)		(4.06)	(−14.01)	(−3.72)	(0.69)	(5.49)	
5	6.45	−0.49	−0.44	0.02	0.06	0.47	9.86	−0.55	−0.44	−0.04	0.32	0.48
	(3.41)	(−11.56)	(−5.42)	(0.65)	(1.19)		(4.19)	(−15.19)	(−4.77)	(−0.71)	(5.34)	

Table 5. *Cont.*

6	5.75	−0.44	−0.39	−0.03	0.13	0.43	8.73	−0.51	−0.42	−0.03	0.26	0.44
	(3.07)	(−11.45)	(−4.98)	(−0.89)	(3.10)		(3.57)	(−13.69)	(−4.82)	(−0.48)	(4.47)	
7	5.43	−0.44	−0.45	−0.07	0.10	0.44	10.83	−0.54	−0.41	−0.08	0.29	0.48
	(2.88)	(−11.79)	(−5.91)	(−1.77)	(2.48)		(4.43)	(−14.70)	(−4.43)	(−1.30)	(4.94)	
8	7.63	−0.48	−0.40	−0.13	0.17	0.49	10.58	−0.55	−0.43	−0.15	0.22	0.48
	(3.83)	(−11.48)	(−4.93)	(−2.87)	(3.83)		(4.24)	(−14.84)	(−4.77)	(−2.20)	(3.58)	
9	5.81	−0.44	−0.40	−0.10	0.12	0.43	8.71	−0.49	−0.25	−0.17	0.29	0.44
	(2.94)	(−11.57)	(−5.15)	(−2.19)	(2.85)		(3.64)	(−13.22)	(−2.98)	(−2.77)	(5.22)	
High	3.83	−0.41	−0.33	−0.13	0.14	0.42	9.73	−0.54	−0.39	−0.21	0.18	0.48
	(1.94)	(−10.87)	(−4.39)	(−2.84)	(3.06)		(4.23)	(−15.22)	(−4.60)	(−3.34)	(3.18)	
High–Low	−3.41	0.02	0.22	−0.35	0.00	0.12	−1.22	−0.05	0.14	−0.30	−0.02	0.04
	(−1.83)	(1.09)	(3.05)	(−7.28)	(−0.03)		(−0.60)	(−2.46)	(1.90)	(−6.23)	(−0.45)	
TLS	11.12	0.04	−0.05	−0.41	0.19	0.09	19.32	−0.11	0.22	−0.52	0.06	0.05
	(3.42)	(0.52)	(−0.31)	(−5.62)	(2.25)		(5.20)	(−1.81)	(1.61)	(−5.35)	(0.70)	

The two sub-periods are before and after the non-tradable stock reform. The first sub-period is from 1 July 1995 to 30 June 2005 and the second sub-period is from 1 July 2005 to 30 June 2015. Panel A presents the results of the Kolmogorov–Smirnov test which checks the normality of the two subsamples. Panel B presents the results of the Wilcoxon rank-sum test which checks the difference between the two sample periods after knowing they do not follow normal distributions. Panel C presents results of the time-series regressions with the LIQ4F model for the two sub-periods. *t*-test statistics are presented in the parentheses.

4.2. Business Cycles

We now come to the question of whether there is any relation between the moving average signals and business cycles. Here, we use two methods to test the influence of business cycles. First, Liew and Vassalou (2000) construct the following model, which uses the GDP growth rate as a proxy for good and bad business states

$$\begin{aligned} MAP_{j,t,L} \quad &= \alpha_{j.L} + \beta_{j,L,MKT}R_{MKT,t} + \beta_{j,L,SMB}R_{SMB,t} + \beta_{j,L,HML}R_{HML,t} + \beta_{j,L,Good}D^{GDP}_{Good,t} + \\ &\beta_{j,L,Bad}D^{GDP}_{Bad,t} + \varepsilon_{j,t,L}, \quad j = 1, \ldots, 10, \end{aligned} \tag{10}$$

$$\begin{aligned} TLS_{t,L} = \quad &\alpha_L + \beta_{L,MKT}R_{MKT,t} + \beta_{L,SMB}R_{SMB,t} + \beta_{L,HML}R_{HML,t} + \beta_{L,Good}D^{GDP}_{Good,t} + \beta_{L,Bad}D^{GDP}_{Bad,t} + \\ &\varepsilon_{t,L}, \end{aligned} \tag{11}$$

In the model, $D^{GDP}_{Good,t}$ and $D^{GDP}_{Bad,t}$ are the dummy variables for good and bad business states. When the GDP growth rate in the quarter is in the top 25% of the whole sample period, $D^{GDP}_{Good,t}$ will be one, which indicates that business cycles are in a good period. $D^{GDP}_{Bad,t}$ indicates the bad state when the quarterly GDP growth rate is in the bottom 25% of the overall sample. We can determine the contribution of both expansionary (good business state) and recessionary (bad business state) periods from their coefficients. If they are significantly positive, the predictability is strong, and the strategy works in the state.

The other model from Cooper et al. (2004) uses a dummy variable for bad market performance. We follow them and perform the following regression using market return data:

$$\begin{aligned} MAP_{j,t,L} \quad &= \alpha_{j.L} + \beta_{j,L,MKT}R_{MKT,t} + \beta_{j,L,SMB}R_{SMB,t} + \beta_{j,L,HML}R_{HML,t} + \beta_{j,L,Bad}D^{Market}_{Bad,t} + \varepsilon_{j,t,L}, \\ &j = 1, \ldots, 10, \end{aligned} \tag{12}$$

$$TLS_{t,L} = \alpha_L + \beta_{L,MKT}R_{MKT,t} + \beta_{L,SMB}R_{SMB,t} + \beta_{L,HML}R_{HML,t} + \beta_{L,Bad}D^{Market}_{Bad,t} + \varepsilon_{t,L}, \tag{13}$$

$D^{Market}_{Bad,t}$ is the dummy variable that denotes the bad state of the business cycle. We calculate the market return of the past three years before every yearly holding period. If the result is negative, $D^{Market}_{Bad,t}$ will be one, and zero otherwise. We can determine the effect of a bad market environment on our excess return from its coefficients. If the coefficients on $D^{Market}_{Bad,t}$ are significantly positive, our strategy works in the bad market state.

Panels A and B of Table 6 show the results of these two regressions. We find that the pattern of the alphas in the two models changes only slightly from before. However, the coefficients on most of the dummy variables are insignificant. For the first model, 9 of the 10 portfolio coefficients are insignificant at the 10% level. For the second model, only two of the coefficients of the dummy variable $D^{Market}_{Bad,t}$ are significant at either the 5% or 10% level. These results clearly show that business cycles have a very weak influence on the average returns of MA strategy.[3]

[3] From unablated robustness test results, we find that other famous cycle effects like the January effect and the Lunar cycle (Wong and McAleer 2009) also have weak influence over the MA and TLS strategies.

Table 6. Business cycle.

Rank	Good and Bad States Are Identified by GDP Growth (Past 20 Years)								Good and Bad States Are Identified by Past Three-Year Market Returns						
	α	βmkt	βsmb	βhml	βliq	βGood	βBad	Adj. R^2	α	βmkt	βsmb	βhml	βliq	βBad	Adj. R^2
Low	9.74	−0.46	−0.59	0.20	0.15	1.91	−4.45	0.45	9.60	−0.46	−0.59	0.20	0.15	−1.29	0.45
	(4.93)	(−18.36)	(−9.43)	(6.16)	(4.13)	(0.50)	(−1.46)		(4.88)	(−18.38)	(−9.46)	(6.21)	(4.13)	(−0.47)	
2	7.55	−0.49	−0.52	0.15	0.17	6.48	−3.94	0.46	8.68	−0.49	−0.53	0.15	0.17	−1.45	0.46
	(3.78)	(−18.33)	(−8.89)	(4.99)	(4.98)	(1.79)	(−1.21)		(4.53)	(−18.35)	(−8.93)	(5.03)	(4.99)	(−0.52)	
3	7.27	−0.47	−0.51	0.15	0.16	1.69	−3.88	0.42	7.19	−0.47	−0.51	0.15	0.16	−1.22	0.42
	(3.61)	(−16.77)	(−7.93)	(4.81)	(4.36)	(0.44)	(−1.20)		(3.48)	(−16.79)	(−7.96)	(4.84)	(4.37)	(−0.44)	
4	8.77	−0.51	−0.43	0.07	0.19	2.01	−2.85	0.46	10.33	−0.51	−0.43	0.07	0.19	−4.49	0.47
	(4.29)	(−18.28)	(−6.92)	(2.21)	(5.39)	(0.50)	(−0.89)		(4.97)	(−18.30)	(−6.96)	(2.24)	(5.40)	(−1.56)	
5	8.49	−0.52	−0.53	0.05	0.15	2.00	−3.36	0.47	9.59	−0.52	−0.53	0.05	0.15	−3.65	0.47
	(4.14)	(−18.58)	(−8.17)	(1.52)	(4.21)	(0.51)	(−1.03)		(4.57)	(−18.60)	(−8.21)	(1.55)	(4.21)	(−1.28)	
6	7.67	−0.48	−0.43	−0.01	0.19	1.29	−3.42	0.44	8.59	−0.48	−0.44	−0.01	0.19	−3.66	0.44
	(3.66)	(−17.55)	(−7.32)	(−0.31)	(5.42)	(0.32)	(−1.06)		(4.00)	(−17.56)	(−7.35)	(−0.28)	(5.42)	(−1.27)	
7	8.31	−0.49	−0.47	−0.04	0.18	5.03	−6.01	0.45	9.56	−0.49	−0.48	−0.04	0.18	−3.90	0.45
	(3.99)	(−18.31)	(−7.42)	(−1.29)	(5.14)	(1.28)	(−1.75)		(4.47)	(−18.31)	(−7.47)	(−1.23)	(5.15)	(−1.33)	
8	9.63	−0.51	−0.43	−0.12	0.19	1.65	−4.18	0.48	11.75	−0.51	−0.43	−0.12	0.19	−6.91	0.48
	(4.46)	(−18.33)	(−6.78)	(−3.24)	(5.19)	(0.41)	(−1.21)		(5.27)	(−18.35)	(−6.86)	(−3.20)	(5.19)	(−2.33)	
9	8.26	−0.47	−0.37	−0.09	0.18	0.05	−3.89	0.43	7.94	−0.47	−0.37	−0.09	0.18	−1.60	0.43
	(3.95)	(−17.39)	(−6.25)	(−2.49)	(5.36)	(0.01)	(−1.18)		(3.63)	(−17.40)	(−6.29)	(−2.46)	(5.36)	(−0.55)	
High	6.04	−0.48	−0.39	−0.14	0.15	3.46	−1.15	0.45	8.74	−0.48	−0.40	−0.14	0.15	−5.41	0.45
	(2.90)	(−17.92)	(−6.57)	(−3.57)	(4.20)	(0.84)	(−0.37)		(3.98)	(−17.93)	(−6.60)	(−3.56)	(4.21)	(−1.91)	
High–Low	−3.70	−0.02	0.19	−0.33	0.00	1.55	3.30	0.08	−0.85	−0.02	0.19	−0.33	0.00	−4.12	0.08
	(−1.95)	(−1.25)	(3.67)	(−8.31)	(−0.09)	(0.43)	(1.11)		(−0.49)	(−1.23)	(3.68)	(−8.35)	(−0.08)	(−1.50)	
TLS	14.84	−0.04	0.15	−0.46	0.12	5.53	−4.02	0.06	18.04	−0.04	0.14	−0.46	0.12	−7.22	0.06
	(4.30)	(−0.86)	(1.42)	(−8.01)	(1.90)	(0.84)	(−0.77)		(5.05)	(−0.86)	(1.37)	(−8.00)	(1.91)	(−1.57)	

Two models are used to test the influence of business cycle. One is $MAP_{j,t,L} = \alpha_{j.L} + \beta_{j,L,MKT}R_{MKT,t} + \beta_{j,L,SMB}R_{SMB,t} + \beta_{j,L,HML}R_{HML,t} + \beta_{j,L,Good}D^{GDP}_{Good,t} + \beta_{j,L,Bad}D^{GDP}_{Bad,t} + \varepsilon_{j,t,L}$. In the model, $D^{GDP}_{Good,t}$ and $D^{GDP}_{Bad,t}$ are the dummy variables for good and bad business states. When the GDP growth rate in the quarter is in the top 25% of the whole sample period, $D^{GDP}_{Good,t}$ will be one, which indicate the business cycle is in good period. On the other hand, $D^{GDP}_{Bad,t}$ indicates the bad state when the quarterly GDP growth rate is in the bottom 25% of the overall sample. The other model is $MAP_{j,t,L} = \alpha_{j.L} + \beta_{j,L,MKT}R_{MKT,t} + \beta_{j,L,SMB}R_{SMB,t} + \beta_{j,L,HML}R_{HML,t} + \beta_{j,L,Bad}D^{Market}_{Bad,t} + \varepsilon_{j,t,L}$. We use $D^{Market}_{Bad,t}$ as the dummy variable to denote the bad state of the business cycle. We calculate the market return of past three years before the yearly holding period. If the result is negative, $D^{Market}_{Bad,t}$ will be one and zero otherwise. *t*-test statistics are presented in the parentheses.

4.3. Market Timing Ability

To find out more about how the moving average and TLS strategies can outperform the buy-and-hold strategy, we also investigate their timing ability, which may drive the performance. We take use approaches proposed by Treynor and Mazuy (1966) and Henriksson and Merton (1981) to test the market timing ability of the two strategies in our paper.

Treynor and Mazuy (1966)'s model is

$$MAP_{j,t,L} = \alpha_{j.L} + \beta_{j,L,MKT}R_{MKT,t} + \beta_{j,L,MKT^2}R^2_{MKT,t} + \varepsilon_{j,t,L}, \quad j = 1, \ldots, 10, \tag{14}$$

$$TLS_{t,L} = \alpha_L + \beta_{L,MKT}R_{MKT,t} + \beta_{L,MKT^2}R^2_{MKT,t} + \varepsilon_{t,L}, \tag{15}$$

These is a quadratic model where $R^2_{MKT,t}$ is the squared market excess return. If the coefficients are significantly positive, it indicates that the strategies may have some market timing ability.

Henriksson and Merton (1981) propose the following model to test market timing ability:

$$MAP_{j,t,L} = \alpha_{j.L} + \beta_{j,L,MKT}R_{MKT,t} + \gamma_{j,L,MKT}R_{MKT,t}I_{r_{MKT,t}>0} + \varepsilon_{j,t,L}, \quad j = 1, \ldots, 10, \tag{16}$$

$$TLS_{t,L} = \alpha_L + \beta_{L,MKT}R_{MKT,t} + \gamma_{L,MKT}R_{MKT,t}I_{r_{MKT,t}>0} + \varepsilon_{t,L}, \tag{17}$$

In these regressions, the value of the indicator function, $I_{r_{MKT}}$, will be one if the market excess return is positive and zero otherwise. If the parameter $\gamma_{L,MKT}$ is significantly positive, it suggests that there is market timing ability.

The regression results of these two tests are shown in Table 7. Different from the results of Han et al. (2013) and Ko et al. (2014), most of the coefficients on β_{j,L,MKT^2} and $\gamma_{j,L,MKT}$ in our regressions are insignificant. In particular, both of the market timing coefficients for the TLS strategy are insignificant. In addition, the alpha values do not change substantially from our main findings. The overall results suggest that the profits generated by our strategy are not due to market timing ability.

Table 7. Market timing ability.

Rank	TM Regression				HM Regression			
	α	βmkt	βmkt²	Adj. R²	α	βmkt	γmkt	Adj. R²
Low	7.22	−0.45	0.30	0.40	3.39	−0.49	0.08	0.40
	(3.93)	(−18.54)	(0.50)		(1.23)	(−13.02)	(1.41)	
2	3.88	−0.49	1.03	0.43	−1.46	−0.56	0.14	0.43
	(2.01)	(−18.82)	(1.55)		(−0.50)	(−13.55)	(2.40)	
3	4.14	−0.46	0.52	0.39	0.21	−0.51	0.09	0.39
	(2.05)	(−17.14)	(0.73)		(0.07)	(−11.84)	(1.48)	
4	6.13	−0.51	0.41	0.43	1.51	−0.56	0.10	0.44
	(3.05)	(−18.65)	(0.57)		(0.49)	(−12.74)	(1.53)	
5	4.29	−0.53	0.76	0.44	−0.20	−0.58	0.11	0.44
	(2.18)	(−19.11)	(1.09)		(−0.07)	(−13.19)	(1.82)	
6	5.86	−0.49	−0.07	0.40	2.56	−0.51	0.05	0.40
	(3.14)	(−17.54)	(−0.10)		(0.86)	(−11.55)	(0.81)	
7	4.72	−0.51	0.49	0.41	−0.43	−0.56	0.11	0.41
	(2.44)	(−18.15)	(0.72)		(−0.14)	(−12.77)	(1.76)	
8	3.22	−0.53	1.20	0.43	−3.06	−0.61	0.16	0.43
	(1.61)	(−18.61)	(1.65)		(−0.99)	(−13.30)	(2.51)	
9	4.92	−0.49	0.23	0.39	0.93	−0.52	0.08	0.39
	(2.61)	(−17.38)	(0.33)		(0.31)	(−11.72)	(1.21)	
High	2.73	−0.50	0.61	0.40	−2.15	−0.55	0.11	0.40
	(1.45)	(−17.70)	(0.88)		(−0.72)	(−12.29)	(1.74)	
High–Low	−4.49	−0.05	0.31	0.01	−5.53	−0.06	0.03	0.01
	(−3.61)	(−3.22)	(1.15)		(−3.29)	(−2.77)	(0.94)	
TLS	11.88	−0.09	0.43	0.01	7.52	−0.14	0.09	0.01
	(3.58)	(−1.86)	(0.35)		(1.42)	(−1.85)	(0.86)	

Two methods are used to test the market timing ability. One is $MAP_{j,t,L} = \alpha_{j.L} + \beta_{j,L,MKT}R_{MKT,t} + \beta_{j,L,MKT^2}R^2_{MKT,t} + \varepsilon_{j,t,L}$. These are quadratic models, where $R^2_{MKT,t}$ the squared market excess return. The other model is $MAP_{j,t,L} = \alpha_{j.L} + \beta_{j,L,MKT}R_{MKT,t} + \gamma_{j,L,MKT}R_{MKT,t}I_{r_{MKT,t}>0} + \varepsilon_{j,t,L}$. In these regressions, we have $I_{r_{MKT,t}>0}$. The value of this indicator function will be one if the market excess return is positive and will be zero otherwise. *t*-test statistics are presented in the parentheses.

4.4. Subsample of Short-Selling

As China's stock market is very young, the government and stock exchanges have implemented a number of regulations to stabilize investors' trading behaviors and control risks. On 31 March 2010, China lifted the restriction on short-selling and allowed certain large cap stocks to be short-sold by qualified investors. The list quickly expanded in the following years, and short-selling activities in China developed rapidly.

Because short-selling was not allowed before 2010, it may not be possible to implement the MA and TLS strategies for our whole sample period. To check whether the profits generated from our strategies are realistic, we re-ran our tests in the period after 2010, when short-selling was flexible. Because not all stocks can be short-sold, when we conduct the TLS strategy, some stocks in the low BM portfolio cannot be shorted in the real market. We exclude those stocks and perform a subsample test from 31 March 2010 to 30 June 2015. We repeat the method used in Section 4.1 to obtain the summary statistics of the average returns of BM deciles, MA(20), and MAP(20) strategy.

From the summary statistics in Table 8, we find that the moving average strategy still outperforms the tradition buy-and-hold strategy, with higher returns on all portfolios. Almost all of the MAPs are positive. The result of the zero-cost trading strategy (TLS) for MA(20) is 10.50 points (t = 3.25), which is much bigger than the result from the high-minus-low with buy-and-hold strategy. Obviously, the moving average indicator is useful, and the TLS strategy is profitable.

Table 8. Subsample of short-selling.

Rank	BM Decile Portfolios				MA(20) Timing Portfolios				MAPs			
	Ave Ret	Std Dev	Skew	*t*	Ave Ret	Std Dev	Skew	*t*	Ave Ret	Std Dev	Skew	*t*
Low	−0.53	20.78	−0.45	−0.06	4.31	16.94	0.01	0.62	4.22	7.02	0.33	1.47
2	1.68	21.79	−0.30	0.19	10.07	10.94	1.74	2.25	7.57	13.07	1.74	1.42
3	2.10	26.75	−0.25	0.19	2.44	24.12	−0.58	0.25	−0.25	5.58	0.92	−0.11
4	2.41	25.37	−0.24	0.23	10.17	14.66	1.67	1.70	6.93	14.02	1.69	1.21
5	0.48	27.54	−0.62	0.04	7.44	13.93	0.47	1.31	6.01	14.94	1.45	0.99
6	1.80	28.38	−0.49	0.16	9.07	15.86	1.16	1.40	6.47	15.42	1.41	1.03
7	0.48	29.43	−0.45	0.04	4.70	16.32	0.08	0.71	3.39	13.41	0.92	0.62
8	0.52	30.35	−0.59	0.04	5.97	19.34	0.77	0.76	4.63	13.11	1.16	0.87
9	0.67	31.17	−0.57	0.05	7.78	19.22	1.03	0.99	6.17	13.88	1.80	1.09
High	−0.81	32.97	−0.53	−0.06	6.77	16.41	1.63	1.01	6.84	19.27	1.99	0.87
High–Low	−0.94	12.81	−0.55	−0.18	1.76	7.90	−0.28	0.55	2.25	15.05	2.15	0.37
	(−0.18)				(0.99)				(0.45)			
TLS					10.50	14.12	1.61	1.82	10.86	15.62	0.43	1.70
					(3.25)				(2.81)			

Stocks that cannot be shorted are excluded from the lowest BM portfolio and a subsample test is performed for the period from 31 March 2010 to 30 June 2015. Summary statistics of average return of BM decile portfolios, MA(20) strategy and MAP returns. *t*-test statistics are presented in the parentheses.

In conclusion, excluding stocks that cannot be shorted in the lowest BM portfolio, the moving average technical analysis indicator and proposed TLS strategy work well and still contribute impressive and significant excess returns. This subsample test provides further evidence for the validity and usefulness of our two trading strategies.

5. Conclusions

In this paper, we first use the buy-and-hold strategy to confirm the existence of value premium in China's stock market. We then use a technical analysis tool, the moving average indicator, to conduct trade on the decile BM portfolios. The results suggest that technical analysis is workable and has superior performance compared to the buy-and-hold strategy. Next we construct a zero-cost trading strategy by longing the high BM portfolio and shorting the low BM portfolio at the same time using the moving average indicator and find a much higher average excess return. Using the CAPM, FF3F, and LIQ4F models, the returns of our strategy are still positive and significant. In addition, the profits remain positive and significant after tests are conducted using different lag length moving average indicators and considering transaction costs.

Robustness tests are essential in our study. We discover that non-tradable share reforms and business cycles do not affect the predictability of technical analysis, and market-timing ability cannot explain it either. Finally, we conduct tests in the period in which short-selling is allowed and find that significant positive profits still exist in the subsample.

This study makes an initial attempt to unveil the profitability of combined trading strategies in China's stock market. Extensions of our combined strategies would include other technical analysis, such as candlestick analysis and relative strength index, and firm characteristics, such as size and liquidity. Another direct extension would be to identify more drivers of profitability by investigating more macroeconomic and risk factors, such as investment and profitability.

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Review

Review on Efficiency and Anomalies in Stock Markets

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Abstract: The efficient-market hypothesis (EMH) is one of the most important economic and financial hypotheses that have been tested over the past century. Due to many abnormal phenomena and conflicting evidence, otherwise known as anomalies against EMH, some academics have questioned whether EMH is valid, and pointed out that the financial literature has substantial evidence of anomalies, so that many theories have been developed to explain some anomalies. To address the issue, this paper reviews the theory and literature on market efficiency and market anomalies. We give a brief review on market efficiency and clearly define the concept of market efficiency and the EMH. We discuss some efforts that challenge the EMH. We review different market anomalies and different theories of Behavioral Finance that could be used to explain such market anomalies. This review is useful to academics for developing cutting-edge treatments of financial theory that EMH, anomalies, and Behavioral Finance underlie. The review is also beneficial to investors for making choices of investment products and strategies that suit their risk preferences and behavioral traits predicted from behavioral models. Finally, when EMH, anomalies and Behavioral Finance are used to explain the impacts of investor behavior on stock price movements, it is invaluable to policy makers, when reviewing their policies, to avoid excessive fluctuations in stock markets.

Keywords: market efficiency; EMH; anomalies; Behavioral Finance; Winner–Loser Effect; Momentum Effect; calendar anomalies; BM effect; the size effect; Disposition Effect; Equity Premium Puzzle; herd effect; ostrich effect; bubbles; trading rules; technical analysis; overconfidence; utility; portfolio selection; portfolio optimization; stochastic dominance; risk measures; performance measures; indifference curves; two-moment decision models; dynamic models; diversification; behavioral models; unit root; cointegration; causality; nonlinearity; covariance; copulas; robust estimation; anchoring

JEL Classification: A10; G10; G14; O10; O16

1. Introduction

The efficient-market hypothesis (EMH) is one of the most important economic and financial hypotheses that have been tested over the past century. Traditional finance theory supporting EMH is based on some important financial theories, including the arbitrage principle (Modigliani and Miller 1959, 1963; Miller and Modigliani 1961), portfolio principle (Markowitz 1952a), Capital Asset Pricing Model (Treynor 1961, 1962; Sharpe 1964; Lintner 1965; Mossin 1966), arbitrage pricing theory (Ross 1976), and option pricing theory (Black and Scholes 1973). In addition, Adam Smith (Smith 1776) commented that the rational economic man will chase the maximum personal profit. When a rational economic individual comes to stock markets, they become a rational economic investor who aims to maximize their profits in stock markets.

However, an investor's rationality requires some strict assumptions. When not every investor in the stock market looks rational enough, the assumptions could be relaxed to include some "irrational" investors who could trade randomly and independently, resulting in offsetting the effects from each other so that there is no impact on asset prices (Fama 1965a).

What if those "irrational" investors do not trade randomly and independently? In this situation, Fama (1965a) and others have commented that rational arbitrageurs will buy low and sell high to eliminate the effect on asset prices caused by "irrational" investors. Fama and French (2008) pointed out that the financial literature is full of evidence of anomalies. Another school (see, for example, Guo and Wong (2016) and the references therein for more information) believes that Behavioral Finance is not caused by "irrational" investors but is caused by the existence of many different types of investors in the market.

In this paper, we review the theory and the literature on market efficiency and market anomalies. We give a brief review on market efficiency and define clearly the concept of market efficiency and the efficient-market hypothesis (EMH). We discuss some efforts that challenge the EMH. For example, we document that investors may not carry out the dynamic optimization problems required by the tenets of classical finance theory, or follow the Vulcan-like logic of the economic individual, but use rules of thumb (heuristic) to deal with a deluge of information and adopt psychological traits to replace the rationality assumption, as suggested by Montier (2004). We then review different market anomalies, including the Winner–Loser Effect, reversal effect; Momentum Effect; calendar anomalies that include January effect, weekend effect, and reverse weekend effect; book-to-market effect; value anomaly; size effect; Disposition Effect; Equity Premium Puzzle; herd effect and ostrich effect; bubbles; and different trading rules and technical analysis.

Thereafter, we review different theories of Behavioral Finance that might be used to explain market anomalies. This review is useful to academics for developing cutting-edge treatments of financial theory that EMH, anomalies, and Behavioral Finance underlie. The review is also beneficial to investors for making choices of investment products and strategies that suit their risk preferences and behavioral traits predicted from behavioral models. Finally, when EMH, anomalies, and Behavioral Finance are used to explain the impacts of investor behavior on stock price movements, it is invaluable to policy makers in reviewing their policies to avoid excessive fluctuations in stock markets.

The plan of the remainder of the paper is as follows. In Section 2, we define the concept of market efficiency clearly, review the literature on market efficiency, and discuss several models to explain market efficiency. We discuss some market anomalies in Section 3 and evaluate Behavioral Finance in Section 4. Section 5 gives some concluding remarks.

2. Market Efficiency

The concept of market efficiency is used to describe a market in which relevant information is rapidly impounded into the asset prices so that investors cannot expect to earn superior profits from their investment strategies. In this section, we define the concept of market efficiency clearly, review the literature of market efficiency, and discuss several models to explain market efficiency.

2.1. Definition of Market Efficiency

The definition of market efficiency was first anticipated in a book written by Gibson (1889), entitled *The Stock Markets of London, Paris and New York*, in which he wrote that, when "shares become publicly known in an open market, the value which they acquire may be regarded as the judgment of the best intelligence concerning them".

In 1900, a French mathematician named Louis Bachelier published his PhD thesis, *Théorie de la Spéculation* (Theory of Speculation) (Bachelier 1900). He recognized that "past, present and even discounted future events are reflected in market price, but often show no apparent relation to price changes". Hence, the market does not predict fluctuations of asset prices. Moreover, he deduced that "The mathematical expectation of the speculator is zero", which is a statement that is in line with Samuelson (1965), who explained efficient markets in terms of a martingale. The empirical implication is that asset prices fluctuate randomly, and then their movements are unpredictable. Bachelier's contribution to the origin of market efficiency was discovered when his work was published in English by Cootner (1964) and discussed in Fama (1965a, 1970).

2.2. Early Development in EMH

Pearson (1905) introduced the term *random walk* to describe the path taken by a drunk, who staggers in an unpredictable and random pattern. Kendall and Hill (1953) examined weekly data on stock prices and finds that they essentially move in a random-walk pattern with near-zero autocorrelation of price changes. Working (1934) and Roberts (1959) found that the movements of stock returns look like a random walk. Osborne (1959) showed that the logarithm of common stock prices follows Brownian motion and finds evidence of the square root of time rule.

If prices follow a random walk, then it is difficult to predict the future path of asset prices. Cowles (1933, 1944) and Working (1949) documented that professional forecasters cannot successfully forecast, and professional investors cannot beat the market. Granger and Morgenstern (1963) found that short-run movements of the price series obey the random-walk hypothesis, using spectral analysis, but that long-run movements do not. There is evidence of serial correlation in stock prices (Cowles and Jones 1937) which, however, could be induced by averaging (Working 1960, and Alexander 1961). Cowles (1960) reexamined the results in Cowles and Jones (1937) and still found mixed evidence of serial correlation even after correcting an error caused by averaging.

2.3. Recent Developments in Market Efficiency

The 2013 Nobel laureate, Eugene Fama, provided influential contributions to theoretical and empirical investigation for the recent development of market efficiency. According to Fama (1965a), an efficient market is defined as a market in which there are many rational, profit-maximizing, actively competing traders who try to predict future asset values with current available information. In an efficient market, competition among many sophisticated traders leads to a situation where actual asset prices, at any point in time, reflect the effects of all available information, and therefore, they will be good estimates of their intrinsic values.

The intrinsic value of an asset depends upon the earnings prospects of the company under study, which is not known exactly in an uncertain world, so that its actual price is expected to be above or below its intrinsic value. If the number of the competing traders is large enough, their actions should cause the actual asset price to wander randomly about its intrinsic value through offsetting mechanisms in the markets, and then the resulting successive price changes will be independent. Independent successive price changes are then consistent with the existence of an efficient market.

A market in which the prices of securities change independently of each other is defined as a random-walk market (Fama 1965a). Fama (1965b) linked the random-walk theory to the empirical study on market efficiency. The theory of random walk requires successive prices changes to be independent and to follow some probability distribution.

When the flow of news coming into the market is random and unpredictable, current price changes will reflect only current news and will be independent of past price changes. Hence, independence of successive price changes implies that the history of an asset price cannot be used to predict its future prices and increase expected profits. It is then consistent with the existence of an efficient market. Using serial correlation tests, run tests, and Alexander's (1961) filter technique, Fama (1965b) concluded that the independence of successive price changes cannot be rejected. Then, there are no mechanical trading rules based solely on the history of price changes that would make the expected profits of the market traders higher than buy-and-hold.

The random-walk theory does not specify the shape of the probability distribution of price changes, which needs to be examined empirically. Fama (1965b) found that a Paretian distribution with characteristic exponents less than 2 fit the stock market data better than the Gaussian distribution; this finding is in line with the findings of Mandelbrot (1963). Hence, the empirical distributions have more relative frequency in their extreme tails than would be expected under a Gaussian distribution while the intrinsic values change by large amounts during a very short period of time.

2.4. EMH

A comprehensive review of the theory and evidence on market efficiency was first provided by Fama (1970). He defined a market in which asset prices at any time fully reflect all available information as efficient and then further introduced three kinds of tests of EMH that are concerned with different sets of relevant information. They are the weak-form tests based on the past history of prices; the semi-strong tests based on all public information, including the past history of price; and finally the strong-form tests based on all private, as well as public, information.

2.4.1. Weak-Form Tests

Weak-form tests are tests used to examine whether investors can earn abnormal profits from the past data on asset prices. If successive price changes are independent and then unpredictable, it is impossible for investors to earn more than buy-and-hold. In the literature, there is evidence of random walk and independence in the successive price changes in support of weak-form market efficiency (e.g., Alexander 1961; Fama 1965a, 1965b; Fama and Blume 1966). However, Fama (1970) documented some evidence of departures from random walk with non-zero serial correlations in successive price changes on stocks (e.g., Cootner 1964; Neiderhoffer and Osborne 1966). Nevertheless, Fama (1970) recognized that rejection of random-walk model does not imply market inefficiency. The independence assumption is too restrictive and not a necessary condition for EMH because market efficiency only requires the martingale process of asset returns (Samuelson 1965) with zero expected profits to the investors.

2.4.2. Semi-Strong-Form Tests

Semi-strong-form tests involve an event study, which is used to test the adjustment speed of asset prices in response to an event announcement released to the public. An event study averages the cumulative abnormal return (CAR) of assets of interest over time, from a specified number of pre-event time periods to a specified number of post-event periods. Fama et al. (1969) provided evidence on the reaction of share prices to stock split. The market seems to expect public information, and most price adjustments are made before the event is revealed to the market, with the rest quickly and accurately adjusted after the news is released. Fama et al. (1969) concluded that their results support the EMH. Apart from stock split, other event studies on earnings announcements (Ball and Brown 1968), announcements of discount rate changes (Waud 1970) and secondary offerings of common stocks (Scholes 1972) generally provide supportive evidence for the semi-strong form of market efficiency.

2.4.3. Strong-Form Tests

Strong-form tests are used to assess whether professional investors have monopolistic access to all private, as well as public, information so that they can outperform the market. Jensen (1968) evaluates the performance of mutual funds over the nineteen-year period of 1945–1964, on a risk-adjusted basis. The findings indicate that the funds cannot beat the market in favor of the strong-form market efficiency, regardless of whether loading charges, management fees, and other transaction costs are ignored.

Table 1 briefly summarizes Fama's (1970) taxonomy of EMH tests.

Table 1. Fama's (1970) taxonomy of efficient-market-hypothesis (EMH) tests.

Kinds of Tests	Relevant Information Sets	Methodology	Literatures
Weak form	Past history of price	Filter tests, run tests, random-walk tests	Alexander (1961); Fama (1965a, 1965b); Fama and Blume (1966)
Semi-strong form	Public information including past history of price	Event study	Fama et al. (1969); Ball and Brown (1968); Waud (1970); Scholes (1972)
Strong form	All private and public information	Mutual fund performance	Jensen (1968)

2.5. Explaining Market Efficiency by Factor Models

Under the traditional framework of rational and frictionless agents, the price of a security equals its "fundamental value". This is the present value sum of expected future cash flows, where at the time of forming the expectation, the investor handles all available information properly, and the discount rate is in line with the normal acceptable preference norm. In an efficient market, no investment strategy can obtain a risk-adjusted excess average return, or higher than the average return guaranteed by its risk, which means that there is no "free lunch" (Barberis and Thaler 2003). If EMH is applied to understand the volatility of stock market prices, there should be enough evidence to justify price changes, by showing that real investment values change over time.

Taking the American stock market as an example, from 1871 to 1986, the change of the total real investment value of the stock market was measured by three factors: the change of dividend, the change of real interest rate, and the direct measure of the inter-period marginal substitution rate (Shiller 1987). In this section, we introduce some famous models, using different factors that help examine reasons behind price changes of securities or abnormal profits. Although there are abnormal profits in the market, as long as methods are provided to predict or calculate the price that brings out the abnormal returns, the abnormal profits will return to zero and make the market efficient again, with the help of rational arbitrageur's buying low and selling high.

2.5.1. Fama–French Three-Factor Model

Merton (1973)'s ICAPM and Ross's APT (1976), Fama and French (1993) first documented that a Three-Factor Model could be established to explain stock returns, which is more significant than ICAPM and APT. The model considers that the excess return of a portfolio (including a single stock) can be explained by its exposure to three factors: market risk premium (*RMRF*), market value factor (*SMB*, Small market capitalization Minus Big market capitalization), book-to-market ratio factor (*HML*, High book-to-market ratio Minus Low book-to-market ratio). Based on monthly data of Pakistan financial and non-financial firms from 2002 to 2016, Ali et al. (2018) showed that the Pakistani stock market is satisfactorily explained by the Three-Factor Model, especially with the addition of SMB and HML.

2.5.2. Carhart Four-Factor Model

There are limitations in the Fama–French Three-Factor Model, as factors like short-term reversal, medium-term momentum, volatility, skewness, gambling, and others are not considered or included. Based on the Fama–French Three-Factor Model, Carhart (1997) developed an extended version which includes a momentum factor for asset pricing in stock markets. The extra consideration is *PR1YR*, which is the return for the one-year momentum in stock returns. By applying this Four-Factor Model, Carhart (1997) claimed that it helps to explain a significant amount of variations in time series. Furthermore, the high average returns of *SMB*, *HML*, and *PR1YR* indicate that these three factors could explain the large cross-sectional variation of the average returns of stock portfolios.

2.5.3. Fama–French Five-Factor Asset-Pricing Model

Although Carhart's Four-Factor Model helped develop the Fama–French Three-Factor Model, Fama and French (2015) figured out a new augmentation of the Three-Factor Model by considering profitability and investment factors, which is called the Five-Factor Asset-Pricing Model, to fix more anomaly variables that cause problems to the Three-Factor Model. In addition, Fama and French (2015) concluded that the ability of the Five-Factor Model on capturing mean stock returns performs better than the Three-Factor Model.

However, the Five-Factor Model did have its drawbacks. For those low mean returns on small stocks, just like returns of those firms invest heavily regardless of low profitability, it fails to seize, and it was tested in North America, Europe, and Asia-Pacific stock markets by Fama and French (2017). Furthermore, the performance of the model is insensitive to the way in which the factors are defined. With the increase of profitability and investment factors, the value factors of the Three-Factor Model become superfluous for describing the mean return in the samples that Fama and French (2015) test.

2.5.4. Factor Models in Chinese Markets

Given the development of the factor model itself, Fama–French Three-Factor Model remains the benchmark in US stock markets for many years. Yet many studies copying Fama–French three factors in China's A-share market, have not achieved very satisfactory results until Liu et al.'s (2019) Chinese version Three-Factor Model. Given the strict IPO regulation rules in China's A share market, which consists of the fact that most of the smallest listed firms are targeted as potential, and reflecting the value of, shells, in order to develop this model, Liu, Stambaugh and Yuan deleted 30% of stocks at the bottom to avoid small listed firms whose values are contaminated by shell-values. Furthermore, they use EP (earning-to-price ratio) to replace BM (book-to-market ratio) due to the former capturing the value effect more accurately in China in the sense that it is the most significant factor.

Using this Chinese version of the Three-Factor Model, most reported anomalies in China's A-share market are well explained, where profitability and volatility anomalies are included. Furthermore, Liu et al. (2019) add the turnover factor PMO (Pessimistic minus Optimistic) into the model to make it a Four-Factor Model and help explain reversal and turnover anomalies. Same on the studies of China stock markets, based on the Fama–French Five-Factor Model, Li et al. (2019) developed a Seven-Factor Model by adding trading volume and turnover rates factors.

When additional factors are included, the Chinese version of the Seven-Factor Model performs well in empirical testing of herding behavior in China's A-share market, especially during three famous stock market crash periods.

Table 2 briefly summarizes factor models that explain market efficiency.

Table 2. Explaining market efficiency by factor models.

Kinds of Models	Factors in Models	Literatures
Fama–French Three-Factor Model	*RMRF*, *SMB*, and *HML*	Fama and French (1993)
Carhart Four-Factor Model	*RMRF*, *SMB*, *HML*, and *PR1YR*	Carhart (1997)
Fama–French Five-Factor Asset Pricing Model	*RMRF*, *SMB*, *HML*, and profitability and investment factors	Fama and French (2015)
Chinese version Three-Factor Model	*RMRF*, *SMB*, and *EP*	Liu et al. (2019)
Chinese version Four-Factor Model	*RMRF*, *SMB*, *EP*, and *PMO*	Liu et al. (2019)
Chinese version Seven-Factor Model	*RMRF*, *SMB*, *HML*, profitability factors, investment factors, trading volume, and turnover rates factors	Li et al. (2019)

Apart from above models, there are methods measuring or explaining liquidity in stock markets. For low-frequency data, there are spread proxies, including Roll's (1984) spread (ROLL), Hasbrouck's (2009) Gibbs estimate (HASB), LOT measure provided by Lesmond et al.'s (1999) study, and others, while there are also price impact proxies, including the AMIHUD, a measure came up by Amihud (2002), the Amivest measure, or AMIVEST set up by Cooper et al. (1985), and the PASTOR estimate put up by Pástor and Stambaugh (2003). Ahn et al. (2018) studied tick data of 1183 stocks of 21 emerging markets and proved that LOT measure and AMIHUD are the best proxy among the three, respectively.

2.6. Explaining Market Efficiency in Subdividing Areas

There is substantial evidence to show that markets are inefficient (see, for example, Jensen 1978; Lehmann 1990; Fama 1998; Chordia et al. 2008). Loughran and Ritter (2000) suggested that multifactor models and time-series regressions should not be used to test for market efficiency.

Market efficiency has withstood the challenge of the long-term return anomaly literature. Consistent with the assumption that anomalies in market efficiency are accidental outcomes, apparent overreactions to information are as common as underreactions, and the after-event continuation of abnormal returns before an event is as frequent as the reversal after an event. Most importantly, the obvious anomalies can be methodological, and most long-term outliers, tend to disappear as technology makes sense, as market efficiency predicts (Fama 1998). Dimson and Mussavian (1998) recorded a large number of studies showing that abnormal behaviors seem inconsistent with market efficiency at first glance.

The review and analysis of market efficiency above are not the whole stories due to continuous studies are ongoing. There are supportive academics showing that EMH is significant in subdividing areas. Jena et al. (2019) proved that both volumes Put–Call Ratio and open interest Put–Call Ratio could be sufficient predictor of market returns under certain conditions. Chang et al. (2019) pointed out that the use of financial constraints has a significant positive impact on the long-term performance of companies after issuing convertible bonds.

Based on a Structure Equation Model (SEM), Li and Zhao (2019) claimed that the comprehensive effect of housing on stock investment is positive under the background of Chinese cities. Chiang (2019) studied monthly data from 15 stock markets, along with economic policy uncertainty (EPU) as a news variable, and found that news is able to predict stock market future returns. Ehigiamusoe and Lean (2019) pointed out that financial development has a long-term positive impact on economic growth, while the real exchange rate and its volatility weaken this impact. The development of the financial sector will not bring ideal economic benefits unless it is accompanied by the decline and stability of the real exchange rate.

Moreover, in some simulation cases, possibilities are found to help explain market efficiency. For example, in the experiment of Zhang and Li (2019), AR and TAR models with gamma random errors were tested on empirical volatility data of 30 stocks, with 33% of them being very suitable, indicating that the model may be a supplement to the current Gaussian random error model with appropriate adaptability. In addition, in some cases, scholars will examine and compare several methods on market efficiency explanation, before applicable practical prediction. Guo et al. (2017b) used first-order stochastic dominance and the Omega ratio in market efficiency examination and applied the theory they put forward to test the relationship between the scale of assets and real-estate investment in Hong Kong.

It is possible that scholars will find conflicts again. When studying impacts of exchange rates on stock markets, Ferreira et al. (2019) found that the exchange rate has a significant impact on Indian stock market, while there is no significant impact on European stock market. In the research of Lee and Baek (2018), although changes in oil prices do have a significant and positive impact on renewable energy stock prices in an asymmetric manner, it is a short-term impact only. Although in some of the cases, the existing models could not be considered, or quantitative analysis and modeling are still in progress, it is reasonable to postulate that, if the abnormal returns underlying anomalies are well explained, the market will become efficient with arbitrage.

Many scholars hypothesize that stock prices that are determined in efficient markets cannot be cointegrated. Nonetheless, Dwyer and Wallace (1992) showed that market efficiency or the existence of arbitrage opportunities are not related to cointegration. However, Guo et al. (2017b) developed statistics that academics and practitioners can use to test whether the market is efficient, whether or not there are any arbitrage opportunities, and whether there is any anomaly. Stein (2009) examined whether the market is efficient by both crowding and leverage factors for sophisticated investors.

Chen et al. (2011) applied cointegration and the error-correction method to obtain an interdependence relationship between the Dollar/Euro exchange rate and economic fundamentals. They found that both price stickiness and secular growth affect the exchange rate path. Clark et al. (2011) applied stochastic dominance to get efficient portfolio from an inefficient market. By applying a stochastic dominance test, Clark et al. (2016) examined the Taiwan stock and futures markets,

Lean et al. (2015) examined the oil spot and futures markets; Qiao and Wong (2015) examined the Hong Kong residential property market; and Hoang et al. (2015b) examined the Shanghai gold market. Each of these papers concluded that the markets are efficient. However, Tsang et al. (2016) examined the Hong Kong property market by using the rental yield, and concluded that the market is not efficient and there exist arbitrage opportunities in the Hong Kong property market.

3. Market Anomalies

There are many market anomalies that are important areas of theoretical and practical interest in Behavioral Finance. As many market anomalies have been observed that EMH cannot explain, many academics have to think of a new theory to explain market anomalies found, and this make a very important new area in finance, Behavioral Finance, which can be used to explain many market anomalies. We discuss some market anomalies in this section and discuss Behavioral Finance in the next section.

3.1. Winner–Loser Effect/Reversal Effect

De Bondt and Thaler (1985, 1987) found that investors are too pessimistic about the past loser portfolio and too optimistic about the past winner portfolio, resulting in the stock price deviating from its basic value. After a period of time, when the market is automatically correct, past losers are winning positive excess returns, while past winners are having negative excess returns, which support the Winner–Loser Effect. In particular, stocks used in the experiment of De Bondt and Thaler (1985) are those top 35 and those worst 35 in the long-term (five years period), then a return reversal happens in the next three years. Thus, a new method can be advanced to predict stock returns: using reversal strategy to buy the loser portfolio in the past three to five years and sell the winner portfolio.

This strategy enables investors to obtain excess returns in the next three to five years. Further, Jegadeesh (1990) and Lehmann (1990), respectively, proved that return reversal also happens in the short-term. The representative heuristic (Tversky and Kahneman 1974), for example, people tend to rely too heavily on small samples and rely too little on large samples, inadequately discount for the regression phenomenon, and discount inadequately for selection bias in the generation or reporting of evidence (Hirshleifer 2001), can be used to explain the Winner–Loser Effect.

Thus, due to the existence of representative heuristics, investors show excessive pessimism about the past loser portfolio and excessive optimism about the past winner portfolio, that is, investors overreact to both good news and bad news. This will lead to the undervaluation of the loser portfolio price and the overvaluation of the winner portfolio price, causing them to deviate from their basic values.

3.2. Momentum Effect

At the moment when more and more empirical evidences are gathered to testify Winner–Loser Effect, Jegadeesh and Titman (1993) found that stock returns are positively correlated in the period of 3–12 months, i.e., the Momentum Effect. If stock returns are examined over a period of six months, the average return of the "winner portfolio" is about 9% higher than that of the "loser portfolio". Chan et al. (1996) enlarged Jegadeesh and Titman's (1993) research samples and obtained the same results.

Research conducted by Rouwenhorst (1998) showed that the Momentum Effect also exists in other developed markets and some emerging stock markets. Moskowitz and Grinblatt (1999) studied the Momentum Effect of portfolio selected by industry, and they found that the industry portfolio has significant Momentum Effect in the US stock market, and the abnormal return is larger than that of individual portfolio.

Unlike other researchers in the literature, Asness et al. (2014) challenged the existence of momentum itself, instead of explaining it by claiming the limitation of momentum. They proved that momentum return is small in size, fragmentary, under the concern of disappearing, and only applicable in short position. In the second place, momentum itself is unstable to rely on, behind which there is no theory. Last but not least, momentum might not exist or be limited by taxes or transaction costs, and it provides various results, depending on different momentum measures in a given period of time.

3.3. Calendar Anomalies—January Effect, Weekend Effect, and Reverse Weekend Effect

3.3.1. January Effect

The January Effect was first discovered by Wachtel (Wachtel). In a further research, Rozeff and Kinney (1976) found that the return of NYSE's stock index in January from 1904 to 1974 was significantly higher than that of other 11 months. Gultekin and Gultekin (1983) studied the stock returns of 17 countries from l959 to l979, and found that 13 of them had higher stock returns in January than in other months. Lakonishok et al. (1998) found that, between l926 and l989, the smallest 10% of stock returns exceeded those of other stocks in January. Nippani and Arize (2008) found strong evidence of the January Effect in the study of three major US market indices: corporate bond index, industrial index, and public utility index from, 1982 to 2002. However, according to Riepe (1998), the January Effect is weakening.

The most important explanations for the January Effect are the Tax-Loss Selling Hypothesis (Gultekin and Gultekin 1983) and the Window Effect Hypothesis (Haugen and Lakonishok 1988): the Tax-Loss Selling Hypothesis holds that people will sell down stocks at the end of the year, thereby offsetting the appreciation of other stocks in that year, in order to achieve the purpose of paying less tax. After the end of the year, people buy back these stocks. This collective buying and selling leads to a year-end decline in the stock market and a January rise in the stock market the following year.

The Window Effect Hypothesis holds that institutional investors want to sell losing stocks and buy profitable stocks to decorate year-end statements. This kind of trading exerts positive price pressure on profitable stocks at the end of the year, and negative pressure on losing stocks. When the selling behavior of institutional investors stops at the end of the year, the losing stocks that were depressed in the previous year will rebound tremendously in January, leading to a larger positive trend of income generation.

Sias and Starks (1997), Poterba and Weisbenner (2001), and Chen and Singal (2004) compared and analyzed the explanatory effect of the Window Effect Hypothesis and Tax-Loss Selling Hypothesis on the January Effect, and preferred the explanation of Tax-Loss Selling Hypothesis. Starks et al. (2006), based on the above research, through the study of closed-end funds of municipal bonds, further proved that the Tax-Loss Selling Hypothesis is the real reason for the January Effect.

3.3.2. Weekend Effect and Reverse Weekend Effect

In distinguish or test between the Weekend Effect and Reverse Weekend Effect is easy. When one gets higher returns on Friday than on Monday, it is regarded as the Weekend Effect, and when one gets higher returns on Monday rather on Friday, it is called the Reverse Weekend Effect. Weekend effects have been identified in the foreign-exchange and money markets, as well as in stock market returns by many scholars. Based on daily data from 1990 to 2010, in the world, Europe, and other countries, Bampinas et al. (2015) investigated the weekend effect of the Securitization Real Estate Index and concluded that the average return rate on Friday is significantly higher than that on other days of the week. Chan and Woo (2012) found the evidence of reverse weekend effect when Monday exhibited the highest returns for the H-shares index in Hong Kong from 3 January 2000 to 1 August 2008.

However, Olson et al. (2015) examined the US stock market with cointegration analysis and breakpoint analysis and concluded that, after the discovery of the weekend effect in 1973, the weekend effect tends to weaken and disappears in the long run. In the United States, although the effect appears to be stronger in the 1970s than in earlier or later times, there already exist various explanations for stock market behavior on weekends. For example, the regular Weekend Effect has been attributed to payment and check-clearing settlement lags.

Kamstra et al. (2000) claimed that the importance of daylight-saving-time changes indicated in their paper makes the issue something well worth sleeping on, and a matter that is as worthy of further study as to other explanations of the weekend anomaly. When the Weekend Effect weakens and disappears, the Reverse Weekend Effect will appear. In the continuous studies of Brusa et al. (2000, 2003, 2005), the Reverse Weekend Effect was found: (1) The main stock indexes have the Reverse Weekend Effect. (2) The Weekend Effect tends to be related to small firms, while the Reverse Weekend Effect tends to be related to large firms. During the period in which Reverse Weekend Effect is observed, the Monday returns of large firms tend to follow the positive Friday returns of last Friday, but they do not follow the negative Friday returns. (3) After 1988, both the broad market index and the industry index showed positive returns on Monday. Returns were regressed, with Monday as a dummy variable, in Brusa et al.'s (2011) research, and they emphasized that the Reverse Weekend Effect is widely distributed in large companies, not just a few.

3.4. Book-to-Market Effect/Value Anomaly

Many studies have been undertaken on the Book-to-Market (BM) effect by scholars around the world. Fama and French (1992) studied all stocks listed in NYSE, AMEX and NASDAQ from 1963 to 1990 and found that the combination with the highest BM value (value portfolio) had a monthly average return of 1.53% over the combination with the lowest BM value (charm portfolio). Wang and Xu (2004) took A-share stocks in Shanghai and Shenzhen stock markets from June 1993 to June 2002 as samples, calculated the return data of holding one, two, and three years, and considered that the BM effect exists. The same conclusion was drawn by Lam et al.'s (2019) study covering data from July 1995 to June 2015 in Chinese stock markets.

Black (1993) and MacKinlay (1995) argued that BM effect exists only in a specific sample during a specific test period, and is the result of data mining, which is not the same as what Kothari et al. (1995) found: It is the selection bias in the formation of BM combination that causes the BM effect. However, Chan et al. (1991), Davis (1994), and Fama and French (1998) tested the stock market outside the United States or during the extended test period, and still found that the BM effect existed significantly, negating the argumentation of Black (1993) and MacKinlay (1995).

Fama and French (1992, 1993, 1996) asserted that BM represents a risk factor, i.e., financial distress risk. Companies with high BM generally have poor performance in profitability, sales, and other fundamental aspects. Their financial situation is also more fragile, making their risk higher than that of companies with low BM. What is also considered is that the high return obtained by companies with high BM is only the compensation for their own high risk, and is not the unexplained anomaly. Furthermore, for the BM effect on the international level, Fama and French (1998) confirmed that a Two-Factor Model with a relative distress risk factor added could explain it rather than an international CAPM.

De Bondt and Thaler (1987) and Lakonishok et al. (1994) agreed that the BM effect is caused by investors' overreaction to company fundamentals. On the premise of confirming the positive correlation between BM and the company's fundamentals, as investors are usually too pessimistic about companies with poor fundamentals and too optimistic about companies with good fundamentals, when the overreaction is corrected, the profits of high BM companies will be higher than those of low BM companies.

3.5. The Size Effect

Banz (1981) found that the stock market value decreased with the increase of company size. The phenomenon that small-cap stocks earn higher returns than those calculated by CAPM (Reinganum 1981) and large-cap stocks (Siegel 1998) clearly contradicts EMH especially in January, as size of the firm and arrival of January are regarded as public information. Lakonishok et al. (1994) found that, since the stock with high P/E ratio is riskier, if P/E ratio is presumed to be known information, then this negative relationship between P/E ratio and return rate provides a considerable prediction on the latter, bringing a serious challenge to EMH.

On the contrary, Daniel and Titman (1997) claimed that BM and size only represent the preference of investors, not the determinants of returns. Due to the poor fundamentals of high BM companies and good fundamentals of low BM companies, while investors prefer to hold value stocks with good fundamentals rather than those with poor fundamentals, the return rate of companies with high BM is higher.

3.6. Disposition Effect

Shefrin and Statman (1985) proposed that the Disposition Effect refers to two phenomena of the stock market: The first is that investors tend to have a strong psychology of holding loss-making stocks and are not willing to realize losses; and the second is that investors tend to avoid risks before profits, thereby willing to sell stocks in order to lock in profits. In these cases, two kinds of psychology are added to describe investors where regret and embarrassment cause the first phenomenon, and arrogance leads to the second.

The Disposition Effect is one implication of extending Kahneman and Tversky's prospect theory (1979) to investments. For example, suppose an investor purchases a stock that she believes to have an expected return high enough to justify its risk. If the stock appreciates and she continues to use the purchase price as a reference point, the stock price will then be in a more concave, risk-averse part of the investor's value function. The stock's expected return may continue to justify its risk, but if the investor lowers her expectation for the stock's return somewhat, she will be likely to sell the stock. If instead of appreciating, the stock declines, its price is in the convex, risk-seeking part of the value function.

Consequently, the investor will continue to hold the stock even if its expected return falls lower than would have been necessary for her to justify its original purchase. Thus, the investor's belief about expected return must fall further, to motivate the sale of a stock that has already declined rather than one that has appreciated. Similarly, suppose an investor holds two stocks. One is up, and the other is down. If he is facing a liquidity demand and has no new information about either stock, he is more likely to sell the stock that is up (Barber and Odean 1999).

In addition, Kahneman and Tversky (1979) argued that investors are more concerned with regret than arrogance, and therefore are more willing to take no action, which leads investors to be reluctant to lose or make a profit, while those who do not sell profitable shares worry that prices will continue to rise. In other words, if one investor is not confident enough in trading stocks, he or she tends to follow investment advisers' decision or advice to buy or sell a stock, which, at least, no matter the selected stock gains or losses, he or she is not the one to be blamed and thus reduces the feeling of regret.

Locke and Mann (2015) provided evidence that professional futures floor traders appear to be subject to Disposition Effect. These traders as a group hold losing trades longer on average than gains. Their evidence also indicates that relative aversion to loss realization is related to contemporaneous and future trader relative success. Though many factors can coordinate trading (e.g., tax-loss selling, rebalancing, changing risk preference, or superior information), Barber et al. (2005) argued their empirical results are primarily driven by three behavioral factors: the representativeness heuristic, limited attention, and the disposition. When buying, similar beliefs about performance persistence in individual stocks may lead investors to buy the same stocks—a manifestation of the representativeness heuristic.

Investors may also buy the same stocks simply because those stocks catch their attention. In contrast, when selling, the extrapolation of past performance and attention play a secondary role. Attention is less of an issue for selling, since most investors refrain from short selling and can easily give attention to the few stocks they own. If investors solely extrapolated past performance, they would sell losers. However, they do not. This is because, when selling, there is a powerful countervailing factor—the Disposition Effect—a desire to avoid the regret associated with the sale of a losing investment. Thus, investors sell winners rather than losers.

Barber et al. (2008) analyzed all trades made on the Taiwan Stock Exchange between 1995 and 1999 and provided strong evidence that, in aggregate and individually, investors have a Disposition Effect; that is, investors prefer to sell winners and hold losers. The Disposition Effect exists for both long and short position, for both men and women (to roughly the same degree), and tends to decline following periods of market appreciation.

Odean (1998a, 1999) proposed an indicator to measure the degree of Disposition Effect and used this indicator to verify the strong selling, earning, and losing tendency of US stock investors. Meanwhile, Odean also found that US stock investors sold more loss-making shares in December, making the effect less pronounced because of tax avoidance. In the research on the Disposition Effect of the Chinese stock market, Zhao and Wang (2001) concluded that Chinese investors are more inclined to sell profitable stocks and continue to hold loss-making stocks, which is more serious than foreign investors.

3.7. Equity Premium Puzzle

The Equity Premium Puzzle, first proposed by Mehra and Prescott (1985), refers to the fact that equity yields far exceed Treasury yields. Rubinstein (1976) and Lucas (1978) showed that the stock premium could only be explained by a very high-risk aversion coefficient. Kandel and Stambaugh (1991) argued that risk aversion is actually higher than traditionally thought. However, this leads to the risk-free interest rate puzzle of Weil (1989): In order to adapt to the low real interest rate, they observed, investors can only be assumed to give preference weights equal to or higher than their current consumption in the future. This results in low or even a negative time preference rate of investors where, in practice, negative time preferences are impossible.

In order to solve the risk-free interest rate puzzle suggested by Weil (1989), Epstein and Zin (1991) further introduced the utility function of investors' first-level risk aversion attitude, which is unrelated to the risk-aversion coefficient and the cross-time substitution elasticity of consumers. With generalized expected utility proposed, this model solves the risk-free interest rate puzzle rather than the equity premium. At the same time, more and more revised versions of the utility function occur: a utility function containing the past consumer spending habits' effect shows that equity premium is due to individuals being more sensitive to the shrinking of short-term consumption (Constantinides 1990).

The consumption utility function, affected by the average consumption level of the society, is defined to explain the risk-free interest rate puzzle to a certain extent from the demand for bonds (Abel 1990). Studies that explain the Equity Premium Puzzle under certain economic conditions, apart from the catastrophic event with low probability, as studied by Rietz (1988), will increase the stock premium. In the research of Berkman et al. (2017), the expected market risk premium was successfully explained by using a measure of global political instability as an indicator of disaster risk, a profit–price ratio, and a dividend–price ratio, respectively.

Campbell and Cochrane (1999), adding the probability of the recession which will lead to future consumption levels included in the utility function, concluded the following: The increase in the probability, on the one hand, can lead to investor risk aversion increases, so they prefer a higher risk premium; on the other hand, this will increase the investor demand to meet the motives of prevention, so that the risk-free interest rate will fall.

Cecchetti et al. (2000) proposed an irrational expectation method to explain the equity premium by comparing it with the rational expectations of Campbell and Cochrane (1999). Chen (2017) explained that the Equity Premium Puzzle is due to habits formed during the life cycle of the economy, especially during recessions; for example, households develop a habit of maintaining comfortable lifestyles, which leads to macroeconomic risks that are not reflected in asset-pricing models. Not until 2019, in a model that uses age-dependent increased risk aversion but no other illogical levels of risk aversion assumptions, did DaSilva et al. (2019) obtain results consistent with US equity premium data.

In terms of the risk of labor income, which will produce losses, Heaton and Lucas (1996, 1997) claimed that investors require higher equity premium as compensations, so that they are willing to hold stocks, then generating equity premium. However, Constantinides and Duffie (1996) argued that the corresponding situation happens at a time of economic depression, when investors are more reluctant to hold stocks, for the fear of decline in the value of their equity assets; thus, higher equity premium is necessary to attract investors.

Kogan et al. (2007) found out that equity premium could be achieved in an economy that imposes borrowing constraints, while Constantinides et al. (2002) noted that equity premium is determined by middle-aged investors under the conditions of relaxed lending constraints. Bansal and Coleman (1996) claimed that negative liquidity premium of bonds reduces the risk-free interest rate and further expands the gap with stock returns, causing the Equity Premium Puzzle.

De Long et al. (1990) claimed that dividend generation is a high-risk process that leads to a high equity premium. Lacina et al. (2018) got rid of the use of the way forecasts, proving a near-zero risk premium. In addition, individual income tax rates (McGrattan and Prescott 2010), GDP growth (Faugere and Erlach 2006), and information (Gollier and Schlee 2011; Avdisa and Wachter 2017) and spatial dominance (Lee et al. 2015) are also used to explain the Equity Premium Puzzle.

With the rise of Behavioral Finance, some scholars began to use theories from Behavioral Finance to explain the Equity Premium Puzzle. Benartzi and Thaler (1995) proposed a causal relationship between loss aversion and equity premium based on prospect theory: Precisely due to the fact that investors are afraid of stock losses, equity premium is an important factor to attract investors to hold stock assets and maintain the proportion of stocks and bonds in their portfolios.

Furthermore, Barberis et al. (2001) emphasized in the BHS model they constructed that investors' loss aversion would constantly change, thus generating equity premium, while Ang et al. (2005), Xie et al. (2016), and others explained the Equity Premium Puzzle by introducing disappointment aversion of Behavioral Finance as an influence factor. Hamelin and Pfiffelmann (2015) used Behavioral Finance to explain why entrepreneurs who are aware of their high exposure still accept low returns and show the cognitive traders the riddle of how to explain the private equity.

Mehra and Prescott (2003) analyzed 107 papers on the research of the Equity Premium Puzzle, and drew a conclusion that none has provided a plausible explanation. Given the above review in this paper, a conclusion can be drawn that, with the existing and unsolved anomalies in stock markets, efficiency in stock markets requires certain assumptions. In other words, on the way to solve and explain anomalies, a large number of models will be set up, along with new assumptions inside those models. Many long-standing puzzles can already be solved with different techniques (Ravi 2018), though extra efforts need to be paid on academic research as the world grows quicker with technological developments, making economics complicated.

3.8. Herd Effect and Ostrich Effect

Patel et al. (1991) introduced two behavioral hypotheses to help explain financial phenomena: Barn Door Closing for mutual fund purchases and Herd Migration Behavior for debt–equity ratio. Barn Door Closing, in the horse protection sense, refers to undertaking behavior today that would have been profitable yesterday. Herd Migration in finance occurs when market conditions change, so that individual decision makers wish to alter their holdings substantially.

Their transition is slowed because they seek protection by traveling with the herd. Herd behavior (i.e., people will do what others are doing rather than what is optimal, given their own information) refers to behavior patterns that are correlated across individuals—but could also be caused by correlated information arrival in independently acting investors.

Herding is closely linked to impact expectations, fickle changes without new information, bubbles, fads, and frenzies. Barber et al. (2003) compared the investment decisions of groups (stock clubs) and individuals. Both individuals and clubs are more likely to purchase stocks that are associated with good reasons (e.g., a company that is featured on a list of most-admired companies). However, stock clubs favor such stocks more than individuals, despite the fact that such reasons do not improve performance. The mentioned Seven-Factor Model by Li et al. (2019) also indicates that herd behavior of Chinese A-share market is more prevalent in times of market turmoil, especially when the market falls.

Hon (2015b) found a significant correlation between the reason given by small investors for changing their current security holdings, and the reason given for the sharp correction in the bank stock market. This empirical finding suggests that herding behavior occurred frequently among the small investors, and they tend to sell their stock during the sharp correction period. Hon (2013d) found that there was a change in the behavior of small investors during and immediately after the buoyant stock market of January 2006 to October 2007, in Hong Kong. During the buoyant market, small investors were overconfident and bought stock. The small investors also exhibit herd behavior, and, once the sharp correction to the market began after October 2007, they sold the stock.

In Galai and Sade (2006)'s paper, it is recorded that government Treasury bonds provide higher maturity rates than non-current assets with the same risk level in Israel. Additional research shows that liquidity is positively correlated with market information flows. As ostriches are thought to deal with obvious risk situations by hopefully pretending that risk does not exist, so the ostrich effect is used to describe the above investors' behavior. Karlsson et al. (2009) presented a decision theoretical model in which information collection is linked to investor psychology.

For a wide range of plausible parameter values, the model predicts that the investor should collect additional information conditional on favorable news, and avoid information following bad news. Empirical evidence collected from Scandinavian investors supports the existence of the ostrich effect in financial markets.

3.9. Bubbles

The first study to report bubbles in experimental asset markets was published by Smith et al. (1988). Bubbles feature large and rapid price increases which result in the rising of share prices to unrealistically high levels. Bubbles typically begin with a justifiable rise in stock prices. The justification may be a technological advance or a general rise in prosperity. The rise in share prices, if substantial and prolonged, leads to members of the public believing that prices will continue to rise.

People who do not normally invest begin to buy shares in the belief that prices will continue to rise. More and more people, typically those who have no knowledge of financial markets, buy shares. This pushes up prices even further. There is euphoria and manic buying. This causes further price rises.

There is a self-fulfilling prophecy wherein the belief that prices will rise brings about the rise, since it leads to buying. People with no knowledge of investment often believe that if share prices have risen recently, those prices will continue to rise in the future (Redhead 2003). A speculative bubble can be described as a situation in which temporarily high prices are sustained largely by investors' enthusiasm rather than by consistent estimations of real value. The essence of a speculative bubble is a sort of feedback, from price increases to increased investor enthusiasm, to increased demand, and hence further price increases. According to the adaptive expectations' version of the feedback theory, feedback takes place because past price increases generate expectations of further price increases.

According to an alternative version, feedback occurs as a consequence of increased investor confidence in response to past price increases. A speculative bubble is not indefinitely sustainable. Prices cannot go up forever, and when price increases end, the increased demand that the price increases generated ends. A downward feedback may replace the upward feedback.

Shiller's (2000) paper presents evidence on two types of investor attitudes that change in important ways through time, with important consequences for speculative markets. The paper explores changes in bubble expectations and investor confidence among institutional investors in the US stock market at six-month intervals for the period 1989 to 1998 and for individual investors at the start and end of this period.

Since current owners believe that they can resell the asset at an even higher price in the future, bubbles refer to asset prices that exceed an asset's fundamental value. There are four main strands of models that identify conditions under which bubbles can exist.

The first class of models assumes that all investors have rational expectations and identical information. These models generate the testable implication that bubbles have to follow an explosive path. In the second category of models, investors are asymmetrically informed and bubbles can emerge under more general conditions because their existence need not be commonly known.

A third strand of models focuses on the interaction between rational and behavioral traders. Bubbles can persist in these models since limits to arbitrage prevent rational investors from eradicating the price impact of behavioral traders.

In the final class of models, bubbles can emerge if investors hold heterogeneous beliefs, potentially due to psychological biases, and they agree to disagree about the fundamental value. Experiments are useful to isolate, distinguish, and test the validity of different mechanisms that can lead to or rule out bubbles (Abreu and Brunnermeier 2003).

West (1987) suggested that the set of parameters needed to calculate the expected present discounted value of a stream of dividend can be estimated in two ways. One may test for speculative bubbles, or fads, by testing whether the two estimates are the same. When the test is applied to some annual US stock market data, the data usually reject the null hypothesis of no bubbles. The test is generally interesting, since it may be applied to a wide class of linear rational expectations models. The seeming tendency for self-fulfilling rumors about potential stock price fluctuations to result in actual stock price movements has long been noted by economists.

For example, in a famous passage, Keynes describes the stock market as a certain type of beauty contest: speculators devote their "intelligence to anticipating what average opinion expects average opinion to be". In recent rational expectations' work, this possibility has been rigorously formalized, and the self-fulfilling rumors have been dubbed speculative bubbles.

Craine (1993) suggests that the fundamental value of a stock is the sum of the expected discounted dividend sequence. Bubbles are deviations in the stock's price from the fundamental value. Rational bubbles satisfy an equilibrium pricing restriction, implying that agents expect them to grow fast enough to earn the expected rate of return. The explosive growth causes the stock's price to diverge from its fundamental value.

Whether the actual volatility of equity returns is due to time variation in the rational equity risk premium or to bubbles, fads, and market inefficiencies is an open issue. Bubble tests require a well-specified model of equilibrium expected returns that have yet to be developed, and this makes inference about bubbles quite tenuous.

Chan and Woo (2008) employed a new test to detect the existence of stochastic explosive root bubbles. If a speculative bubble exists, the residual process from the regression of stock prices on dividends will not be stationary. The data series include the monthly aggregate stock price indices, dividend yields and price indices for the stock markets of Taiwan, Malaysia, Indonesia, the Philippines, Thailand, and South Korea. The sample period spans from March 1991 to October 2005 for all markets.

The dividend series are estimated by multiplying the price indices by dividend yields. The stock price indices and dividends are deflated by the producer price index for Malaysia, and by the consumer price indices for the other markets. They found evidence of bubble in stock markets of Taiwan, Malaysia, Indonesia, the Philippines and Thailand, but no evidence of bubbles in South Korea over their sample period.

Homm and Breitung (2012) proposed several reasonable bubble-testing methods, which are applied to NASDAQ index and other financial time series, to test their power properties, covering changes from random walk to explosion process. They concluded that a Chow-type break test provides the highest power and performs well relative to the power envelope, and they also put forward a program to monitor speculative bubbles in real time.

In order to explore bubbles further, in the next section, we introduce several factors underlying the bubble that help explain bubbles.

3.9.1. The Internet

Investors, in general, and online investors, in particular, now make decisions in a very different environment than investors in the past. They have access to far more data via the Internet. They often act without personal intermediaries. They can conduct extensive searches and comparisons on a wide variety of criteria. A critical and largely unexplored research question is how this different environment affects the decision-making of investors (Barber and Odean 2001b).

Barber and Odean (2002) analyzed 1607 investors who switched from phone-based to online trading during the 1990s. Those who switched to online trading performed well prior to going online, beating the market by more than 2% annually. After going online, they traded more actively, more speculatively, and less profitably than before, lagging the market by more than 3% annually.

Reductions in market frictions (lower trading costs, improved execution speed, and greater ease of access) do not explain these findings. Overconfidence—augmented by self-attribution bias and the illusions of knowledge and control—can explain the increase in trading and reduction in performance of online investors.

3.9.2. Derivatives

Hon (2013a) attempted to identify the ways that the Hong Kong companies in the Hang Seng Index Constituent Stocks manage their financial risk with derivatives. By analyzing the companies' annual reports and financial reviews, it was found that 82.6% of these companies used derivatives in 2010. Specifically, 58.7% of them used swaps to hedge interest rate risk, and 54.3% of them used forward contracts to hedge foreign-exchange risk. The results are largely consistent with the prediction that companies use derivatives to manage their financial risk.

By investing in stocks, bonds, and other financial assets, people have been able to build up a buffer in case of being dismissed. Firms have tilted their compensation packages to management away from fixed salaries toward participation and result-based compensations, such as stock options. With such options, management has an incentive to do everything possible to boost share prices. They have an incentive to maintain an appearance of corporate success and a corporation working its way toward an impressive future with increasing profits. It seems as a strategy to boost the stock value and to refine the company's objectives and announcing that it was a part of the e-business society.

Heath et al. (1999) investigated stock-option-exercise decisions by over 50,000 employees at seven corporations. Controlling for economic factors, psychological factors influence exercise. Consistent with psychological models of beliefs, employee exercise in response to stock price trends—exercise is positively related to stock returns during the preceding month and negatively related to returns over longer horizons. Consistent with psychological models of values that include reference points, employee exercise activity roughly doubles when the stock price exceeds the maximum price attained during the previous year. Options have no purchase price to serve as a reference point.

Employees do not purchase options; they receive them at a strike price that is equal to the stock price on the date of the grant. Because employees can only exercise their options when the stock price exceeds the strike price, reference points, if they exist, will be dynamically determined by stock price movement after the grant.

CEO compensation has grown dramatically. Average CEO compensation as a multiple of average worker compensation rose from 45 in 1980, to 96 in 1990, and to an astounding 458 in 2000. A large portion of this compensation comes in the form of stock options. Economists fear that managers will behave more conservatively than is in the best interests of shareholders because managers' careers are tied to the firm. Executive stock options mitigate this problem by rewarding managers when the firm's share price goes up but not punishing them when it goes down. Such convex compensation contracts encourage managers to take risks.

Gervais et al. (2011) argued that executives are likely to be overconfident and optimistic, and thus biased, when assessing projects, and that many shareholders are under-diversified and do care about specific risk. A manager may further manipulate investor expectations by managing earnings through discretionary accounting choices. Furthermore, research indicates that earnings manipulations can affect prices.

Derivatives are a new segment of secondary market operations in India. Ganesan et al. (2004) found that a buoyant and supporting cash market is a must for a robust derivative market. Hon's (2015a) found that the majority of respondents who invested in their derivative investments during January 2013 to January 2014 in Hong Kong were relatively younger. More than 58.1% of the respondents had tertiary education for their derivatives investments. Males preferred to invest in warrants more than females did, while females preferred to invest in stock options more than males did.

Hon (2015c), based on the survey results, derived the ascending order of importance of reference group, return performance, and personal background (reference group is the least important and personal background is the most important) in the Hong Kong derivatives markets. The results of Hon's paper (Hon 2013c) indicate that small investors mostly tend to trade Callable Bull/Bear Contacts (35% of total) and warrants (23% of total). Hon (2012) identified five factors that capture the behavior of small investors in derivatives markets in Hong Kong. The factors are personal background, reference group, return performance, risk tolerance, and cognitive style.

3.9.3. Feedback Models

The essence of a speculative bubble is the familiar feedback pattern—from price increases to increased investor enthusiasm to increased demand and, hence, to further price increase. The higher demand for the asset is generated by the public's memory of high past returns and optimism the high returns generate for the future (Shiller 2002).

When speculative prices go up, creating successes for some investors, this may attract public attention, promote word-of-mouth enthusiasm, and heighten expectations for further price increases. The talk attracts attention that justifies the price increases. This process, in turn, increases investor demand and thus generates another round of price increases. If the feedback is not interrupted, it may produce after many rounds a speculative "bubble", in which high expectations for further price increases support very high current prices. The high prices are ultimately not sustainable, since they are high only because of expectations of further price increases, and so the bubble eventually bursts, and prices come falling down.

The feedback that propelled that bubble carries the seeds of its own destruction, and the end of the bubble may be unrelated to news stories about fundamentals. The same feedback may also produce a negative bubble, downward price movements propelling further downward price movements, promoting word-of-mouth pessimism, until the market reaches an unsustainably low level (Shiller 2003).

3.9.4. Smart Money

The efficient markets theory, as it is commonly expressed, asserts that when irrational optimists buy a stock, smart money sells, and when irrational pessimists sell a stock, smart money buys, thereby eliminating the effect of the irrational traders on market price. From a theoretical point of view, it is far from clear that smart money has the power to drive market prices to fundamental values. For example, in one model with both feedback traders and smart money, the smart money tended to amplify, rather than diminish, the effect of feedback traders, by buying in ahead of the feedback traders in anticipation of price increases they would cause (Shiller 2003). In addition to search costs, investors might choose mutual funds with high expenses if high-expense funds provided better service than other funds.

Barber et al. (2005) asserted that different levels of service are unlikely to explain their results, since first-rate service and low expenses are not mutually exclusive. For example, Vanguard, which is well-known for its low-cost mutual fund offerings, has won numerous service awards. Barber and Odean (2003) concluded that either models of optimal asset location are incomplete or a substantial fraction of investors are misallocating their assets. Though tax considerations leave clear footprints in the data they analyzed, many households could improve their after-tax performance by fully exploiting the tax-avoidance strategies available on equities.

3.9.5. The Media

Media may well have an important role in directing this public attention toward markets, which may consequently result in abnormal market behavior. Stock-market price increases generate news stories, which generate further stories about new-era theories that explain the price increases, which, in turn, generate more news stories about the price increases (Shiller 2002). In the United Kingdom, Diacon (2004) found that lay investors perceive higher risks in investing in financial services products than do their financial advisers (coupled with an inherent optimism about likely benefits) has substantial ramifications in the light of recent reports, such as the "Sandler Review". This may have the effect of encouraging consumers to deal directly with providers rather than via independent financial advisers.

Dispensing with the services of financial advisers is likely to lead consumers to make more conservative investment choices: for example, by investing too little in equities and too much in fixed-income assets when saving retirement. As a result, consumers may find themselves with surprisingly inadequate levels of savings to meet future commitments such as a pension on retirement. Hon (2013b) studied the investment attitude and behavior of the small investors on derivatives markets in Hong Kong. He found that the most decisive factor that could influence small investor's decision making is highly accessible and updated. In total, 37.8% and 25.8% of respondents considered the Internet and news/magazines/newspaper, respectively, as the decisive factor.

3.9.6. Emotions and Sentiments

There are serious questions concerning whether the phenomenon on excess volatility exists in the first place and, and if it does, whether abandonment of assumptions of rational expectations in favor of assumptions of mass psychology and fads as primary determinants of price changes is the best avenue for current research (Kleidon 1986). Using common sense, one knows that the stock market could repeat the performance of recent years. That possibility seems quite real, just as real as the possibility of a major correction in the market. The question is how the private investor feels when he fills out his choice of mutual funds for his retirement scheme. How this person feels depends on his experiences in investing.

If one has been out of the market without participating in earning money that other investors may have done, one may be feeling a sharp pain of regret. Regret has been found by psychologists to be one of the strongest motivations to make a change in something. Envy is another dominant characteristic: To see other people having made more money in the stock market than oneself has made from work is a painful experience, especially since it diminishes one's ego. In case the other people were smarter, one feels like a fool, and even if they were not any smarter, just lucky, it may not feel any better.

A common feeling in this situation is that if one can participate just one more year in rising stock market everything will be much better and mitigate the pain. One may also think that the potential loss will be much more diminishing to one's ego than the failure to participate has already been. One may also realize that one takes the risk of entering the market just as it begins a downward turn. However, the psychological cost of such a potential future loss may not be so much greater relative to the very real regret of having been out of the market in the past.

Barberis et al. (1998) presented a parsimonious model of investor sentiment, or of how investors form expectations of future earnings. The model they proposed was motivated by a variety of psychological evidence; in making forecasts, people pay too much attention to the strength of the evidence they are presented with and too little attention to its statistical weight. Loewenstein et al. (2001) proposed an alternative theoretical perspective, the risk-as-feelings hypothesis, which highlights the role of affect experienced at the precise moment of decision-making. Drawing on research from clinical, physiological, and other subfield of psychology, they showed that emotional reactions to risky situations often diverge from cognitive assessments of those risks. When such divergence occurs, emotional reactions often drive behavior. The risk-as-feelings hypothesis is shown to explain a wide range of phenomena that have resisted interpretation in cognitive–consequentialist terms.

If one participates in the market today for a while and ponders whether get out or not, he has a fundamentally different emotional frame of mind. This person feels satisfaction and probably pride in his past successes, and he will certainly feel wealthier. One may feel as gamblers do after they have "hit big-time", i.e., that one is gambling with the "house money", and therefore has nothing to lose emotionally by wagering again. The concept of gambling with the house money is a theory about people's risk preferences and is related to mental accounting. Investors will generally become more risk-averse in the case of prior losses and less risk-averse in the case of prior gain (Barberis and Thaler 2003); they will also take greater risks as their profits grow.

This provides support for the notion that successful traders are more likely to be overconfident. The emotional state of investors when they decide on their investment is no doubt one of the most important factors causing bull market. From the neuroscience literature, Peterson (2002) demonstrated correlations between reward anticipation and the arousal of affect (feelings, emotions, moods, attitudes, and preferences). He briefly outlined an investment strategy for exploiting the event-related security-price pattern described by the trading strategy "buy on the rumor and sell on the news".

In their research, Chow et al. (2015) conducted a survey to examine whether the theory developed in Lam et al. (2010, 2012) and Guo et al. (2017a) holds empirically, by studying the behavior of different types of Hong Kong small investors in their investment, especially during financial crisis. They found that determinants of the Hong Kong small investors' investment decision have uniform views as to the ascending order of importance of time horizon, sentiment, and risk tolerance. Time horizon is the least important factor, and risk tolerance is the most important factor.

3.10. Volume and Volatility

Fong and Wong (2007) applied the volatility–volume regressions to the daily realized volatility of common stocks to study sources of volatility predictability. They found that unexpected volume can explain half of the variations in realized volatility and that the ARCH effect is robust in the presence of volume.

Xiao et al. (2009) studied the relationship between volume and volatility in the entire Australian Stock Market for different firm size and trading volume. They found that daily trading volume has significant explanatory power on the variance of daily returns. Actively traded stocks having a larger number of information arrivals per day will have a larger impact of volume on the variance of daily returns. Low trading volume and small firm lead to a higher persistence of GARCH effects, unlike the elimination effect for the top most active stocks. In general, the elimination of both ARCH and GARCH effects by introducing the volume variable on all other stocks, on average, is not as much as that for the top most active stocks. The elimination of both ARCH and GARCH effects by introducing the volume variable is higher for stocks in the largest volume and/or the largest market capitalization quartile group. Their empirical findings rejected the pure random-walk hypothesis for stock returns, and they concluded that the relationship between volume and volatility is not a statistical fluke. Unlike most anomalies, the volume effect on volatility is not likely to be eliminated after its discovery.

3.11. Trading Rules and Technical Analysis

If investors could make significant profit when they use any tool in technical analysis, adopt any trading rule, or employ any indicator in their investment, then we will consider this is an anomaly because this shows that the market is not efficient so that investors could have opportunity to make profit. There are many studies in this area. We list a few here.

We first discuss the adaptation of indicators and trading rules. For instance, Wong et al. (2001) introduced a new stock market indicator by using both E/P ratios and bond yields, and developed two statistics to test the following hypotheses:

Hypothesis 1 (H1). *Using the proposed indicator could make significantly good profit from the markets.*

Hypothesis 2 (H2). *Using the proposed indicator could beat the buy-and-hold (BH) strategy.*

In order to test the hypotheses, they examined the performance of their proposed indicator in five different stock markets, namely the UK, USA, Japan, Germany, and Singapore stock markets. Firstly, from their empirical study, they did not reject the hypothesis H1 in (i) and concluded that their indicator could produce buy and sell signals that investors could escape from most, if not all, of the major crashes, catch many of the bull markets, and generate significantly good profit.

Thereafter, they conducted an analysis to test the hypothesis H2 in (ii), and their analysis led them not to reject the hypothesis in (ii) and to conclude that their proposed indicator performs better than the BH strategy, because using their proposed indicator enabled investors to make significant higher profit then the BH strategy.

McAleer et al. (2016) developed some new indicators, or new trading rules, that can profiteer from any main financial crisis, and they examined the applicability of their proposed indicators/trading rules on the 1997 Asian Financial Crisis (AFC), the 2000 dot-com crisis (DCC), and the 2007 Global Financial Crisis (GFC). They examined the two hypotheses H1 and H2 in (i) and (ii) with their proposed indicators.

The empirical study did not reject (i) and concluded that using the signals generated by their proposed indicators/trading rules generate significantly good profit from the markets during AFC, DCC, and GFC. Their empirical study also did not reject (ii), and they concluded that their proposed indicators/trading rules beat the BH strategy, because by using their proposed indicators/trading rules, investors could make very huge profit from the markets during AFC, DCC, and GFC; nonetheless, by adopting the BH strategy, all the profits are eaten up by the downtrend of the crisis and investors end up not having any profit or even bear big loss.

Chong et al. (2017) developed a new market sentiment index by using HIBOR, short-selling volume, money flow, the turnover ratio, the US and Japanese stock indices, and the Shanghai and Shenzhen Composite indices. Thereafter, they used the index as a threshold variable to determine different states in the market and applied the threshold regression to generate buy-and-sell signals. They illustrated the applicability of their proposed trading rules on the HSI or S&P/HKEx LargeCapIndex by testing the two hypotheses H1 and H2 in (i) and (ii), with the now-proposed indicator as their proposed approach.

Their empirical study did not reject (i), and they concluded that the use of their proposed approach generated significant profit from the Hong Kong market; the study did not reject (ii), and it concluded that their proposed approaches beat the BH strategy when investors buy the stock indices when the sentiment index is smaller than the lower threshold value, and vice versa.

Using both intraday and daily data, Lam et al. (2007) examined both surges and plummets of stock price and construct momentums and five trading rules of trading in stocks. They found that all their proposed trading rules cannot get any significant profit in both European and American stock markets but can get significant profit from the Asian stock markets. Their findings accept market for European and American stock markets but reject efficiency in the Asian stock markets, implying that the Asian stock markets are not as efficient as American and European stock markets.

There are many trading rules. An easy one is the single lump-sum investment rule (LS) that one invests all the fund at the beginning. Another popular one is the dollar-cost averaging investment rule (DCA) in which, regardless of ups and downs in the markets, one invests a fixed amount of money periodically over a given time interval in equal installments. This approach could avoid risk and the devastating effect when the market crashes suddenly. The literature shows that the LS rule outperforms the DCA rule when the market is uptrend, and the DCA rule outperforms the LS rule when the market is downtrend or mean-reverted.

Does the LS rule really outperform the DCA rule when the market is uptrend? Lu et al. (2020) conjectured that the DCA rule could still outperform the LS rule when the market is uptrend. To show that their conjecture could hold true, they applied both Sharpe Ratio (SR) and economic performance measure (EPM) and compared the performance of both LS and DCA rules in both accumulative and disaccumulative situations. They showed that, when the trend is not too upward, the DCA rule performs better than the LS rule in almost all the situations. In addition, when the market is uptrend, the DCA rule could still outperforms the LS rule in many situations, especially when volatility is high and when longer investment horizon is chosen.

Thus, the authors concluded that their conjecture hold true that the DCA rule could outperform the LS rule in many situations even in the situation the market is in the uptrend. Together with the findings in the literature that the DCA rule outperforms the LS rule when the market is downtrend or mean-reverted, the authors recommended that investors not choose the LS rule but use the DCA rule in their investment.

We note that one could apply the rules in the above papers to make good profit in their studying periods. If this is the case, then we will consider this is an anomaly, because this shows that the market is not efficient so that investors could have opportunity to make profit. However, there is a chance that the rules may not be able to make money after the rules released. If this is the case, then the market is still efficient and the anomaly disappears. Now, we turn to discuss using technical analysis (TA) to generate profit.

There are many studies that show that technical analysis can be used to generate profit. For example, to examine whether TA is profitable, Wong et al. (2003) used two popular technical tools—moving average (MA) and relative strength index (RSI)—and introduced two statistics to test the two hypotheses, H1 and H2, in (i) and (ii), with the now-proposed indicators MA and RSI. Using the data from the Singapore stock market, they accepted both H1 and H2 and concluded that both MA and RSI could be used to make significantly positive profit and both MA and RSI beat the BH strategy significantly.

In addition, to examine whether TA is profitable, Wong et al. (2005) examined the performance of different MAs in the Taiwan, Shanghai, and Hong Kong stock markets and tested the hypotheses H1 and H2 in (i) and (ii) with the now-proposed indicators, are MA rules from MA family, by using the Greater China data. Their empirical findings did not reject H1, and they concluded that, in general, all MAs from the entire MA family can generate significantly positive profit and accept H2, and conclude that, in general, all MAs from the entire MA family generate significantly higher profit than the BH strategy in the two subperiods before and after the 1997 AFC, and in the entire period, as well as in all the bull, bear, and mixed markets.

Moreover, they conducted a wealth analysis and examined how much more wealth one can get by using all the MA rules from the entire MA family and concluded that different MA rules could yield different cumulative wealth, which could be as much as hundreds of times more than that obtained by choosing the BH strategy, when transaction costs have been considered. Without considering transaction costs, the cumulative wealth is much higher. Their findings and observations imply that the MA family is useful in investment that can create significant higher wealth so that we can reject market efficiency in the Greater China markets.

Like many other studies in TA rules, the above studies conclude that the TA rules are useful and can generate higher profit so that we can consider this is an anomaly. Nonetheless, not all studies make the same conclusions. Some could conclude that TA rules are not useful or at least not useful in some periods or in some markets. For example, to test the hypotheses H1 and H2 in (i) and (ii), Kung and Wong (2009a) made the following conjecture:

Conjecture 1. *Using TA rules may not be able to generate significant profit recently and the anomaly is disappearing.*

In order to test whether their conjecture holds true, they applied three most commonly used MA rules and tested whether using these three MAs rules could enable investors to make a significant profit in all the periods they studied in the Singapore stock market. From their empirical study, they did accept H1 in (i) and concluded that using the three MAs did generate significantly higher profit in the 1988–1996 period, but they reject H1 in (i), and they concluded that the three MAs did not generate significantly higher profit in the 1999–2007 periods.

In addition, their analysis led them to accept H2 in (ii) and conclude that using the three MAs did generate significantly higher profit than adopting the BH strategy in the 1988–1996 period, but they rejected H2 in (ii) and concluded that the three MAs did not generate significantly higher profit than adopting the BH strategy in the 1999–2007 periods. Based on their findings, market efficiency was rejected before the 1997 AFC, but was rejected for the period after the 1997 AFC in the Singapore stock market. This could mean that the anomaly is disappearing after the trading rules being introduced.

In addition, to test the hypotheses H1 and H2 in (i) and (ii) and test whether Conjecture 1 holds true, Kung and Wong (2009b) conducted a similar analysis in the Taiwan market. From their analysis, H1 in (i) was strongly accepted, and they concluded that the two popular TA rules could be used to generate significant profit in the 1983–1990 period. However, H1 in (i) was not so strongly accepted in the 1991–1997 period, and they concluded that the two popular TA rules could be used to generate only marginally significant profit in the 1991–1997 period.

Moreover, H1 in (i) was strongly rejected in the 1998–2005 period, and they concluded that the two popular TA rules could not be used to generate any significant profit in the 1998–2005 period. Based on their findings, market efficiency was strongly rejected in the 1983–1990 period, weakly rejected in the 1991–1997 period, and strongly accepted in the 1985–2005 period for the Taiwan stock market. Thus, the empirical findings from Kung and Wong (2009a, 2009b) support their conjecture that using TA rules could be useful in the past, but it may not be able to generate significant profit recently, and the anomaly is disappearing. Readers may refer to Chan et al. (2014) for further information.

4. Behavioral Finance

There are many different areas in Behavioral Finance, including the topics discussed in the next section. Readers may refer to Wagner and Wong (2019) and the references therein for more information. Here, we only discuss a few.

4.1. Behavioral Finance and Market Efficiency

Behavioral Finance is a new approach to financial markets that has emerged, at least in part, in response to the difficulties faced by the traditional paradigm. In broad terms, it argues that some financial phenomena can be better understood using models in which some agents are not fully rational. More specifically, it analyzes what happens when we relax one, or both, of the two tenets that underlie individual rationality (Barberis and Thaler 2003). Behavioral Finance is the study of the influence of psychology on the behavior of financial practitioners and the subsequent effect on markets. In any situation that causes market inefficiency, as long as there exist sufficient explanations that can help to explain any of the anomalies or there is any way to maintain the relationship between information and stock price, it is the weak-form market efficiency, at least (Mullainathan et al. 2005). If Behavioral Finance makes it, then Behavioral Finance supports EMH. Since Behavioral Finance studies the behavior of investors and helps explain that market anomalies are caused by investors, it means that Behavioral Finance supports EMH when the below three assumptions of Fama (1965a) might not hold:

Assumption 1 (A1). *Rational investor.*

Assumption 2 (A2). *Independent deviation from rationality.*

Assumption 3 (A3). *Arbitrage.*

As Fama (1965a, 1970) claimed that any one of above three assumptions holds will make EMH effective, and A1 is stricter that A2, and meanwhile A2 is stricter than A3, Behavioral Finance explains why A1 or A2 or A3 hold does not hold.

4.2. Overconfidence

The key behavioral factor and perhaps the most robust finding in the psychology of judgment needed to explain A1 or A2 or A3 is overconfidence. Overconfidence is sometimes reversed for very easy items. Overconfidence implies over-optimism about the individual's ability to succeed in his endeavors (Frank 1935). Such optimism has been found in a number of different settings. Men tend to be more overconfident than woman, though the size of difference depends on whether the task is perceived to be masculine or feminine (Hirshleifer 2001). Economists have long asked whether investors who misperceive asset returns can survive in a competitive asset market such as a stock or a currency market.

De Long et al. (1991) concluded that there is, in fact, a presumption that overconfident investors—even grossly overconfident investors—will tend to control a higher proportion of the wealth invested in securities markets as time passes. This presumption is based on the empirical observations that (a) most investors appears to be more risk-averse than log utility; and (b) idiosyncratic risk is large relative to systematic risk. Under these conditions, investors who are mistaken about the precision of their estimate of the returns expected from a particular stock will end up taking on more systematic risk. Taken as a group, these investors will exhibit faster rates of wealth accumulation than fully rational investors with risk aversion greater than given by log utility.

Kyle and Wang (1997) showed that overconfidence may strictly dominate rationality since an overconfident trader may not only generate higher expected profit and utility than his rational opponent, but also higher if he is also rational. This occurs because overconfidence acts like a commitment device in a standard Cournot duopoly. As a result, for some parameter values the Nash equilibrium of two-fund game is a Prisoner's Dilemma in which both funds hire overconfident managers. Thus, overconfidence can persist and survive in the long run.

Daniel et al. (1998) developed a theory based on investor overconfidence and on changes in confidence resulting from biased self-attribution of investment outcomes. The theory implies that investors will overreact to private information signals and underreact to public information signals. Odean (1998b) finds that people are overconfident. His paper examines markets in which price-taking traders, a strategic-trading insider, and risk-averse market-makers are overconfident. Overconfidence increases expected trading volume, increases market depth, and decreases the expected utility of overconfident traders.

Benos (1998) studied an extreme form of posterior overconfidence where some risk-neutral investors overestimate the precision of their private information. The participation of overconfident traders in the market leads to higher transaction volume, larger depth, and more volatile and more information prices. An important anomaly in finance is the magnitude of volume in the market. For example, Odean (1999) noted that the annual turnover rate of shares on the New York Stock exchange is greater than 75 percent, and the daily trading volume of foreign-exchange transactions in all currencies (including forwards, swaps, and spot transactions) is equal to about one-quarter of the total annual world trade and investment flow. Odean (1999) then presented data on individual trading behavior, suggesting that extremely high volume may be driven, in part, by overconfidence on the part of investors.

Individual investors who hold common stocks directly pay a tremendous performance penalty for active trading. Of 66,465 households with accounts at a large discount broker during 1991 to 1996, those that trade most earn an annual return of 11.4 percent, while the market returns 17.9 percent. The average household earns an annual return of 16.4 percent, tilts its common stock investment toward high-beta, small-value stocks, and turns over 75 percent of its portfolio annually. Overconfidence can explain high trading levels and the resulting poor performance of individual investors (Barber and Odean 2000a).

Barber and Odean (2000b) reported their analysis, using account data from a large discount brokerage firm, of the common stock investment performance of 166 investment clubs from February 1991 through January 1997. The average club tilts its common stock investment toward high-beta, small-cap growth stocks and turns over 65 percent of its portfolio annually. The average club lags the performance of a broad-based market index and the performance of investors. Moreover, 60 percent of the clubs underperform the index.

Gervais and Odean (2001) developed a multi-period market model describing both the process by which traders learn about their ability and how a bias in this learning can create overconfident traders. A trader's expected level of overconfidence increases in the early stages of his career. Then, with more experience, he comes to better recognize his own ability. The patterns in trading volume, expected profits, price volatility, and expected prices resulting from this endogenous overconfidence are analyzed. Theoretical models predict that overconfident investors trade excessively.

Barber and Odean (2001a) tested this prediction by partitioning investors on gender. Psychological research demonstrates that, in areas such as finance, men are more overconfident than women. Thus, theory predicts that men will trade more excessively than women. They documented that men trade 45 percent more than women. Trading reduces men's net return by 2.65 percentage points a year, as opposed to 1.72 percentage points for women. People (especially males) seem to trade too aggressively, incurring higher transactions costs, without higher return. From the view that the behavior of overconfident investors is irrational, and the anomaly arises because investors are not rational, Behavioral Finance does not confront, but supports EMH. Once A1 or A2 or A3 is satisfied, the market is still efficient.

4.2.1. Utility

One of the main reasons that EMH is rejected in many cases and there are many market anomalies in the market is that different investors could have different types of utilities.

4.2.2. Investors with Different Shapes in Their Utility Functions

Many scholars, for example, Bernoulli (1954), believe that investors are risk averse; that is, their utility is increasing concave. Many financial models are developed based on the foundational assumption that investors are risk averse or their utility is increasing concave. For example, Markowitz (1952a) developed the mean–variance (MV) portfolio optimization theory based on this assumption.

In reality, investors' utility may not be increasingly concave. It could be increasingly convex (that is, investors are risk-seeking) or S-shaped or reverse S-shaped. Tobin (1958), Hammond (1974), Stoyan (1983), Wong and Li (1999), Li and Wong (1999), Wong (2006, 2007), Wong and Ma (2008), Levy (2015), Bai et al. (2015), Guo and Wong (2016), and many others have built up their theories by assuming that investors could be risk averse or risk seeking.

Kahneman and Tversky (1979) suggested investors' utility[1] could be concave for gains and convex for losses, implying that investors have a S-shaped utility function. On the other hand, Thaler and Johnson (1990) observed that investors are more risk-seeking on gains and more risk-averse on losses, inferring that investors have a reverse S-shaped utility function. Other academics, for example, Levy and Wiener (1998), Levy and Levy (2002, 2004), Wong and Chan (2008), and Bai et al. (2011b) developed their theories based on the assumption that investors possess S-shaped or reverse S-shaped utility function.

4.2.3. Other Utility Functions

Academics not only use the shape of utility functions to measure the behaviors of different investors, but also use other forms of utility functions to measure their behaviors, for example, regret-aversion (Guo et al. 2015; Egozcue et al. 2015), disappointment-aversion (Guo et al. 2020), and many others. In addition, Guo et al. (2016) developed the exponential utility function with a 2n-order and established an estimation approach to find the smallest possible n to provide a good approximation for any integer n.

Chan et al. (2019a) proposed using polynomial utility functions to measure the behavior of risk-averters and risk-seekers. Wong and Qiao (2019) proposed including both risk-averse and risk-seeking components to measure the behavior of investors who could gamble and buy insurance together, or buy any less risky and more risky assets at the same time. Egozcue and Wong (2010a) propose a utility function for Segregation and Integration.

4.3. Portfolio Selection and Optimization

Portfolio optimization and portfolio selection are the founding theories of modern finance, and they are one of the major areas in Behavioral Finance. They are related to Behavioral Finance because different investors with different utilities could make different selections and get different optimizations. The foundational portfolio optimization theory developed by Markowitz (1952a), to find out how investors will choose their portfolios, requests assumption of risk-aversion on investors.

Nevertheless, the MV portfolio optimization theory developed by Markowitz (1952a) has been found to have serious problem in its (plug-in) estimation (Michaud 1989), while Bai et al. (2009a) not only prove that the serious estimation problem is natural and it is overestimation, not underestimation. In addition, they find out the magnitude of the overestimation. Thus, one is not surprised they can apply the asymptotic properties of eigenmatrices for large sample covariance matrices (Bai et al. 2011c)

[1] Kahneman and Tversky (1979) and others call it value function, while we call it utility function.

to find out the estimation (they call it bootstrap-corrected estimation) that is consistent to the true optimal return.

Nonetheless, the problem of the bootstrap-corrected estimation is that it does not have a closed-form. To solve the problem, Leung et al. (2012) extended the theory by developing the estimation with closed-form, and Bai et al. (2009b) extended the theory of portfolio optimization for the problem of self-financing. In addition, Bai et al. (2016) further extended the model by employing the spectral distribution of the sample covariance to develop the spectral-corrected estimation that performs better than both plug-in and bootstrap-corrected estimations.

The problem of all the above estimations developed by Markowitz (1952a), Bai et al. (2009a, 2009b), Leung et al. (2012), and many others is that the estimations are the same for any investor with risk-averse utility. Nonetheless, it is well-known that different investors could choose different optimal portfolios. In addition, Guo et al. (2019b) established some properties on efficient frontiers and boundaries of portfolios by including background risk in the model and by using several approaches, including MV, mean–VaR, and mean–CVaR approaches.

Many studies have explored how to get solutions for different investors. For example, Li et al. (2018) applied the Maslow portfolio selection model (MPSM) to develop a model that could take care of the need of investors with low financial sustainability who will first look into their lower-level (safety) need, and thereafter look into their higher-level (self-actualization) need, to obtain their optimal return. They illustrated their model by comparing the out-of-sample performance of the traditional model and their proposed model by using the real American stock data. They observed that their proposed model outperformed the traditional model to get the best out-of-sample performance.

We note that one can modify the model developed by Li et al. (2018) to find the optimal return for investors with high financial sustainability who prefer to looking into their higher-level need first, and then satisfying their lower-level need. Though both investors with high and low financial sustainability are risk-averse, their choices are different in the portfolio selections.

There are many applications using the theory of portfolio optimization (for example, Abid et al. (2009, 2013, 2014), Hoang et al. (2015a, 2015b, 2018, 2019), Mroua et al. (2017), Bouri et al. (2018), and many others).

4.4. Stochastic Dominance

Stochastic dominance (SD) is one of the most important areas in Behavioral Finance, because SD can be used to compare the performance of different assets, which is equivalent is the preferences of investors with different utilities. We discuss some important SD papers in this section. Readers may refer to Levy (2015), Sriboonchitta et al. (2009), and the references therein for more information.

4.4.1. Stochastic Dominance for Risk-Averters and Risk-Seekers

SD is one of the most important selection rules for both risk-averters and risk-seekers. Quirk and Saposnik (1962), Fishburn (1964, 1974), Hadar and Russell (1969, 1971), Hanoch and Levy (1969), Whitmore (1970), Rothschild and Stiglitz (1970, 1971), Tesfatsion (1976), Meyer (1977), and others developed the SD rules for risk-averters. On the other hand, Hammond (1974), Meyer (1977), Hershey and Schoemaker (1980), Stoyan (1983), Myagkov and Plott (1997), Wong and Li (1999), Li and Wong (1999), Anderson (2004), Post and Levy (2005), Wong (2006, 2007), Levy (2015), Guo and Wong (2016), and others developed the SD rules for risk-seekers.

4.4.2. Stochastic Dominance for Investors with (Reverse) S-Shaped Utility Functions

Friedman and Savage (1948) observed that many individuals buy insurance, as well as lottery tickets, and it is well-known that utility with strictly concavity or strictly convexity cannot explain this phenomenon. To solve this problem, academics developed S-shaped and reverse S-shaped utility functions, while Levy and Levy (2002, 2004) and others developed the SD theory for investors with S-shaped and reverse S-shaped utility functions. We call the SD theory for individual with S-shaped prospect SD (PSD) and the SD theory for individual with reverse S-shaped utility function Markowitz SD (MSD).

Wong and Chan (2008) extended the PSD and MSD theory to the first three orders. They developed several important properties for MSD and PSD. For example, they showed that the dominance of assets in terms of PSD (MSD) is equivalent to the expected utility preference of the assets for investors with (reverse) S-shaped utility function.

4.4.3. Almost Stochastic Dominance

The theory of almost stochastic dominance (ASD) was developed by Leshno and Levy (2002, LL) to measure a preference for "most" decision makers but not all decision makers. However, Tzeng et al. (2013, THS) found that expected-utility maximization does not hold in the second-degree ASD (ASSD) defined by LL. Thus, they suggested to use another definition of the ASSD definition that possesses the property. Nonetheless, Guo et al. (2013) proved that, though LL's ASSD does not satisfy the expected-utility maximization, it possesses the hierarchy property, whereas though THS's ASSD possesses the expected-utility maximization, it does not possess the hierarchy property.

Guo et al. (2014) extended the ASD theory by developing the necessary conditions for the ASD rules. In addition, they established several important properties for ASD. Guo et al. (2016) further extended the theory of ASD theory by including the theory of ASD for risk-seekers. In addition, they established some relationships between ASD for both risk-averters and risk-seekers. Tsetlin et al. (2015) established the theory of generalized ASD (GASD), and Guo et al. (2016) compared ASD and GASD and pointed out their advantages and disadvantages.

4.4.4. Stochastic Dominance Tests and Applications

There are many stochastic dominance tests that can be used in Behavioral Finance. The commonly used SD tests include Davidson and Duclos (2000), Linton et al. (2005), Linton et al. (2010), Bai et al. (2011b, 2015), and Ng et al. (2017). We note that Lean et al. (2008) conducted simulations to compare the performance of different SD tests and found that the SD test developed by Davidson and Duclos (2000) has decent size and power.

The SD tests developed by Bai et al. (2011b, 2015) are improvements of the SD test developed by Davidson and Duclos (2000). Thus, the SD tests developed by Bai et al. (2011b, 2015) also have decent size and power. Ng et al. (2017) conducted simulations and found that their proposed SD test also had decent size and power. Chan et al. (2019a) developed a third-order SD test.

There are many studies that have applied stochastic dominance tests to test for market efficiency and check whether there is any anomaly in the market (for example, Fong et al. (2005, 2008), Wong et al. (2006, 2008, 2018a), Lean et al. (2007, 2010a, 2010b, 2013, 2015), Gasbarro et al. (2007, 2012), Wong (2007), Chiang et al. (2008), Abid et al. (2009, 2013, 2014), Qiao et al. (2010, 2012, 2013), Chan et al. (2012), Qiao and Wong (2015), Hoang et al. (2015a, 2015b, 2018, 2019), Tsang et al. (2016), Mroua et al. (2017), Bouri et al. (2018), and Valenzuela et al. (2019), among others).

4.5. Risk Measures and Performance Measures

The theory of risk measures and performance measures is one of the most important theories in Behavioral Finance because it can be used to measure the preferences of investors from different types of utilities. We discuss some different risk measures in this section.

4.5.1. Mean Variance Rules

Markowitz (1952b) and Tobin (1958) first proposed the mean–variance (MV) selection rules for risk-averters, while Wong (2007) extended the theory by introducing the MV selection rules for risk-seekers and established the relationship between SD and MV rules for both risk-averters and risk-seekers. Chan et al. (2019b) further extended the theory by introducing the moment rules for both risk-averters and risk-seekers, and establishing the relationship between SD and the moment rules.

4.5.2. Sharpe Ratio

The Sharpe ratio, developed by Sharpe (1966), is one of the most commonly used reward-to-risk measures, but it does not provide the testing of the ratio. To circumvent the limitation, Lo and others developed the testing statistics for the Sharpe ratio. Leung and Wong (2008a) extended the theory further by establishing the testing statistic to multivariate settings and developing the asymptotic distribution of the statistic and related properties. Chow et al. (2019b) showed the relationship between SD and the Sharpe ratio. Wong et al. (2012) introduced the mixed Sharpe ratio to the theory and showed that the mixed Sharpe ratio changes over time.

4.5.3. Mean–Variance Ratio

It is well-known that the Sharpe ratio test is not uniformly most powerful unbiased (UMPU). To get a UMPU test, Bai et al. (2011d) established the mean–variance-ratio (MVR) statistic to test the equality of mean–variance ratios for different assets. Bai et al. (2012) further improved the test by removing the background risk. They showed that their proposed MVR statistic is UMPU in any sample, no matter whether the sample is big or small.

4.5.4. Omega Ratio

The Omega ratio introduced by Keating and Shadwick (2002) is one of the most important performance measures by using the probability-weighted ratio of gains and losses for any threshold return target. Guo et al. (2017b) developed the properties to study the relationships between the Omega ratio and (a) the first-order SD; (b) the second-order SD for risk-averters; and (c) the second-order SD for risk-seekers. Chow et al. (2019b) further established the necessary conditions between the Omega ratio and SD for both risk-averters and risk-seekers, and demonstrated that the Omega ratio outperforms the Sharpe ratio in many cases.

4.5.5. Economic Performance Measure

Homm and Pigorsch (2012) developed the economic performance measure (EPM), which is related to Behavioral Finance, because it is related to SD, which, in turn, is related Behavioral Finance. Thus, EPM is related to Behavioral Finance. To make the EPM become useful in the comparison of different assets, Niu et al. (2018) developed the theory of construction confidence intervals for EPMs, including one-sample and two-sample confidence intervals, and derived the asymptotic distributions for one-sample confidence interval and for two-sample confidence interval for samples that are independent. The testing approach developed by Niu et al. (2018) is robust for many dependent cases.

4.5.6. Other Risk Measures and Performance Measures

Because variance gives the same weight in measuring downside risk as well as upside profit for any prospect, it is not a good measure to capture the downside risk. To circumvent the limitation, several risk measures and performance measures have been proposed, including Value-at-Risk (VaR, Jorion 2000; Guo et al. 2019b), conditional-VaR (C-VaR, Rockafellar and Uryasev 2000; Guo et al. 2019b), Kappa ratio (Kaplan and Knowles 2004), Farinelli and Tibiletti (FT, Farinelli and Tibiletti 2008), economic performance measure (Homm and Pigorsch 2012), and others. In addition, Ma and Wong (2010) proved that VaR is related to first-order SD and C-VaR is related to second-order SD. Niu et al. (2017) proved that the Kappa ratio is related to SD, and Guo et al. (2019a) proved that the F–T ratio is related to SD for both risk-averse and risk-seeking investors under some conditions.

4.5.7. Applications of Risk Measures and Performance Measures

There are many applications of using risk measures and performance measures to test for market efficiency, and check whether there is any anomaly in the market. Examples include Sharpe (1966), Keating and Shadwick (2002), Kaplan and Knowles (2004), Broll et al. (2006, 2011, 2015), Wong et al. (2008, 2018a), Leung and Wong (2008a), Fong et al. (2008), Abid et al. (2009, 2013, 2014), Qiao et al. (2010, 2012, 2013), Lean et al. (2010a, 2010b, 2013, 2015), Homm and Pigorsch (2012), Chan et al. (2012, 2019a, 2019b), Bai et al. (2013), Qiao and Wong (2015), Hoang et al. (2015a, 2015b, 2018, 2019), Tsang et al. (2016), Guo et al. (2017b, 2019a), Mroua et al. (2017), Niu et al. (2017), Bouri et al. (2018), and Chow et al. (2019b), among others.

4.5.8. Indifference Curves

The indifference curve, which was first developed by Tobin (1958), is one of the important areas in Behavioral Finance, because it reveals the behavior of both risk-averters and risk-seekers in the mean and variance diagram. Tobin (1958) proved that the indifference curve is increasingly convex for risk-averters, decreasingly convex for risk-seekers, averse (seeking) investors, and is horizontal for risk-neutral investors when assets follow the normal distribution. Meyer (1987) extended the theory by relaxing the assumption of normality and including the location-scale (LS) family to the theory of indifference curve.

Wong (2006, 2007) extended the theory to include the general conditions that were presented in Meyer (1987)Meyer Wong and Ma (2008) further extended the theory by introducing some general non-expected utility functions and the LS family with general n random seed sources, and established some important properties of the theory of indifference curves. To date, the literature only discusses indifference curves for risk-averters and risk-seekers. Broll et al. (2010) extended the theory by examining the behavior of indifference curves for investors with S-shaped utility functions.

4.6. Two-Moment Decision Models and Dynamic Models with Background Risk

The two-moment decision model is related to Behavioral Finance because it can be used to measure the behaviors of both risk-averters and risk-seekers. Many works have been done in this area. For instance, Alghalith et al. (2017) showed that the change of the price of expected energy will affect the demand for both energy and non-risky inputs, but the uncertain energy price only affects uncertain energy price but not the demands for the non-risky inputs for any risk-averse firm.

Alghalith et al. (2017) showed that the variance of energy price affects the demands of both non-risky inputs and energy decrease when the variance is vulnerable, but does not affect the demands of the non-risky inputs when there is only uncertain in energy price for any risk-averse firm. Guo et al. (2018a) contributed to the MV model with multiple additive risks by establishing some properties on the marginal rate of substitution between mean and variance. They also illustrated the properties by using the MV model with multiple additive risks to study banks' risk-taking behaviors.

In addition, Alghalith et al. (2016) extended the theory of the stochastic factor model with an additive background risk and the dynamic model with either additive or multiplicative background risks by including a general utility function in the models in which the risks are correlated with the factors in the models.

4.7. Diversification

Diversification is one of the important areas in Behavioral Finance. It is related to Behavioral Finance because different investors will have different behaviors in diversification. In the theory of portfolio selection developed by Markowitz (1952a), investors are assumed to be risk-averse, and there is only one best optimal portfolio that investors should choose. Li et al. (2018) showed that even investors are risk-averse, as they can choose different optimal portfolios if one looks into their safety need first, and thereafter, look into his/her self-actualization need while another one looks into his/her self-actualization need first, and then look into his/her safety need.

In addition, Li and Wong (1999) have shown that if all assets are independently and identically distributed, then it is true that risk-averters will choose the same optimal portfolio, which is the completely diversified portfolio. However, they found that investing in a single asset is the best choice for risk-seekers. Wong (2007) extended the theory for the diversification behaviors of both risk-averters and risk-seekers to the gain, as well as to the loss, while Guo and Wong (2016) extended the theory further, in order to study the diversification behaviors of both risk-averters and risk-seekers in the multivariate settings.

To date, Li and Wong (1999), Wong (2007), and Guo and Wong (2016) only developed the diversification theory to study the diversification behaviors of both risk-averters and risk-seekers, to compare any pair of asset/portfolio(s) among a single asset, partially diversified portfolios, and completely diversified portfolio, but they have not developed any result in the comparison between any two portfolios of partial diversification. To circumvent the limitation, Egozcue and Wong (2010b) established a diversification theory to compare any pair of partially diversified portfolios, including completely diversified portfolios and individual asset.

Using the out-of-sample performance tool, DeMiguel et al. (2009) showed that the naive 1/N portfolio outperforms the "optimal" portfolio from the 14 models in terms of several commonly used measures in their study, and thus, they drew conclusion that the "optimal" portfolio is not optimal. Hoang et al. (2015b) found that risk-averters agree with Markowtiz to select the portfolios from the efficient frontier, while risk-seekers agree with De Miguel, Garlappi, and Uppal to select the equal-weighted portfolio. On the other hand, Bouri et al. (2018) found that risk-averters prefer the portfolios from the efficient frontier for low-risk with-wine portfolios but are indifferent between the portfolios from the efficient frontier and the naïve portfolio for any high-risk with-wine portfolios.

Statman (2004) showed that investors do not follow Markowtiz's suggestion to invest in the completely diversified portfolio and do not buy only one stock but buy a few. This is the well-known diversification puzzle. To provide a possible solution to the puzzle, Lozza et al. (2018) showed that investors' choices on optimal assets are similar if their utility are not too different.

Egozcue et al. (2011a) bridged the gap in the literature to develop some properties for the diversification behaviors for investors with reverse S-shaped utility functions that have never studied before. They found that the diversification preference for investors with reverse S-shaped utility functions are complicated and depend on the sensitivities toward losses and gains.

4.8. Behavioral Models

In this section, we discuss several behavioral models for Behavioral Finance that relate to market efficiency and anomalies in stock markets. So far, all the models discussed in Sections 4.1–4.7 are behavioral models. Thus, in this section, we discuss the behavioral models that are not discussed in Sections 4.1–4.7.

4.8.1. Behavioral Models for Some Financial Anomalies

By applying the concept of both conservatism and representativeness heuristics, Barberis et al. (1998) and others developed the Bayesian models, which can be used to explain investors' behavioral biases. Lam et al. (2010) extended their work by introducing a pseudo-Bayesian approach to reflect the biases from investors' behavior on each of each dividend being assigned (Thompson and Wong 1991, 1996; Wong and Chan 2004). Their model can be used to explain excess volatility, long-run overreaction, short-run underreaction, and their magnitude effect. Lam et al. (2012) improved the theory by establishing some new properties by using the pseudo-Bayesian model to explain the market anomalies and the investors' behavioral biases.

Fung et al. (2011) further improved the theory by considering the impact of a financial crisis. Guo et al. (2017a) improved the theory by first relaxing the normality assumption to any exponential family distribution for the earning shock of an asset that follows a random-walk model, with and without drift. They established additional properties to explain excess volatility, long-term overreaction, short-term underreaction, and their magnitude effects during financial crises, as well as the period of recovery thereafter.

The theory developed by Guo et al. (2017a) and the references therein can only explain some market anomalies, like excess volatility, long-run overreaction, short-run underreaction, and their magnitude effect, but cannot be used to test it empirically. To circumvent the limitation, Fabozzi et al. (2013) developed several statistics that can be used to test whether there is any long-run overreaction and short-run underreaction, and their magnitude effect in the markets. They applied their statistics empirically and concluded that long-run overreaction, short-run underreaction, and their magnitude effect did exist in the markets they studied.

In addition to conducting statistical analysis to real data of stock prices to test whether there is any market anomaly, scholars could also use questionnaires to conduct surveys to examine investors' attitude on the market anomaly. For example, Wong et al. (2018b) distributed their questionnaires to small investors in Hong Kong, to conduct a survey to examine the behavior of investor behavior on long-term overreaction, short-term underreaction, and their magnitude effect. Their empirical findings support the theory developed by Guo et al. (2017a), and the references therein, that small investors in Hong Kong have both conservative and representative heuristics and they do use momentum and contrarian strategies in their investment.

4.8.2. Other Behavioral Models

The regret-aversion model is an important model for Behavioral Finance; for example, it can be used for investors to make decision in their portfolio investment (Barberis et al. 2006; Muermann et al. 2006). It can be used in many other areas, as well, for example, options (Sarver 2008) and hedging (Egozcue et al. 2015; Guo et al. 2015; Guo and Wong 2019).

On the other hand, the disappointment-aversion model developed by Bell (1982) and Loomes and Sugden (1982) can also be used in Behavioral Finance. For example, it can be used to determine the weights investors should hold stock and bond. Readers may refer to Guo et al. (2020) and the reference therein for more information.

Wan and Wong (2001) developed a behavioral model with incomplete information that can be used in refinancing during finance crisis. They found out the conditions to make financial crisis happen from one country to another one. In addition, Fry et al. (2010) and Fry-McKibbin and Hsiao (2018) developed statistics to test for contagion effect.

Given the studies in Sections 3.1 and 3.2, Fama (1998) claims that EMH survives in the abnormal returns brought by the Winner–Loser Effect and Momentum Effect. In particular, Fama insists that anomalies are chance results, which is consistent with the EMH, as it is obvious that overreaction to information is as common as underreaction to information. Moreover, the duration of abnormal returns before and after events is similar to the frequency of reversal of past events. Most importantly, consistent with market efficiency forecasts, the obvious anomalies may be due to different methodologies, as most long-term earnings anomalies tend to disappear as technology changes reasonably.

Some of the other literature has attempted to explain the above anomalies through the Behavioral Finance perspective, and the authors developed models. The first one is BSV model. Barberis et al. (1998) consider that there are two wrong paradigms when people make investment decisions: representative bias and conservative bias. The former refers to investors paying too much attention to the change patterns of recent data, but not enough attention to the overall characteristics of these data. The latter describes how investors cannot modify the increased forecasting model in time according to the changed situation. These two biases lead to underreaction and overreaction, separately. The BSV model explains how investors' decision-making models lead to market price changes deviating from the EMH.

By importing investor overconfidence and biased self-attribution, another two well-known psychological biases, Daniel et al. (1998) set up the DHS model. In the DHS model, overconfident investors are believed to overestimate their own prediction ability, underestimate their own prediction errors, over-trust private information, and underestimate the value of public information, which makes the weight of private signals in the eyes of overconfident investors higher than previous information and causes overreaction. While noisy public information can partially correct price inefficiencies when it arrives, overreacting prices tend to reverse when additional public information is available.

The third model to fix momentum anomalies is the HS model. The HS model, also known as the unified theoretical model, differs from the BSV model and DHS model in that it focuses on the mechanism of different actors rather than the cognitive bias of the actors (Hong and Stein 1999). The model divides participants into two categories: observers and momentum traders. Observers are assumed to make predictions based on future value information, while momentum traders rely entirely on past price changes.

Under the above assumptions, the model unifies the underreaction and overreaction as the basis. The model argues that the tendency of observers to underreact to private information first leads momentum traders to try to exploit this by hedging strategies, which in turn leads to overreaction at the other extreme.

4.9. Unit Root, Cointegration, Causality, and Nonlinearity

Unit root test, cointegration, and causality are important areas in Behavioral Finance because they can measure many different behaviors in Behavioral Finance. For example, Lam et al. (2006) developed three test statistics that can be used to test whether a series follows a random-walk or a stationary general-mean-reversed (GMR) model. It is investors' behavior to make stock prices follow a stationary general-mean-reversed (GMR) model. If the market is efficient, the stock price should follow a random-walk model. It is also because of investors' behavior that some stocks are moving together (cointegration) or not moving together, or one stock price could cause (causality) another one.

The authors have developed some unit root (Tiku and Wong 1998), cointegration (Penm et al. 2003; Wong et al. 2007), causality (Bai et al. 2010, 2011a, 2018), and nonlinearity (Hui et al. 2017) tests that related to Behavioral Finance.

There are many applications of unit root, cointegration, causality, and nonlinearity tests in many different areas of Behavioral Finance, including Manzur et al. (1999), Wong et al. (2004a, 2004b, 2007), Lam et al. (2006), Qiao et al. (2008a, 2008b, 2008c, 2009, 2011), Zheng et al. (2009), Chiang et al. (2009), Liew et al. (2010), Owyong et al. (2015), Vieito et al. (2015), Chow et al. (2018a, 2018b, 2019a), Batmunkh et al. (2018), Demirer et al. (2019), Gupta et al. (2019b), Zhu et al. (2019), Cheng et al. (2019), Lv et al. (2019), and many others.

4.10. Covariance and Copulas

Covariance and copulas are important areas in Behavioral Finance because they can measure the time-varying covariances that are caused by investors' different behavior over time; for example, Lam et al. (2010, 2012), Fung et al. (2011), Guo et al. (2017a), and many others showed that investor conservatism and representativeness heuristics cause excess volatility in financial markets.

We have developed some theories in covariance and copulas (see, for example, Egozcue et al. (2009, 2010, 2011a, 2011b, 2011c, 2012, 2013), Bai et al. (2009a, 2009b, 2011c), and Ly et al. (2019a, 2019b)). We have also conducted some analysis by using covariance and copulas (Tang et al. 2014).

4.11. Robust Estimation and Other Econometric Models/Tests

Robust estimation and other econometric models/tests are an important area in Behavioral Finance because they can measure the models in Behavioral Finance better. For example, Wong and Bian (2000) found that the robust Bayesian estimation introduced by Bian and Dickey (1996) could lead to mean square error (MSE) being greater than one thousand times smaller than that of the traditional least squares (LS) estimates when the error terms follow very heavy tails that are common in Behavioral Finance.

We have developed some theories in robust estimation and other econometric models/tests (see, for example, Wong and Miller (1990); Matsumura et al. (1990); Tiku et al. (1999a, 1999b, 2000); Wong and Bian (2005); Wong et al. (2001); Leung and Wong (2008b); Bian et al. (2011); and many others).

We have also used robust estimation to conduct many applications (see, for example, Wong and Bian (2000); Phang et al. (1996); Phang and Wong (1997); Wong et al. (2001); Fong and Wong (2006);

Qiao et al. (2008c); Bian et al. (2011); Raza et al. (2016); Xu et al. (2017); Chan et al. (2018); Guo et al. (2018b); Tsendsuren et al. (2018); Gupta et al. (2019a); Pham et al. (2020); and many others).

Fong and Wong (2007) applied the volatility–volume regressions to the daily realized volatility of common stocks to study sources of volatility predictability. They found that unexpected volume can explain half of the variations in realized volatility and find that the ARCH effect is robust in the presence of volume.

4.12. Anchoring and Adjustment

In many situations, people make estimates by starting from an initial value that is adjusted to yield the final answer. The initial value, or starting point, may be suggested by the formulation of the problem, or it may be the result of a partial computation. In either case, adjustments are typically insufficient. That is, different starting points yield different estimates, which are biased toward the initial values. We call this phenomenon anchoring (Tversky and Kahneman 1974).

Thus, anchoring refers to the decision-making process where quantitative assessments are required and where these assessments may be influenced by suggestions. People have in their minds some reference points (anchors), for example, in the study of Momentum Effect, anchors are previous stock prices. When they get new information, they adjust this past reference insufficiently (under-reaction) to new information acquired. Anchoring describes how individuals tend to focus on recent behavior and give less weight to longer time trends.

Anchoring can cause investors to underreact to new information (Fuller 1998). Values in speculative markets, like the stock market, are inherently ambiguous. It is hard to tell what the value of the Hang Seng Index should be. There is no agreed-upon economic theory that would provide an answer to this question. In the absence of any better information, past prices are likely to be important determinants of prices today. Therefore, the anchor, being the most recently remembered prices, causes the Momentum Effect.

5. Conclusions

Scholars could use data from stock markets all over the world to check whether the markets are efficient, as well as find whether there is any market anomaly. When there is any anomaly being discovered, scholars first confirm the existence of the market anomaly and thereafter look for any existing model to explain the anomaly. If scholars cannot estimate, evaluate, and forecast any model to explain the anomaly, scholars will then explain the anomaly by using quantitative analysis, modeling, or even building up a new theory to explain the anomaly that built up the theory of Behavioral Finance. However, if there is any unexplained anomaly, one may grasp the methods to profiteer by using the anomaly. On the one hand, this is a good way to offer investors valuable investment advice. On the other hand, in the long run, these anomalies may disappear unconsciously.

Many studies, for example, Frankfurter and Mcgoun (2000), argue that numerous empirical researches are not consistent with the EMH, and they conclude that debate on Behavioral Finance is not rigorous enough. In this paper, we revisited the issue on market efficiency and market anomalies. We first gave a brief review on market efficiency, including discussing some theories for market efficiency and reviewing some important works in market efficiency. We then reviewed different market anomalies, including Winner–Loser Effect, reversal effect, Momentum Effect, calendar anomalies that include January effect, weekend effect and reverse weekend effect, book-to-market effect, value anomaly, size effect, Disposition Effect, Equity Premium Puzzle, herd effect and ostrich effect, bubbles, and different trading rules and technical analysis.

Thereafter, we reviewed different theories of Behavioral Finance that could be used to explain market anomalies. Although we have discussed many studies on market efficiency and anomalies, there are still many theoretical contributions in other areas that could also be useful to explain and interpret market efficiency and anomalies. Readers may refer to Chang et al. (2016a, 2016b, 2016c, 2017, 2018) for contributions in other cognate areas that might be useful in theory and practice that related to market efficiency and anomalies. Finally, we note that this review is useful to academics for their studies in EMH, anomalies, and Behavioral Finance; useful to investors for their decisions on their investment; and useful to policy makers in reviewing their policies in stock markets.

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