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Edited by
Michael McAleer

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Contents

About the Editor

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Preface to "Review Papers for Journal of Risk and Financial Management (JRFM)"

This book comprises an editorial and seven invaluable and interesting review papers for *Journal of Risk and Financial Management (JRFM)*. The covered topics include the rising complexity of bank regulatory capital requirements from global guidelines to their United States (US) implementation; connections among big data, computational science, economics, finance, marketing, management, and psychology; factors, outcome, and the solutions of supply chain finance, with a review and future directions; time-varying price–volume relationships; adaptive market efficiency and a survey of the empirical literature; improved covariance matrix estimation for portfolio risk measurement; stock investment and excess returns with a critical review in the light of the efficient market hypothesis and a cross section analysis of country equity returns; and a review of the empirical literature.

Michael McAleer
Editor

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Editorial

Review Papers for *Journal of Risk and Financial Management* (*JRFM*)

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Abstract: This paper evaluates an editorial and seven invaluable and interesting review papers for the *Journal of Risk and Financial Management* (*JRFM*). The topics covered include the rising complexity of bank regulatory capital requirements from global guidelines to their United States (US) implementation, connections among big data, computational science, economics, finance, marketing, management and psychology, factors, outcome, and the solutions of supply chain finance, with a review and future directions, time-varying price-volume relationship, adaptive market efficiency, and a survey of the empirical literature, improved covariance matrix estimation for portfolio risk measurement, stock investment and excess returns, with a critical review in the light of the efficient market hypothesis, and a cross section analysis of country equity returns, and a review of the empirical literature.

Keywords: bank regulatory capital requirements; big data; computational science; economics; finance; marketing; management; psychology; supply chain finance; price-volume relationship; adaptive market efficiency; covariance matrix estimation; portfolio risk measurement; stock investment; excess returns; efficient market hypothesis; country equity returns

1. Introduction

The *Journal of Risk and Financial Management (JRFM)* was inaugurated in 2008, and has continued to be published successfully, with Volume 13 being published in 2020. Since the journal was established, *JRFM* has published in excess of 350 topical and interesting theoretical and empirical papers in financial economics, financial econometrics, empirical finance, banking, finance, mathematical finance, statistical finance, accounting, decision sciences, information management, tourism economics and finance, international rankings of journals in financial economics, and bibliometric rankings of journals in cognate disciplines.

Papers published in the journal range from novel technical and theoretical papers to innovative empirical contributions. The journal/Special Issue wishes to encourage critical review papers on topical subjects in any of the topics mentioned above, in financial economics and in cognate disciplines.

The number of papers with more than 5000 views and/or downloads continues to increase, and stands at 9 at present. The most highly viewed paper garnered almost 14,000 views and well over 11,000 downloads, and the second most highly viewed paper had than 8000 views and around 5500 downloads. This is testimony to the excellent papers that are being submitted to the journal, and the outstanding efforts of all staff associated with the journal.

The Special Issue on "Review Papers for Journal of Risk and Financial Management (JRFM)" consists of 8 interesting and informative critical reviews of novel technical, innovative theoretical, and new empirical contributions. The following section presents each of the eight papers, and discusses their significant contributions.

2. Discussion of the Review Papers

After the Editorial Note, the remaining seven papers are presented in chronological order.

The editorial by McAleer (2018) considers topical issues that have covered, among many others, risk measures, basis risk, default risk, competing risk, downside risk, upside risk, equity risk, risk calibration, optimal hedging, quadratic hedging, life insurance, reinsurance, financial distress, mergers and acquisitions, stock market integration, forecasting dispersion, stock market crashes, corporate risk and creditworthiness, corporate governance, sensitivity analysis, conserving capital, capital regulation, gammas and deltas, spot and futures markets, financial derivatives, exchange traded funds, generating latent variables, arbitrage, trading strategies, international diversification, domestic diversification, publicly traded companies, Bayesian models, and option pricing.

Moreover, the editorial describes interesting topics that include asymmetry and leverage, implied volatility, local volatility, conditional volatility, stochastic volatility, realized volatility, long memory volatility, collapsing bubbles, mean reversion, quantile regressions, factor analysis, fossil fuels, fertilizers, technical efficiency, nonparametric analysis, entropy, oscillation, default models, executive compensation, portfolio optimization, stochastic dominance, higher-order stochastic dominance, equilibria, stochastic control, finite mixture models, interest rate derivatives, exchange rates, collateralized derivative trading, value-at-risk, conditional value-at-risk, expected shortfall, cross listings, Basel accord, heavy tails, skewness, and higher moments. Furthermore, other challenging topics that have been covered include network analysis, inflation, speculation, expectations, stress testing, credit default swaps, vine copulas, property portfolios, social capital, structured finance, credit scoring, fuzzy support vectors, board structures, firm performance, mortgages, neural networks, integration, fractional integration, cointegration, high frequency, ultrahigh frequency, cloud migration, insolvency, bankruptcies, crypto-currencies, safety evaluation, trade openness, emerging economies, sustainability, foreclosures, experimental evidence, innovations, simulations, text mining, learning, big data, computational science, marketing, management, psychology, contagion, and natural disasters.

The Editor-in-Chief and editorial staff of *JRFM* at MDPI look forward to working with potential authors of review papers, for which the editorial process will be handled efficiently and in a timely manner.

The invaluable paper by Chang et al. (2018) provides a review of the literature that connects Big Data, Computational Science, Economics, Finance, Marketing, Management, and Psychology, and discusses research issues that are related to the various disciplines. Academics could develop theoretical models and subsequent econometric and statistical models to estimate the parameters in the associated models, as well as conduct a simulation to examine whether the estimators in their theories on estimation and hypothesis testing have good size and high power. Thereafter, academics and practitioners could apply theory to analyze some interesting issues in the seven disciplines and cognate areas.

The interesting paper by Barth and Miller (2018) notes that, after the Latin American Debt Crisis of 1982, the official response worldwide turned to minimum capital standards to promote stable banking systems. Despite their existence, however, such standards have still not prevented periodic disruptions in the banking sectors of various countries. After the 2007–2009 crisis, bank capital requirements have, in some cases, increased, and overall have become even more complex. This paper reviews how:

1. Basel-style capital adequacy guidelines have evolved, becoming higher in some cases and overall more complex;
2. the United States (US) implementation of these guidelines has contributed to regulatory complexity, even when omitting other bank capital regulations that are specific to the US;
3. the US regulatory measures still do not provide equally valuable information about whether a bank is adequately capitalized.

The informative paper by Marak and Pillai (2019) observes that, in the current highly competitive and fast-changing business environment, in which the optimization of all resources matters, creating an efficient supply chain is crucial. Earlier studies on supply chains have focused on aligning product/services and information flows, while neglecting the financial aspects. Due to this, in recent times, importance has been given to align financial flows with the other components of the supply chain. The interest in supply chain finance rose after the financial crisis, when the bank loans declined considerably, as the need for better management and the optimization of working capital became obvious.

The paper reviews the articles on supply chain finance based on three themes—factors, outcomes, and solutions—while at the same time, providing directions for future research on supply chain finance. This article is unique, as it investigates the factors affecting supply chains, according to the existing literature. It also sheds light on the outcome of the supply chain, without limiting the discussion only to the benefits. Further, it addresses the question: what are the solutions constituting supply chain finance?

Sun et al. (2019) evaluate that the notable literature on portfolio selection and risk measurement has considerably advanced in recent years. The aim of the present paper is to trace the development of the literature and identify areas that require further research. This paper provides a literature review of the characteristics of financial data, commonly used models of portfolio selection, and portfolio risk measurement. In the summary of the characteristics of financial data, we summarize the literature on fat tail and the dependence characteristic of financial data.

In the portfolio selection model part, we cover three models: mean-variance model, global minimum variance (GMV) model and factor model. In the portfolio risk measurement part, we first classify risk measurement methods into two categories: moment-based risk measurement and moment-based and quantile-based risk measurement. Moment-based risk measurement includes time-varying covariance matrix and shrinkage estimation, while moment-based and quantile-based risk measurement includes semi-variance, VaR and CVaR.

In an informative paper, Ying et al. (2019) examine the expansion of investment strategies and capital markets as altering the significance and empirical rationality of the efficient market hypothesis. The vitality of capital markets is essential for efficiency research. The authors explore here the development and contemporary status of the efficient market hypothesis, by emphasizing anomaly/excess returns. Investors often fail to get excess returns; however, thus far, market anomalies have been witnessed, and stock prices have diverged from their intrinsic value.

The paper presents an analysis of anomaly returns in the presence of the theory of the efficient market. Moreover, the market efficiency progression is reviewed, and its present status is explored. Finally, the authors provide enough evidence of a data snooping issue, which violates and challenges the existing proof, and creates room for replication studies in modern finance.

Patil and Rastogi (2019) conduct an informative review of the literature on the price–volume relationship and its relation to the implications of the adaptive market hypothesis. The literature on market efficiency is classified as efficient market hypothesis (EMH) studies or adaptive market hypothesis (AMH) studies. Under each class, studies are categorized, either as return predictability studies or price–volume relationship studies. Finally, the review in each category is analyzed based on the methodology used. The review shows that the literature on return predictability and price–volume relationship in classical EMH approach is extensive, while studies in return predictability in the AMH approach have gained increased attention in the last decade.

However, the studies in price–volume relationship under adaptive approach are limited, and there is a scope for studies in this area. Authors did not find any literature review on time-varying price–volume relationship. Authors find that there is a scope to study the nonlinear cross–correlation between price and volume using detrended fluctuation analysis (DFA)-detrended cross-correlational analysis (DXA) in the AMH domain. Furthermore, it would be interesting to investigate whether the same cross-correlation holds across different measures of stock indices, within a country and across different time scales.

Zaremba (2019) provides and interesting review of the last three decades, that have brought mounting evidence regarding the cross-sectional predictability of country equity returns. The studies not only documented country-level counterparts of well-established stock-level anomalies, such as size, value, or momentum, but also demonstrated some unique return-predicting signals, such as fund flows or political regimes. Nonetheless, the different studies vary remarkably in terms of their dataset and methods employed.

The authors provide a comprehensive review of the current literature on the cross-section of country equity returns. We focus on three particular aspects of the asset pricing literature. First, we study the choice of dataset and sample preparation methods. Second, we survey different aspects of the methodological approaches. Last but not least, we review the country-level equity anomalies discovered so far. The discussed cross-sectional return patterns not only provide new insights into international asset pricing, but can also be potentially translated into effective country allocation strategies.

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Conflicts of Interest: The author declares no conflict of interest.

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Editorial

Editorial Note: Review Papers for Journal of Risk and Financial Management (JRFM)

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Abstract: The Journal of Risk and Financial Management (JRFM) was inaugurated in 2008 and has continued publishing successfully with Volume 11 in 2018. Since the journal was established, JRFM has published in excess of 110 topical and interesting theoretical and empirical papers in financial economics, financial econometrics, banking, finance, mathematical finance, statistical finance, accounting, decision sciences, information management, tourism economics and finance, international rankings of journals in financial economics, and bibliometric rankings of journals in cognate disciplines. Papers published in the journal range from novel technical and theoretical papers to innovative empirical contributions. The journal wishes to encourage critical review papers on topical subjects in any of the topics mentioned above in financial economics and in cognate disciplines.

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Topical issues have covered, among many others, risk measures, basis risk, default risk, competing risk, downside risk, upside risk, equity risk, risk calibration, optimal hedging, quadratic hedging, life insurance, reinsurance, financial distress, mergers and acquisitions, stock market integration, forecasting dispersion, stock market crashes, corporate risk and creditworthiness, corporate governance, sensitivity analysis, conserving capital, capital regulation, gammas and deltas, spot and futures markets, financial derivatives, exchange traded funds, generating latent variables, arbitrage, trading strategies, international diversification, domestic diversification, publicly traded companies, Bayesian models, option pricing, asymmetry and leverage, implied volatility, local volatility, conditional volatility, stochastic volatility, realized volatility, long memory volatility, collapsing bubbles, mean reversion, quantile regressions, factor analysis, fossil fuels, fertilizers, technical efficiency, nonparametric analysis, entropy, oscillation, default models, executive compensation, portfolio optimization, stochastic dominance, higher-order stochastic dominance, equilibria, stochastic control, finite mixture models, interest rate derivatives, exchange rates, collateralized derivative trading, Value-at-Risk, conditional Value-at-Risk, expected shortfall, cross listings, Basel Accord, heavy tails, skewness, higher moments, network analysis, inflation, speculation, expectations, stress testing, credit default swaps, vine copulas, property portfolios, social capital, structured finance, credit scoring, fuzzy support vectors, board structures, firm performance, mortgages, neural networks, integration, fractional integration, cointegration, high frequency, ultrahigh frequency, cloud migration, insolvency, bankruptcies, crypto-currencies, safety evaluation, trade openness, emerging economies, sustainability, foreclosures, experimental evidence, innovations, simulations, text mining, learning, big data, computational science, marketing, management, psychology, contagion, and natural disasters.

Papers published in the journal range from novel technical and theoretical papers to innovative empirical contributions, all of which are welcome as contributions to the journal.

The journal wishes to encourage critical review papers on topical subjects on any of the topics mentioned above in financial economics and in cognate disciplines.

The Editor-in-Chief and editorial staff of JRFM at MDPI look forward to working with potential authors of review papers, for which the editorial process would be handled efficiently and in a timely manner.

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Conflicts of Interest: The author declares no conflict of interest.

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Review

The Cross Section of Country Equity Returns: A Review of Empirical Literature

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Abstract: The last three decades brought mounting evidence regarding the cross-sectional predictability of country equity returns. The studies not only documented country-level counterparts of well-established stock-level anomalies, such as size, value, or momentum, but also demonstrated some unique return-predicting signals such as fund flows or political regimes. Nonetheless, the different studies vary remarkably in terms of their dataset and methods employed. This study aims to provide a comprehensive review of the current literature on the cross-section of country equity returns. We focus on three particular aspects of the asset pricing literature. First, we study the choice of dataset and sample preparation methods. Second, we survey different aspects of the methodological approaches. Last but not least, we review the country-level equity anomalies discovered so far. The discussed cross-sectional return patterns not only provide new insights into international asset pricing but can also be potentially translated into effective country allocation strategies.

Keywords: cross section of country equity returns; country-level stock market anomalies; empirical asset pricing; international equity markets; return predictability

JEL Classification: G12; G14; G15

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1. Introduction

The last three decades brought an unprecedented growth of exchange traded funds (ETFs) and index funds, which enable investors to quickly move their capital around the world. Currently, more easily than ever before, investors can relocate their equity allocation from Germany to Brazil or from Japan to South Africa. Not surprisingly, the ETF industry has been growing very rapidly. Already in 2017, the assets under management of ETFs exceeded five trillion U.S. dollars, and the compound annual growth rate over the past four years amounted to almost 19% (Lord 2018). The growth of ETFs coincides with a structural change in asset management and a shift from active investing to passive investing. As of December 2017, passive funds accounted for 45% of the aggregate assets under management in U.S. equity funds, compared to less than 5% in 1995 (Anadu et al. 2018). This profound revolution requires a whole new set of tools for equity investors, who now focus much less on which stocks to choose than on which countries to allocate money in.

The asset pricing literature produced a preponderance of trading signals, which help to predict the cross-section of individual stock returns. Recent surveys documented literally hundreds of different equity anomalies (e.g., Harvey et al. 2016; Hou et al. 2018). Notably, many of these cross-sectional patterns, such as value, momentum, or seasonality, have their parallels at the inter-market level and could be potentially used for country allocation. The last 30 years of asset pricing research produced mounting evidence regarding the cross-sectional predictability of country equity returns. The studies documenting numerous country-level equity anomalies not only provide new insights into international asset pricing but can also be translated into efficient country allocation strategies. Moreover, they are invaluable to practical investors.

The studies of the cross section of country equity returns not only examined different return patterns but also employed different methodologies and data sources. Issues such as choice of the index provider, return computation methodology, or portfolio formation can visibly influence the results. The diversity of empirical design and data sources and preparation methods calls for systematic review and for introducing a structure into the methodological choices in the field of country-level asset pricing.

The major objective of this article is to provide a comprehensive review of the current state of literature on the cross section of country equity returns. In particular, our survey considers data sources and preparation, research methods, and, last but not least, the cross-sectional return patterns documented in the country-level equity returns. The cross-section of stock-level returns is summarized in many excellent surveys, concerning both the anomalies themselves (e.g., Nagel 2013; Harvey et al. 2016; Hou et al. 2018; Bali et al. 2016), as well as methodological and data choices (Jagannathan et al. 2010; Waszczuk 2014a, 2014b). For country-level cross-sectional asset pricing, such surveys are clearly missing. To the best of our knowledge, any such review has not been yet presented. This work aims to fill this gap. We not only review, but we also structure and introduce some order into the current state of country-level asset pricing literature.

The article reviews three aspects of the studies of cross-section of country equity returns. First, we focus on the choice of data and the underlying asset universe as well as on dataset preparation. At the same time, we review the approaches regarding the country coverage, study period, return measurement, currency unit, and asset universe. Second, we survey some common methodological choices in the asset pricing literature, such as the number of portfolios, return calculation, and portfolio weighting scheme. Finally, we examine the current state of knowledge on country-level cross-sectional return patterns. We review the most prominent of such patterns, such as momentum, value, long-run reversal, size, seasonality, and price and non-price risk, as well as a basket of minor anomalies. We also discuss several additional aspects of these return patterns, including their fundamental sources and implementation details. Finally, we also consider additional practical aspects of country-level return patterns: the role of trading costs and strategy timing.

The remainder of the article proceeds as follows. Section 2 focuses on datasets, data preparation, and asset universe. Section 3 focuses on some specific methodological choices. Section 4 reviews the documented cross-sectional patterns in country equity returns. Finally, Section 5 concludes the article.

2. Datasets and Sample Preparation

This section concentrates on the choice of dataset representing country equity returns and preparation of the sample. We survey the approaches to selection of country coverage, study period, return measurement period, currency unit, and asset universe.

2.1. Country Coverage

The datasets used in examinations of the cross-sectional patterns in country index returns are obviously smaller than in the stock-level studies, which often encompass several thousand companies. Naturally, the scope in this case is limited to the countries with operating stock markets. The early studies usually focused on less than 20 developed markets. For example, Keppler (1991a), Ferson and Harvey (1994a), and Richards (1995) considered 18 developed markets. Modern studies usually concentrate on about 40 countries selected on the basis of classification into developed and emerging by one of the major index providers. For instance, Clare et al. (2016) investigate 40 markets, and Fisher et al. (2017) examine 37. The broadest studies take into account also less tradeable frontier markets, and their sample size can exceed 70. The article by Avramov et al. (2012), investigating 75 equity markets, may serve as an example of such an approach. Perhaps one of the broadest studies was conducted by Suleman et al. (2017), who took into consideration 83 countries. The detailed outline of the sample size in selected studies is presented in Table 1.

Table 1. Research samples in the studies of the country equity returns.

Article	Number of Countries in the Sample	Sample Period	Asset Universe
Angelidis and Tessaromatis (2018)	23	1980–2014	Datastream indices
ap Gwilym et al. (2010)	32	1970–2008	MSCI indices
Asness et al. (2013)	18	1978–2011	MSCI indices
Avramov et al. (2012)	75	1989–2009	MSCI and Datastream indices
Bali and Cakici (2010)	37	1973–2006	Datastream indices
Baltussen et al. (2019a)	14	1799–2016	Local country indices
Balvers and Wu (2006)	18	1969–1999	MSCI indices
Balvers et al. (2000)	18	1969–1996	MSCI indices
Berrada et al. (2015)	18	1975–2010	MSCI indices
Bhojraj and Swaminathan (2006)	38	1975–1999	Datastream indices
Cenedese et al. (2016)	42	1983–2011	MSCI indices
Chan et al. (2000)	23	1980–1995	Local country indices
Clare et al. (2016)	40	1993–2011	MSCI indices
Daniel and Moskowitz (2016)	18	1978–2013	Index futures
Desrosiers et al. (2007)	19	1988–2005	MSCI indices
Dobrynskaya (2015)	40	1983–2014	MSCI indices
Ellahie et al. (2019)	30	1993–2014	Aggregated stock-level data
Erb et al. (1995)	40	1980–1993	MSCI and IFC indices
Estrada (2000)	28	1988–1998	MSCI indices
Ferson and Harvey (1994a)	18	1970–1989	MSCI indices
Fisher et al. (2017)	37	1990–2015	MSCI indices
Geczy and Samonov (2017)	47	1800–2014	Global Financial Data and Bloomberg indices
Guilmin (2015)	18	1975–2014	MSCI indices
Hedegaard (2018)	25	1988–2018	MSCI indices
Hurst et al. (2017)	11	1880–2016	Index futures
Ilmanen et al. (2019)	23	1877–2018	Global Financial Data, Bloomberg Datastream
Kasa (1992)	5	1974–1990	MSCI indices
Keimling (2016)	17	1979–2015	MSCI indices
Keloharju et al. (2019)	15	1987–2016	MSCI indices
Keloharju et al. (2016)	15	1970–2011	MSCI indices
Keppler (1991a)	18	1970–2001	MSCI indices
Keppler (1991b)	18	1970–1989	MSCI indices
Kortas et al. (2005)	23	1986–2003	MSCI indices
L'Her et al. (2004)	18	1975–2003	MSCI indices
Macedo (1995c)	18	1977–1996	MSCI indices
Malin and Bornholt (2013)	44	1970–2011	MSCI indices
Moskowitz et al. (2012)	9	1965–2009	Index futures
Muller and Ward (2010)	70	1970–2009	MSCI indices
Novotny and Gupta (2015)	34	2002–2014	MSCI indices
Pungulescu (2014)	61	1973–2014	Datastream indices
Richards (1995)	18	1969–1994	MSCI indices
Richards (1997)	16	1969–1995	MSCI indices
Rikala (2017)	17	1990–2016	Datastream indices
Smith and Pantilei (2015)	45	1971–2012	MSCI indices, Exchange-traded funds
Spierdijk et al. (2012)	17	1900–2008	Dimson et al. (2002) data
Andreu et al. (2013)	16	1970–2009	Exchange-traded funds

Note. The table summarizes the data samples used in selected studies of the cross-section of country equity returns, indicating the number of countries covered, the length of the study period, and the asset universe.

In general, the larger sample size increases the power of statistical tests and allows additional insights on the examined return pattern. However, some studies may deliberately limit the sample of considered countries. One reason for that may be the focus put on some particular geographical region. For example, Grobys (2016) concentrates solely on the European Monetary Union. Another motivation to limit the number of countries in the sample may be alignment of the study with research practice. Since very liquid futures or ETFs cover only a small number of countries, the examinations may be reduced to just 10–20 of the most tradable markets. For example, the highly influential studies of Asness et al. (2013) or Keloharju et al. (2016) examined the samples of only 18 and 16 equity indices, respectively. Furthermore, the studies utilizing early security data tend to be sometimes quite narrow due to data unavailability. For example, Hurst et al. (2017), who investigated more than a century of evidence of trend following profits, constrained their scope to only 11 countries.

2.2. Study Period

The study period is usually dictated by the index data availability. Thus, numerous studies focusing on the most prominent cross-sectional patterns start in the years 1969 or 1970, when the coverage of many developed markets by MSCI begins (e.g., Balvers and Wu 2006; Bhojraj and Swaminathan 2006; Muller and Ward 2010; ap Gwilym et al. 2010). Consequently, the research period encompasses usually three to four decades. If the study period is shorter, this is usually due to inability to collect some sort of additional data for the 1970s or 1980s. For example, Berkman and Yang (2019), who focus on country-level analysts' recommendations, reduced their study period to the years 1994–2015. Finally, as an alternative to equity indices, some studies proxy the equity markets with respective ETFs. In such cases, the price availability is, naturally, shorter. Smith and Pantilei (2015), who test the "Dogs of the World" strategy in ETFs, examine their returns for the years 1997–2012.

A separate and rapidly growing field encompasses studies of early security data that allow insights into the long-run nature of the financial market phenomena. In asset pricing studies in particular, examinations of the close-to-century long datasets make it possible to check the true robustness of the return patterns and secure against the risk of false discoveries and data mining. Some data providers, like Global Financial Data, offer their own proprietary indices going back to the 19th or even 18th century. A representative study of this type could be Geczy and Samonov (2017), who examine the momentum effect in the returns on major asset classes for the years 1800–2014. Baltussen et al. (2019a) research several major anomalies for the years 1799–2016. Other studies researching similar long-run data sets include Ilmanen et al. (2019), Hurst et al. (2017), or Spierdijk et al. (2012). For a detailed outline of different lengths of the study period, see Table 1.

2.3. Return Measurement Periods

The most common choice in individual stock studies is to use monthly returns. The motivation is that this choice forms a consensus that allows the large number of observations necessary for statistical tests to be accumulated and, at the same time, mitigates the influence of microstructure effects (Waszczuk 2014a). Nearly all of country-level studies take a similar approach and utilize monthly returns (e.g., Richards 1997; Chan et al. 2000; Blitz and van Vliet 2008). This refers, in particular, to the studies of early security data (e.g., Geczy and Samonov 2017; Baltussen et al. 2019a), where the more frequent observations are hardly available.

The use of different return intervals is rather infrequent and usually limited to examinations of alternative holding periods, as in Andreu et al. (2013) or Kasa (1992). On the other hand, Vu (2012) is one of the very few studies that relies on weekly returns to amass a bigger quantity of observations.

2.4. Currency Unit

Asset pricing studies of firm-level data frequently focus on single countries (e.g., Fama and French 2015) or replicate analyses in multiple individual markets (e.g., Chui et al. 2010). Therefore, the role of currency unit is of lesser importance and the calculations oftentimes rely on local currencies.

On the other hand, in the cross-country analysis the volatile foreign exchange rates and inflation rates—especially in emerging and frontier markets—play a significant role. Consequently, the majority of cross-country studies set a common currency as a unit of calculations, and the most obvious and common choice is the U.S. dollar. Dobrynskaya (2015), Clare et al. (2016), Keppler and Encinosa (2011), or Smith and Pantilei (2015) may serve as examples of papers that denominate all the prices in U.S. dollars. This currency is also a default choice in the studies that utilize futures or ETFs as representation of the country exposure, as it directly expresses the perspective of a U.S. investor (e.g., Andreu et al. 2013; Daniel and Moskowitz 2016; Smith and Pantilei 2015).

The use of returns calculated on the basis of local currency prices is rather rare. Usually such a framework has a sort of robustness check applied or is examined explicitly to evaluate the role of currencies in return predictability (Chan et al. 2000; Bhojraj and Swaminathan 2006). For example, Jordan et al. (2015) examine empirically the importance of the currency numeraire for the stock return predictability. They argue that, for instance, the presence (absence) of predictability for an American investor does not need to imply the existence (absence) of predictability for other international investors. Sometimes the local currency returns are also used in the studies of early security data to alleviate the problem of reliability of more than a century-old foreign exchange rate (Geczy and Samonov 2017). Nonetheless, even for the early asset prices studies the U.S. dollar is the very common choice (Baltussen et al. 2019a).

2.5. Asset Universe

Examination of cross-sectional patterns in country equity markets requires some representation of the market return. In country-level studies the asset universe comprises usually one of two types of instruments: either equity indices or some real investable instruments.

The major benefit of equity indices is that they provide a broad and accurate representation of the local equity markets. The articles investigating samples of international stock market indices basically follow one option. Most commonly, the studies are based on indices from a single provider. Alternatively, a study can rely on an amalgamation of local indices computed by national stock exchanges or local companies.

The use of indices from a single provider certainly has some benefits. They include calculation transparency, result comparability, and consistency in index calculation across many countries. Indices provided by MSCI are the most popular choice in country-level asset pricing. MSCI indices represent value-weighted equity portfolios covering approximately 85% of the largest and most liquid companies in each country. They also form the basis for multiple investment products, including popular iShares ETFs. MSCI estimated that more than 7 trillion US dollars were benchmarked to MSCI indices as of June 2011 (Cenedese et al. 2016). Furthermore, importantly from a practitioner's perspective, MSCI usually does not apply any retroactive changes to the reported returns of its indices, so it reduces the risk of potential biases.

The current coverage encompasses 85 countries, including developed, emerging, frontier, and so-called standalone markets. The data period dates back to December 1969. The additional benefit of the MSCI indices is that they are calculated in several different ways, including different currencies, controlling for taxes, accounting for dividends, etc. For example, the MSCI indices were used by Dobrynskaya (2015), Clare et al. (2016), Fisher et al. (2017), Keppler and Encinosa (2011), Richards (1997), Balvers and Wu (2006), Keimling (2016), Keloharju et al. (2016), Malin and Bornholt (2013), Ferson and Harvey (1994b), and many others.

Datastream Global Equity Indices are the second most popular index choice. These cover currently 64 countries and go back in time to January 1973. Notably, the Datastream indices also assure a broad and consistent international representation, and at certain periods in the past their coverage may be better than in the case of MSCI. This index provider was selected, for example, by Bali and Cakici (2010), Umutlu (2015, 2019), and Zaremba (2019).

The studies of more than a century long dataset usually take advantage of indices computed by Global Financial Data (GFD). This provides time-series going back to the 19th century for numerous developed and emerging markets. Obviously, such long-run datasets are not free from different biases or omissions, and the index portfolios frequently contain very few securities, but certainly they provide a unique look into the past data. The GFD indices were employed by Geczy and Samonov (2017) and Baltussen et al. (2019a), among others.

One of the drawbacks of the indices obtained from different providers is that their coverage may differ; some countries may be taken into account by one provider but not considered by others. Consequently, to maximize the size of the research sample, some studies merge indices from different sources. Erb et al. (1995), in one of the first studies of this type, represent the developed markets by the MSCI indices and the emerging ones by the portfolios calculated by the International Finance Corporation (IFC). Avramov et al. (2012) use MSCI indices and supplement the coverage of missing countries with Datastream portfolios. Geczy and Samonov (2017) blend Bloomberg and GFD indices. Finally, Baltussen et al. (2019b) collect data from Bloomberg, with gaps filled in by Datastream data, spliced with index-level data, as in Baltussen et al. (2019b), and, eventually, backfilled data downloaded from Global Financial Data.

Besides using the indices from acknowledged providers, there are also several other options. Ellahie et al. (2019) use aggregated stock-level data from CRSP and Compustat. In other words, they calculate the country portfolios themselves instead of obtaining them from external sources. The final variant is to use national indices computed by local providers such as DAX, NIKKEI, or S&P. This approach is employed by Chan et al. (2000) and Vu (2012), among others. This approach has two major benefits. First, it may help to increase the dataset, because these local indices may have a longer history available than their counterparts offered by MSCI or Datastream. Second, the most liquid equity index futures are oftentimes linked with local indices rather than with international ones. For instance, in Poland the most liquid equity index future is based on the WIG20 index computed by the Warsaw Stock Exchange. Consequently, the use of local indices may be more aligned with investment practice. Nevertheless, on the other hand, the major shortcoming in relying on the local indices is the lack of computational consistency. Different indexes rely on different selection and weighting methods, so the study outcomes may be potentially influenced by the index calculation methodology, resulting in misleading conclusions. For example, better performance of an index in a certain market may stem from its bigger exposure to small-cap companies rather than from a true factor examined by the researcher.

Instead of investigating "paper" equity indices, some studies focus on actual investment instruments providing exposure to international markets. While this framework may potentially limit the size of the dataset, certainly it reflects most closely the investor's practical perspective. Following this reasoning, Daniel and Moskowitz (2016), Moskowitz et al. (2012), and Hurst et al. (2017) base their computations on futures markets. Alternatively, Andreu et al. (2013), Breloer et al. (2014), and Smith and Pantilei (2015) focus on single-country ETFs.

For more examples of different asset universes used by the studies of the cross-section of country equity returns, see Table 1.

3. Methodological Choices

The country-level asset pricing studies strongly rely on econometric and statistical toolsets very similar to those used in the regular studies applied to the individual firms. The two most common approaches are cross-sectional (or panel) regressions and portfolio sorts. These two complementary approaches are frequently used jointly, as recommended by Fama (2015), and their benefits and shortcomings are discussed in detail by Fama and French (2008).

In the most typical applications of the cross-sectional regressions following Fama and MacBeth (1973), the future returns are regressed against a number of return-predicting variables, i.e., characteristics. Cross-sectional regressions are used, for instance, by Bali and Cakici (2010), Fisher et al. (2017), and

Stocker (2016). Sometimes this approach is supplemented with different types of panel regressions, as in Hjalmarsson (2010), Lawrenz and Zorn (2017), and Bali and Cakici (2010). Wisniewski and Jackson (2018) apply pooled ordinary least squares and two-way fixed-effects regressions.

Portfolio sorts are the second most popular tool. In this framework all the considered assets—which are in this case country equity markets—are ranked based on certain empirical characteristics, such as past returns or valuation ratios. Subsequently, they are grouped into subsets, and portfolios are formed. Finally, the performance of the cross-sectional portfolios is evaluated on the basis of mean returns, volatilities, Sharpe ratios, and with factor pricing models and monotonicity checks in the style of Patton and Timmermann (2010). The portfolio sorts reduce the cross-sectional dimension of the joint distribution of returns and also help to reduce the impact of measurement error (Waszczuk 2014a).

In the evaluation of the portfolios from one-way sorts, called also single-sorts, there is also a common practice to calculate the returns on a differential portfolio (or spread portfolio, long-short portfolio, zero-investment portfolio), which takes long and short positions in the two most extreme quantiles of assets from one-way sorts. The performance of such portfolios is then subsequently evaluated. Importantly, it should be noted that frequently this exercise serves as a quick check of monotonicity rather than a reflection of actual investment performance. Due to tradability and short-sale limitations, forming and rebalancing zero-investment portfolios across many countries is not always possible, unless they are made of liquid futures, as in Daniel and Moskowitz (2016) or Moskowitz et al. (2012). Some further discussion of the details of sorting methods in asset pricing studies is provided in Bali et al. (2016), Vaihekoski (2004), Van Dijk (2011), and Waszczuk (2014a)

The outcomes of the cross-sectional analysis based on portfolio sorts is sensitive to several methodological choices made by the researcher. Importantly, some of the country-level practices may differ from stock-level studies due to different number of assets, data availability, liquidity considerations, etc. I will focus then on several of the most important methodological choices.

3.1. Number of Portfolios

The studies of the cross-section of returns on common stocks rely on datasets of hundreds or thousands of companies. Therefore, decile (e.g., Jegadeesh and Titman 1993, 2001; Lakonishok et al. 1994) or quintile (Banz 1981; Chan et al. 1998) groupings belong to the most common choices. At the country level the number of assets is more limited, so this type of study requires also a smaller number of portfolios. Otherwise, the grouping could result in portfolios containing only a few—or even one—markets, hence being susceptible to the noise in returns. The most popular choices include tertiles (e.g., Daniel and Moskowitz 2016; Geczy and Samonov 2017; Asness et al. 2013; Atilgan et al. 2019), quartiles (Richards 1997; Blitz and van Vliet 2008; Macedo 1995a; Malin and Bornholt 2013; Erb et al. 1995), or quintiles (Clare et al. 2016). Alternatively, some studies which assume different portfolio formation methodologies, consider only two portfolios—long and short (e.g., Moskowitz et al. 2012). Bali and Cakici (2010) consider portfolio groupings including 30%, 40%, and 30% of the markets.

Finally, a number of studies, instead of assuming a certain quantile cut-off point, focus only on the extreme portfolios from single-sorts and assume a fixed number of countries included. For instance, Kortas et al. (2005) include 11 of the most extreme countries in each portfolio. On the other hand, Keloharju et al. (2016) test cross-sectional seasonality based on portfolios including the three equity indices with the highest or lowest average return in the past.

3.2. Portfolio Weighting Scheme

Once the portfolios are formed, the next important step is the selection of the weighting scheme. The most common choice is between the value-weighted portfolios and equal-weighted portfolios. In the first framework, the returns are weighted according to the market capitalization. On the other hand, in the equal-weighted approach, all the returns are assigned an equal-dollar value. At the stock level, the value-weighting approach is markedly more popular, and there are several reasons for that. The equal-weighted portfolios may tend to assume very large positions in small and micro companies, which would be unrealistic in practice, due to liquidity or market capacity issues, for example. In addition, the equal-weighted portfolios have a built-in rebalancing assumption, which may distort the results (Willenbrock 2011). Finally, value-weighting deemphasizes observations that are more likely to suffer from the data errors, thus reducing the variation in average returns. Nevertheless, at the country level the choice is not that obvious. Indeed, the equal-weighted portfolios may gravitate towards small and illiquid frontier markets, where any large exposure of frequent share purchases may be unrealistic. However, on the other hand, in the case of a limited sample size of just 30–40 countries, the value-weighted portfolios may be strongly dominated by only a few of the largest countries. Furthermore, the aggregate market value may not always be available, or it may not have any intuitive equivalent, as is the case with the futures or ETFs. Consequently, the equal-weighted portfolios are much more common, or at least used along with the value-weighted portfolios. The equal-weighted portfolios are used, for example, by Geczy and Samonov (2017), Clare et al. (2016), Hurst et al. (2017), and Balvers and Wu (2006). The value-weighted strategies, on the other hand, are analyzed by Chan et al. (2000) and Rikala (2017).

Besides the classical value- or equal-weighted portfolios, some articles pursue alternative frameworks. Clare et al. (2016) and Moskowitz et al. (2012) use so-called risk-parity, i.e., they weight the portfolio components on their inverse volatility. On the other hand, Ilmanen et al. (2019) and Asness et al. (2013) link the weight with the value or rank of the underlying characteristic so that the absolute weight increases when the sorting variables take more extreme values.

3.3. Return Calculation: The Treatment of Dividends and Taxes

The index-level return calculations face two major methodological choices. The first issue refers to the treatment of dividends. Most of the studies are based on total return indices, which include reinvested dividends, regardless of the particular index provider (e.g., Richards 1997; Balvers and Wu 2006; Bali and Cakici 2010). Accounting for dividends reflects the investor's perspective well; nonetheless, sometimes the coverage and the length of the time-series may be bigger for the price returns. Therefore, price indices, which do not account for dividends, are employed by Keppler (1991a), for instance. On the other hand, ap Gwilym et al. (2010) and Geczy and Samonov (2017) use both price and return indices. Finally, some examinations use the two types of measures in combination as different inputs. For example, Clare et al. (2016) measure portfolio performance with the total return indices but compute return predictive signals based on price indices.

The total returns indices include dividends, which are taxed in various ways in the majority of countries. Importantly, the dividend tax rates may vary both across time and countries, affecting the net portfolio performance. Some groups of investors, like mutual funds, may be exempted from taxation on dividends in many countries. Nonetheless, this is not true for all the countries, at all times, and for all the groups of investors. Consequently, the taxes may still potentially affect the cross-section of country equity returns. The majority of the country-level asset pricing studies use gross returns, not accounting for taxation. On the other hand, Zaremba (2016) also use MSCI Net Return indices, which account for dividend tax rates within the particular countries.

4. Cross-Sectional Patterns in Country-Level Returns

We now turn to the review of patterns demonstrated in the cross-section of country equity returns. We begin by focusing on the most prominent and best-established ones, such as momentum, size, and value and, subsequently, carry on with more minor return regularities. In addition, we consider different types of risk that influence future index-level returns. To introduce some order, we arbitrarily classify these risks into the ones that can be derived from prices (price based), and others, that is, non-price risks such as credit or political risks. Eventually, we survey the studies' treatment of some additional aspects of the country-level anomalies, such as factor timing and the role of trading costs.

4.1. Momentum

The momentum effect, which is the tendency of assets with high (low) past returns to continue to overperform (underperform) in the future, is one the most robust and pervasive asset pricing anomalies ever documented. It has been demonstrated in U.S. and international stocks, including developed, emerging, and frontier, markets, commodities, bonds, currencies, and also in equity market indices.

Index-level evidence. The first empirical evidence for the momentum effect in country equity indices may be found in Ferson and Harvey (1994b), Macedo (1995a, 1995b), Richards (1997), and Asness et al. (1997). Other researchers have continued the examinations of country-level momentum in the subsequent years. Balvers and Wu (2006) investigate a Jegadeesh and Titman (1993)-style portfolio based on stock market indices from 18 developed equity markets within the years 1969–1999. They demonstrate strong momentum effects, which worked particularly well in combination with the mean-reversion patterns. In the same year, Bhojraj and Swaminathan (2006) published a paper which examined a broader sample of 38 country indices within the same period. The authors document that the quintile of the best performing countries over the previous 6 months continued to significantly outperform the laggard indices during the next three quarters. The mean return on the long/short portfolio within a year after its formation amounted to 7.65%.

The following years saw further examinations of the momentum effect that extended the study sample both in terms of number of countries and the length of the study period. Muller and Ward (2010) investigated 70 countries and Zaremba (2016) researched 74. In terms of the sample length, several studies extended the time-series back to the 19th century and researched approximately 200 years of returns (Geczy and Samonov 2017; Hurst et al. 2017; Baltussen et al. 2019a). The momentum effect is robust to many considerations and could be successfully implemented with the use of ETFs (Andreu et al. 2013). Angelidis and Tessaromatis (2018) argue that "country-based factor portfolios offer a viable alternative implementation of factor investing in a world of illiquidity, transaction costs, and capacity constraints." Some other studies that investigated the momentum effect at the country level are Chan et al. (2000), Daniel and Moskowitz (2016), Grobys (2016), Guilmin (2015), Ilmanen et al. (2019), Breloer et al. (2014), Nijman et al. (2004), Clare et al. (2017), L'Her et al. (2004), Vu (2012), Kortas et al. (2005), and Shen et al. (2005).

Formation and holding periods. The seminal study of Jegadeesh and Titman (1993) considered 3–12-month-long sorting and holding periods. Numerous country-level studies, including the early ones, take a similar approach (e.g., Balvers and Wu 2006; Andreu et al. 2013). Later studies frequently used the approach advertised by Fama and French (1996), i.e., 1-month holding period and 12-month sorting period with the most recent month skipped (e.g., Dobrynskaya 2015; Blitz and van Vliet 2008; Asness et al. 2013). The 1-month skip period is usually applied in order to disentangle the short-term reversal effect discovered by Rosenberg et al. (1985), Jegadeesh (1990), and Lehmann (1990). Nonetheless, at the country level no similar one-month reversal effect has been documented, and Zaremba et al. (2019) argue that the returns display rather a short-term continuation. Consequently, the country-level studies do not always assume the one-month skip period, and if they do, this is usually motivated by liquidity and implementation issues (Asness et al. 2013; Baltussen et al. 2019b). For this reason, Geczy and Samonov (2017), who study early security data, decided to skip even two months in part of their tests.

Momentum improvements and alternative implementations. While the classical momentum assumes sorting the indices on raw past returns, a number of studies offer alternative, but closely related approaches. Notably, while some are conceptually very close to momentum, more detailed tests show that they provide incremental information about future returns. Moskowitz et al. (2012) and Hurst et al. (2017) evaluate so called "time-series momentum". This strategy assumes including markets into long or short portfolio depending on whether the excess return in the sorting period was positive or negative. ap Gwilym et al. (2010), Clare et al. (2017), and Baltussen et al. (2019b) test trends following strategies that focus on whether the most recent index value is above or below its moving average. Bornholt and Malin (2010, 2011) research the 52-week high strategy, whereby the return-predicting signal is the distance to the 52-week maximum index value. Avramov et al. (2018) concentrate on the distance between short- and long-run moving averages of prices. Finally, several studies demonstrate that the momentum effect could be efficiently combined with long-run reversal to augment the performance of the strategy (Balvers and Wu 2006; Asness et al. 2013; Bornholt and Malin 2014).

Sources of the momentum effect. The stock-level momentum studies highlight a number of different explanations of the momentum effect, such as risk premium, behavioral underreaction or overreaction, herding, or confirmation. For example, Bhojraj and Swaminathan (2006) highlight the potential overreaction to news about macroeconomic conditions. In addition, Cenedese et al. (2016) link the momentum effect with the tendency of investors to increase their holdings in markets that have recently outperformed (Froot et al. 1992; Bohn and Tesar 1996; Griffin et al. 2004; Chabot et al. 2014). Other studies offer some alternative explanations. Balvers and Wu (2006) link the momentum effect with production-based asset pricing concepts. From the risk-based perspective, Asness et al. (2013) argue that global funding liquidity risk is a partial source of the momentum pattern. Cooper et al. (2019) demonstrate that momentum returns are explained by the portfolio loadings on global macroeconomic risk factors. Eventually, Evans and Schmitz (2015) link the global momentum effect with data mining for anomalies, calling it a likely example of a selection bias.

4.2. Size Effect

The country-level size effect is a phenomenon parallel to the firm-level size effect discovered by Banz (1981). Keppler and Traub (1993) were the first to demonstrate that low-capitalization equity markets outperform large equity markets. The authors found that the smaller national equity markets in the MSCI Developed Markets universe produced an average annual return of 19.19% within the years 1975–1992. This outcome compared favorably with the 12.67% total compound return on the MSCI World Index. Furthermore, the small markets displayed lower downside characteristics. The outperformance of the small firms was later confirmed also by Asness et al. (1997) and by Keppler and Encinosa (2011). The size, measured with market capitalization, also belonged to the risk attributes examined by Harvey (2000).

The size effect was further demonstrated in several more recent studies. Fisher et al. (2017) show that stocks from small equity markets tend to have higher average returns than stocks from large countries. Notably, they accentuate that the country size effect is largely independent of the firm size effect and other country quantitative factors such as the momentum or value effects. Zaremba and Umutlu (2018) also demonstrate the size effect in large international sample, and Li and Pritamani (2015) show that it drives the returns on emerging and frontier markets. Similarly, Pungulescu (2014) points out that the market size effects account for up to 1% per year in terms of expected returns in emerging countries. Finally, Rikala (2017) focuses solely on European markets and finds no consistent evidence that small countries outperform large ones.

Sources of the country size premium. The firm-level size effect is frequently linked to additional risk factors, such as liquidity, information risk (see Norges Bank (2012) for a comprehensive review of the sources of small firm effect). While Fisher et al. (2017) provide evidence that the country-size effect is not simply a firm-size effect "in disguise" (the effect does not arise because smaller markets are populated by smaller firms), the potential explanations usually oscillate around the concept of risk. Rikala (2017) writes that "Intuitively, small countries producing higher returns is logical because of the widely acknowledged return profile of small stocks; investing in small firms produces higher returns in exchange for greater volatility and possibly even a return premium; a return in excess of the required compensation for additional risk." Fisher et al. (2017) conjecture that the small-country effect is due to home bias, but they provide mixed evidence in support of this conjecture. They also demonstrate that the country size effect does not simply stem from lower analysts' coverage. Zaremba (2016) shows that accounting for country-specific risks (sovereign, political, etc.) can largely explain the abnormal returns for small markets. Finally, Pungulescu (2014), similarly to Zaremba (2016), demonstrates that the size effect is more pronounced in emerging countries than in developed countries, and the size premium exists independently of the segmentation premium documented in the literature. Finally, Zaremba and Umutlu (2018) provide evidence that the country size premium is strongly concentrated in January, as in the case of the firm size effect (Keim 1983; Lamoureux and Sanger 1989; Daniel and Titman 1997). Last but not least, a white paper by Evans and Schmitz (2015) argues that the cross-sectional pattern related to market capitalization may be simply a statistical artifact, which cannot be confirmed in the recent data.

4.3. Value Effect

The value effect refers to the tendency of stocks with low valuation ratios, such as the price-to-earnings ratio or price-to-book ratio, to outperform stocks with high valuation ratios. For individual stocks, this phenomenon has been well known for about six decades now (Nicholson 1960; Basu 1975, 1977, 1983; Reinganum 1981), but in the equity indices it has been documented only in the 1990s (Keppler 1991a, 1991b). In one of the earliest studies, Macedo (1995a, 1995b, 1995c) researches the performance of country portfolios based on 18 country equity indices. She forms quartile portfolios from sorts on three different indicators, the book-to-market ratio, dividend yield, and earnings yield, and tests their performance within an almost 20-year period. She concludes that the "cheap" countries outperformed the "expensive" markets, and the differential annual return between the countries with the lowest and highest valuation ratios ranged from 1.25% to 8.54%, depending on the ratio selection, rebalancing frequency, and hedging approach.

The valuation effect was also confirmed in more recent studies that use broader data samples and longer timespans. For example, Angelidis and Tessaromatis (2018) investigated the performance of 23 developed markets within the 1980–2014 period. They found that value portfolios vividly outperformed market portfolios, delivering information ratios ranging from 0.27 to 0.39, depending on the weighting scheme. Further evidence for the value effect across countries was provided by Faber (2012), Klement (2012), Angelini et al. (2012), Ellahie et al. (2019), Novotny and Gupta (2015), Keimling (2016), Kim (2012), Heckman et al. (1996), Ferson and Harvey (1994b, 1998), Kortas et al. (2005), Lawrenz and Zorn (2017), Ferreira and Santa-Clara (2011), Desrosiers et al. (2007), Zaremba and Szczygielski (2019), Asness et al. (1997), and, finally, L'Her et al. (2004). Furthermore, Baltussen et al. (2019b) included the value effect in their two-century study, confirming its pervasive and robust character. However, Kim (2012) and Zaremba (2016) show that the effect is stronger among the emerging markets rather than in developed countries.

Valuation ratios. The value effect in country equity indices can be examined with different valuation rations. The majority of them are parallels of similar ratios or techniques used at the firm level. The most popular include price-to-earnings (P/E) ratio (e.g., Ellahie et al. 2019; Kim 2012; Keimling 2016), price-to-book (P/B) ratio (Ellahie et al. 2019; Angelidis and Tessaromatis 2018; Kortas et al. 2005), or dividend yield (Keimling 2016; Hjalmarsson 2010; Keppler 1991a). Some articles focus also on modified versions of these valuation ratios. For instance, Kortas et al. (2005) use forward P/E ratios and Lawrenz and Zorn (2017) concentrate on conditional price-to-fundamental ratios. The other utilized ratios encompass price-to-cash flow ratio (e.g., Keppler 1991a; Keimling 2016). Desrosiers et al. (2007) offer an alternative framework based on residual income. Zaremba and Szczygielski (2019) review several popular valuation ratios to conclude that the EBITDA-to-EV signal seems to be the most effective predictor of future cross-sectional returns. In addition, Ferreira and Santa-Clara (2011) show that several ratios can be combined to obtain superior performance.

Finally, there is one specific valuation ratio, which was designed purportedly for the country-level predictions: the cyclically adjusted price-to-earnings ratio, abbreviated CAPE. This technique could be traced back to the seminal work "Security Analysis" by Graham and Dodd (1940). The authors put forward an idea of smoothing earnings over the previous few years in order to calculate valuation ratios. Nevertheless, the true father of the application of CAPE to equity premium predictions is Robert Shiller, the Nobel laureate of 2013. In his 1988 study (Campbell and Shiller 1988, p. 675) he demonstrated that "a long moving average of real earnings helps to forecast future real dividends." Consequently, it might be also used to predict future returns. CAPE, called also Shiller P/E, is computed as an index value divided by the average of trailing 10-year earnings adjusted for inflation. Numerous studies demonstrate that CAPE could be also successfully applied to country selection. For example, Faber (2012) examines the role of CAPE in a sample of 30 countries' equity markets for the years 1980–2011. Faber (2012) provides evidence that an equal-weighted quarter portfolio of the countries with the lowest CAPE produces a mean yearly return of 13.5%, whereas the most expensive markets deliver only 4.3% per year. At the same time, the equal-weighted portfolio of all of the countries in the sample returned 9.4% per year. Klement (2012) demonstrates that CAPE can predict returns even within a five- to ten-year horizon. The efficiency of CAPE as the predictor of future returns was later verified and confirmed also by Angelini et al. (2012), Novotny and Gupta (2015), Keimling (2016), and Ilmanen et al. (2019).

Sources of the value effect across countries. The common reasoning regarding the value effect is similar to the parallel effect at the firm level, linking it either to behavioral mispricing or to some risk factors not captured by the established asset pricing models. Nonetheless, the catalogue of risks may be slightly different due to differences in the nature of the asset class. Ellahie et al. (2019) find that low P/B countries face temporarily depressed current earnings, and their recovery in future earnings growth is uncertain. Moreover, the markets with low P/B also exhibit greater downside sensitivity to global earnings growth. Ferson and Harvey (1998) argue, for instance, that the P/B ratio has cross-sectional explanatory power at the global level, mainly because it contains information about global market risk exposures. Zaremba (2016) also shows that the country specific risk explains a large part of the country-level value premium.

4.4. Seasonality

Cross-sectional seasonality is a relatively new phenomenon described by Heston and Sadka (2008) and later confirmed by several other authors in international markets (Heston and Sadka 2010; Keloharju et al. 2016). What Heston and Sadka (2008) found is that the stocks with a high same-month average return in the past tend to outperform stocks with a low same-month return in the past. Notably, Keloharju et al. (2016) extend this evidence to country equity indices. They find that this seasonal return pattern is admittedly weaker than in other asset classes but still visible. The tertile of countries with the highest same-month return outperform the tertile of the markets with the lowest same-month return by 0.48% (t-stat = 2.20). Notably, the markets with the highest average return in the remaining months underperformed the markets with the lowest other-month return by −0.36% (−1.66). Consistent findings were also presented in a later paper by the same authors (Keloharju et al. 2019), but, again, the statistical significance was low. The phenomenon has also been verified in early data samples by Baltussen et al. (2019b).[1]

4.5. Long-Run Reversal

The long-term reversal at the firm level dates back to the seminal study of De Bondt and Thaler (1985), who provided convincing evidence that stocks with a poor (good) performance over the previous 3–5 years tend to produce high (low) returns in the future. Further studies demonstrated that the effect is not only robust, but also pervasive, driving the returns on individual stocks globally (Baytas and Cakici 1999; Blackburn and Cakici 2017), futures (Lubnau and Todorova 2015), currencies (Chan 2013), and commodities (Bianchi et al. 2015; Chaves and Viswanathan 2016). Notably, the effect is also present in country equity indices.

[1] Note that this article focuses only on cross-sectional seasonality. Apart from this, there is some evidence that the equity indices demonstrate some monthly calendar patterns in the time series, for example in Keppler and Xue (2003) or Bouman and Jacobsen (2002).

Index-level evidence. The first evidence of the long-term reversal effect was provided by Kasa (1992) and Richards (1995, 1997). These authors based their research usually on limited samples of developed markets and demonstrated that indices with low (high) long-term performance significantly outperform in the future. The results were later confirmed with larger and longer samples by Kortas et al. (2005), Balvers et al. (2000), Balvers and Wu (2006), and Shen et al. (2005). Gharaibeh (2015) corroborated the long-term reversal phenomenon in the Middle East market indices, and Spierdijk et al. (2012) confirmed the findings in study periods exceeding a century. The strategy works well for 36–60-month sorting periods, and Malin and Bornholt (2013), who develop so-called "late stage" contrarian strategies, experiment also with skipping the most recent 12 months as in Fama and French (1996). Finally, Smith and Pantilei (2015) develop a simple mean-reversion-based strategy, which they called "Dogs of the Word". The technique assumes buying in five countries with the worst performance over the last year and holding them for five years. The strategy proves profitable both in indices and single-country ETFs. Smith and Pantilei (2015) argue that "assuming a five-year holding period, such a portfolio would have produced compounded annual returns of 10.39%", exceeding the profits on the global passive equity portfolios. In the years 1997–2012 their strategy implemented with the ETFs of the worst-performing countries outperforms the MSCI All Country World Index (MSCI ACWI) by 246 bps, delivering a higher Sharpe ratio and net of ETF expenses.

Sources of long-run reversal. Although there is no consensus on the source of long-run reversals, the existing studies offered some potential explanations. Richards (1997) considers whether the contrarian profits may stem from risk-differentials but finds no support for this hypothesis. He argues that no evidence suggests that loser-index returns are riskier in terms of their volatility or exposure to the world equity market returns. Cooper et al. (2019) link some similar patterns to global macroeconomic risks.

The winner-loser reversals profits are larger among the smaller countries than in the larger markets, so there may be an element of a "small-country effect", but still this phenomenon does not fully explain the long-term reversal effect (Zaremba and Umutlu 2018).

Another option is that the long-run reversal is just a statistical artifact and that its returns were purely period specific. Indeed, country-level long-term reversal tends to be very volatile and unstable over time, but its robustness over very long periods casts doubt on such an explanation (Spierdijk et al. 2012). Furthermore, Malin and Bornholt (2013), who employ longitudinal analysis, argue that the mean-reversion effect is present even in the post-1989 sample despite the absence of visible contrarian profits for the developed markets.

Further explanations point to behavioral mispricing that cannot be arbitraged away for many reasons, including cross-border flow limitations. The behavioral overreaction hypothesis is also consistent with the link to the momentum effect (Richards 1997; Balvers and Wu 2006; Malin and Bornholt 2013).

4.6. Price Risk

The relationship between the risk measures calculated on the basis of prices and future returns on stocks has been a controversial and intensively researched topic in recent years. On the one hand, early theoretical models suggest that systematic risk should positively correlate with future returns in the cross section, and some early studies seem to produce consistent evidence (Sharpe 1964; Black et al. 1972; Fama and MacBeth 1973; Blume 1970; Miller and Scholes 1972; Blume and Friend 1973). Similarly, the stock-specific risk should also be either positively correlated or unrelated, depending on market integration (Levy 1978; Tinic and West 1986; Merton 1987; Malkiel and Xu 1997, 2004). However, the empirical evidence mounting over the past two decades documents a contrary phenomenon—the so called low-risk anomaly. The high-risk firms tend to underperform the low-risk firms on the risk adjusted basis, both when the risk is understood as a systematic risk or an idiosyncratic risk (Frazzini and Pedersen 2014; Ang et al. 2006, 2009). The effect is usually explained with the combination of behavioral biases and limits to arbitrage (Blitz et al. 2019). Notably, some other measures of price-based risk, such as value at risk, display a rather positive than negative relationship with future returns in the cross section (Bali and Cakici 2004).

Market beta. The risk-return relationship at the country level is also far from obvious and depends strongly on risk measures. The first studies bring weak evidence on the pricing on systematic risks, especially in emerging markets (Harvey 1991, 1995; Harvey and Zhou 1993). In one of the first studies, Harvey (1995) finds no relationship between beta and future returns across 20 emerging markets. In addition, more recent studies by Estrada (2000) and Bali and Cakici (2010) lead to similar conclusions. Nonetheless, the seminal study of Frazzini and Pedersen (2014) demonstrates that on a risk-adjusted basis, low-beta indices outperform high-beta indices, and the effect is confirmed by Berrada et al. (2015). Hedegaard (2018) also corroborates the low-beta effect in developed and emerging market indices, demonstrating additionally that it is partially predictable by past market returns.

Idiosyncratic risk. The country-level examinations display no evidence of the low-idiosyncratic risk anomaly, which is similar at the firm level. The majority of the studies find either a positive relationship or no significant relationship between idiosyncratic (or total) volatility and expected country returns in the cross section. Bali and Cakici (2010) compute total and idiosyncratic volatility measures of different asset pricing models based on estimation periods ranging from one to six months and find a positive relationship. On the other hand, articles by Umutlu (2015, 2019), Liang and Wei (2019), and Hueng and Ruey (2013) show either very weak on unreliable links between idiosyncratic or total volatility and future returns in the cross section. The pricing of similar measures of price risk has been also considered by Bekaert and Harvey (1995), Estrada (2000), and Hueng (2014).

Other definitions of risk. Several studies examined other definitions of price risk. Some of them documented significant relationships, while others were less successful. Hollstein et al. (2019) investigate the pricing of tail risk in international stock markets. They find that both local and our newly computed global tail risk strongly predict global equity index excess returns. Sorting equity market countries into portfolios by their tail risk generates sizable excess returns across various holding periods. Arouri et al. (2019) examine the role of jump risk. Umutlu and Bengitöz (2017) offer a similar metric based on return range. Finally, Atilgan et al. (2019) test the forecasting power of several measures of downside risk, i.e., downside beta, tail beta, value at risk, and expected shortfall, but find no consistent evidence of return predictability.

4.7. Non-Price Risks

Besides the measures of risk derived from price behavior discussed in the previous section, numerous studies explore the role of alternative definitions and source of risk. The logic behind these studies is the following: if the country-specific risk matters for country-level asset pricing, what actually is this country-specific risk? Can it be conceptualized and captured more precisely with some alternative measures?

Examinations of the country-specific risks as determinants of future market-level performance are found in the earliest studies of cross section of country returns and date back to the 1990s (Ferson and Harvey 1994a, 1994b; Erb et al. 1995, 1996a; Bekaert et al. 1996). Some of these studies focus on just one type of risk, such as credit risk or political risk, while others examine several categories or exposures to them (Ferson and Harvey 1994a; Erb et al. 1996a; Harvey 2004). The types of considered country specific risks could be categorized into several broad classes.

Credit risk. Country credit risk (sovereign risk, default risk) belongs among the best-established predictors of future returns. Not only has it been extensively documented by practitioners, it is also widely employed by practitioners in models of cost of equity. A widely used database in Damodaran (2019) advocates using country risk premia based on local sovereign ratings. Erb et al. (1995) employ measures of credit risk calculated on the basis of the Institutional Investor Semiannual Survey of Bankers and demonstrate that the credit risk is priced in the country equity premium. In a later study, the same authors show how the credit risk could be used to estimate risk premia for 135 different countries—even those without developed stock markets (Erb et al. 1996b). More recent research confirms these early findings with different measures of credit risk. Avramov et al. (2012) use quantified credit ratings for 75 countries in the period 1989–2009. They show that the high credit risk tercile outperforms the stocks in the countries in the low credit risk tercile by 0.57% monthly. Zaremba (2016) further corroborates these findings by using the Economist Intelligence Unit sovereign risk indicator calculated by its Country Risk Service. Having examined 74 countries for the years 1999–2015, Zaremba arrives at a qualitatively similar return on a tertile differential portfolio of 0.50% per month.

Political risk. The political risk is another category of risk that has been examined since the beginning of studies of the cross section of country returns (Erb et al. 1996a; Diamonte et al. 1996). The political risk is most frequently measured with the Political Risk Index, which constitutes a component of the International Country Risk Guide calculated by the PRS Group.[2] In general, the studies find that the political risk is positively related to the expected returns in the cross section. (Erb et al. 1996a; Dimic et al. 2015; Lehkonen and Heimonen 2015; Vortelinos and Saha 2016). Bilson et al. (2002) show that the political risk is more strongly priced in emerging markets rather than in developed ones. Consistently with this, Diamonte et al. (1996) concentrate on changes in political risk and demonstrate that average emerging market returns in countries experiencing declining political risk exceed those of emerging markets experiencing growing political risk by approximately 11% per quarter. In contrast, the analogous return for developed markets amounted to only 2.5%. Furthermore, Zaremba (2016) show that country-risk pricing is stronger in emerging and—in particular—frontier markets. Dimic et al. (2015) explore this difference further and show that while composite political risk is priced in all the types of stock markets (i.e., developed, emerging, and frontier), the role of individual components varies across countries. For example, government action is a common source of risk in all market categories, but the impact of government stability is unique to frontier equities.

Recent studies offer some further insights into the effect of political risk. Pagliardi et al. (2019) propose an international capital asset pricing model that accounts for the political risk. The model explains up to 77% of cross-sectional returns, outperforms some other benchmark models, and has a good predictive power. Gala et al. (2019) offer two new politics and policy risk factors and demonstrate that markets with lower politics and policy rankings produce higher average returns. They also offer some long-short strategies, which are argued to produce returns exceeding 12% per year with a corresponding Sharpe ratio of 0.59.

Other non-price risks. While credit risk and political risk seem to be the most intensively researched categories, other studies also consider alternate types of risks, such as economic and financial risks (Erb et al. 1996a), macroeconomic and political risks and uncertainty (Chang et al. 2017; Rapach et al. 2005), or expropriation risk (Dahlquist and Bansal 2002). Lee (2011) empirically tests the liquidity-adjusted asset pricing model of Acharya and Pedersen (2005) at the global level. The latter provide evidence that liquidity risk is priced internationally, independently of other risks. Additional analyses of country-level risk are also performed by Suleman et al. (2017).

4.8. Other Predictors

In this section, we review an array of less known predictors that have been discovered and examined in recent years.

Fund flows. Srimurthy et al. (2019) offer a new country asset allocation approach based on fund flows. The authors find reliable positive returns on a strategy that goes long in the countries that have attracted indirect investment via equity fund flows and short in the countries that have not. The effect is independent of some other well-established return predictors, such as size or momentum.

Economic freedom. Several studies explore the role of economic freedom for the future stock market returns. Stocker (2005) was, most probably, the first to try to examine this relationship. Having examined the returns on developed and emerging markets in the years 1975–2002, he demonstrates

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2 For details, see https://www.prsgroup.com/explore-our-products/international-country-risk-guide/.

that the rate of increase in economic freedom is directly related to equity returns. He also develops an investment strategy based on this phenomenon, which earns attractive investment returns. Similar evidence is provided by Smimou and Karabegovic (2010), who concentrate on MENA markets. Finally, Stocker (2016) corroborates his own earlier results. He documents that the index of economic freedom provides incremental information about future returns that have low correlation with value, momentum, and size factors. Stocker (2016) christens the abnormal returns from investing in low economic freedom countries "the price of freedom".

News. Calomiris and Mamaysky (2019) develop a new classification methodology for using the content and context of news to forecast the performance of 51 equity markets. They consider issues such as topic-specific sentiment, frequency, and unusualness (entropy) of word flow. They demonstrate significant predictive abilities of the news flow for returns, volatilities, and drawdowns, particularly for longer (one-year) horizons. The effect is more pronounced in emerging markets.

Analyst recommendations. There are numerous studies of the predictive power of analysts' recommendations for individual stock returns (Kothari et al. 2016), but Berkman and Yang (2019) are the first to consider a country-level parallel. The authors digest analysts' reports from 30 countries for the years 1994–2015 to demonstrate that the aggregate recommendation score helps to predict international stock market returns. The country-level recommendations make it possible to predict future aggregate cash flow and returns. A country-allocation strategy based on the insights of Berkman and Yang (2019) yields an approximate abnormal return of 1% per month.

Asset growth. The role of asset growth for future returns on individual stocks has become well known since Cooper et al. (2008); it was even incorporated in some popular recent factor pricing models (Fama and French 2015; Hou et al. 2015). Wen (2019) checked whether any similar effect exist at the country level. The author provides convincing evidence that aggregate asset growth constructed from bottom-up data negatively predicts future market returns across the G7 countries. This information about future performance is not captured by other measures of investment growth and macroeconomic variables.

Growth of government debt. Using a set of 77 countries and data from World Development Indicators, Wisniewski and Jackson (2018) document a negative association between increases in the central government debt-to-GDP ratio and stock index returns, expressed in U.S. dollars. The authors estimate that raising the debt ratio by one percentage point decreases the stock returns by between 39 to 95 basis points. Wisniewski and Jackson (2018) explain this phenomenon with an upward pressure on private interest rates, which appears to signal a greater tax burden in the future.

Democracy. Lei and Wisniewski (2018) explore the role of democracy, proxied with the Political Right Index calculated by the Freedom House. Having researched a sample of 74 countries for the years 1975–2015, they conclude that, compared with autocracies, democratic states are characterized by higher returns despite displaying lower volatility risk. Lei and Wisniewski (2018, p. 1) offer three potential explanations of this effect: "First, the strength of investor protection under authoritarian leaders is relatively weak, making capital holders more vulnerable to expropriation. Second, our findings appear to be partly attributable to investors' sentiment that is driven by media reports. Last but not least, autocracies appear to hinder the development of pension funds, suppressing thereby the demand for stocks."

Gravity. Bae (2017) documents an interesting linkage between performance of different countries, namely, large countries lead returns of small countries, and this predictability decreases with geographical distance of the two countries. The effect could be translated into a long-short strategy producing about 10% risk-adjusted return per annum, which is not explained by the well-established return predictors.

Interest rates. Hjalmarsson (2010) investigates several potential predictors of future stock returns. The empirical results demonstrate that short-term interest rate and the term spread are fairly robust predictors of stock returns in developed markets. In contrast, Hjalmarsson (2010) finds no robust and consistent evidence of predictability by earnings or dividend yields. Consistent evidence is provided by Charles et al. (2017).

4.9. Further Investment Considerations

Besides discovering, testing, and explaining different cross-sectional patterns, separate strains of literature examine different practical aspects of country allocation based on market-level cross-sectional patterns. From the practitioners' perspective, two issues seem of particular importance: (1) the influence of trading costs and (2) the timing and selection of different country-allocation strategies.

Transaction costs. At the individual stock level, Novy-Marx and Velikov (2016) and Chen and Velikov (2019) demonstrate that transaction costs may have a detrimental impact on the profitability of anomaly-based quantitative strategies, in particular in the case of high turnover anomalies. At the inter-market level, the effect could be potentially even worse due to the necessity to move capital across countries. The results may also strongly depend on the implementation method chosen. Nonetheless, several studies document that when implemented with the use of ETFs, the most prominent country allocation strategies may remain profitable. Andreu et al. (2013) examine the momentum effect in single-country ETFs. They find that investors are potentially able to exploit the country momentum strategies with an excess return of about 5% per year. They note that the bid-ask spreads on ETFs are markedly below the implied break-even transaction cost levels, so the momentum effect could be profitable even after accounting for the trading costs. Finally, Blitz and van Vliet (2008) provide similar evidence extending the asset universe to additional asset classes, and Angelidis and Tessaromatis (2018) put forward analogous arguments also for value and size effects.

Factor timing and selection. The large number of different potential factor strategies that could be used to allocate money across countries raises the question of factor timing and factor selection. In other words, which strategies could be selected at a given time and how can we predict their performance? Several studies demonstrate significant time-series variation in country-level strategy returns, which can be linked, for example, to macroeconomic variables, sentiment, or liquidity and arbitrage constraints (Asness et al. 2013; Cooper et al. 2019; Ilmanen et al. 2019). Indeed, some papers provide evidence that country-level strategies could be timed. Yara et al. (2018) argue that value spreads, i.e., the differences in valuations of long and short sides of the spread portfolios, help to predict their performance. Finally, Ilmanen et al. (2019) compare several well-known anomaly selection strategies from the firm-level universe. In particular, they investigate 12 different timing signals. In general, they find weak and inconsistent evidence of factor timing. The strongest results are found for timing based on inverse volatility and valuation spreads.

5. Concluding Remarks

Over the last 30 years the asset pricing literature has accumulated remarkable evidence on the predictability of the country equity returns in the cross section. The empirical findings demonstrate numerous cross-sectional patterns in country equity indices. Some of them resemble their stock-level counterparts, such as value, momentum, or seasonality. Others, such as fund flows or political risk, are strictly characteristic for country-level return patterns.

The studies of the cross section of country equity returns use various data sets and differing methodologies. Such a situation may lead to inconclusive results and inconsistencies across papers. This highlights the need, therefore, of further standardization of country-level asset pricing studies.

In this article, we attempted to capture possibly the broadest survey of the studies of the country-level returns. Nevertheless, we acknowledge that due to possible omissions the presented picture may be incomplete. Furthermore, an additional limitation of this paper is the reliance on previously published research without any replication or verification of the accuracy of their outcomes.

The current landscape of cross sections of market index returns is growing in sophistication. The number of documented patterns is increasing. Meanwhile, the sources of this massive mispricing remain still largely unknown or not commonly agreed upon. The future studies of the topics discussed in this paper should focus on pan-anomaly examinations that will try to bring some order into the factor structure of the country equity returns. Perhaps the multiple return predictive signals could be summarized in only several variables. Furthermore, we still need to improve our understanding of the economic mechanisms behind these patterns. Studies focused on the sources of the cross-sectional patterns in country returns would be very valuable. Finally, future investigations should also consider a practical investor's perspective. The questions of implementability, transaction costs, or potential improvements of the trading strategies based on cross-sectional patterns would be highly valuable for market practitioners.

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Review

Time-Varying Price–Volume Relationship and Adaptive Market Efficiency: A Survey of the Empirical Literature

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Abstract: This paper conducts a review of the literature on the price–volume relationship and its relation with the implications of the adaptive market hypothesis. The literature on market efficiency is classified as efficient market hypothesis (EMH) studies or adaptive market hypothesis (AMH) studies. Under each class, studies are categorized either as return predictability studies or price–volume relationship studies. Finally, review in each category is analyzed based on the methodology used. Our review shows that the literature on return predictability and price–volume relationship in classical EMH approach is extensive while studies in return predictability in the AMH approach have gained increased attention in the last decade. However, the studies in price–volume relationship under adaptive approach are limited, and there is a scope for studies in this area. Authors did not find any literature review on time-varying price–volume relationship. Authors find that there is a scope to study the nonlinear cross–correlation between price and volume using detrended fluctuation analysis (DFA)-detrended cross–correlational analysis (DXA) in the AMH domain. Further, it would be interesting to investigate whether the same cross–correlation holds across different measures of stock indices within a country and across different time scales.

Keywords: market efficiency; price–volume; efficient market hypothesis; adaptive market hypothesis; time-varying or adaptive market efficiency

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1. Introduction

One of the core concepts in the neoclassical finance that has been extensively researched and debated is the market efficiency, and has its roots in the studies conducted by Fama (1965, 1970), Samuelson (1965) and Roberts (1967), who introduced the concepts of efficient markets and efficient market hypothesis (EMH) to the world. Markets are defined to be efficient if prices always fully reflect available information (Fama 1970). This requires that all available information is immediately available to all the participants and prices reflect this information immediately. However, a distinction is made between weak-form, semi-strong form and strong-form of efficiency based on the type of information that is reflected in the price. The weak-form of efficiency tests whether the market prices reflect the information that already is contained in the past market data such as past prices, trading volume or short sales (Rizvi and Arshad 2017).

This weak-form of hypothesis has been extensively tested and debated over the years. Results of some of the studies deduced the existence of the weak form of efficiency while some argued against. The focus of these studies was limited to test whether the markets are efficient. A fresh perspective on the adaptive nature of the market was offered by Lo (2004, 2005) using adaptive market hypothesis

(AMH). According to AMH, market efficiency is related to environmental factors such as the number of competitors in the market, the magnitude of profit opportunities available, and the adaptability of market participants.

Although the AMH is not formally defined, its implications have been studied to indicate the existence of the adaptive nature of the markets. The first implication of AMH indicates that the relationship between risk and reward is unlikely to be stable over time. The second implication is that arbitrage opportunities exist from time to time. The third implication suggests that changing business conditions change investment strategies. The fourth implication is that adaptation to changing market conditions is key to survival (Lo 2004). Moreover, the AMH is not a substitute for the EMH, but supports in understanding the empirical variation of the EMH. For example, time-varying efficiency is better understood in the context of the implications of the AMH.

Although the literature on time-varying efficiency is increasing, authors do not find any review of literature on the time-varying price–volume relationship and/or time-varying market efficiency. Trading volume has played second fiddle to returns in understanding the efficiency of the market. Blume et al. (1994) have shown analytically that volume may act as an indicator of the quality of information revealed by prices. This justifies the use of volume in forecasting future stock returns. While authors do agree that return predictability is the focus of the academic literature, however, Gebka and Wohar (2013) have argued that volume return causality is a robust phenomenon. Volume can reveal investor's future risk preferences and hence expected returns. This time-varying nature of the markets can be studied by testing whether autocorrelation between the returns or price–volume relationship changes over time. Some recent papers that have studied this effect are of Neely et al. (2009); Hiremath and Narayan (2016); Noda (2016), Urquhart and McGroarty (2016); Khuntia and Pattanayak (2018); Rizvi and Arshad (2017); Charles et al. (2017); Ito et al. (2016).

Studies reviewing the conditions of efficiency are of value from the perspective of traders, investors, and policymakers. Such a review also would be valuable as it produces synthesized knowledge base for the future research (Tranfield et al. 2003).

The literature on weak-form market efficiency can be divided into classical and adaptive studies; classical studies focus on the premise that markets move toward efficiency over period whereas adaptive studies focus on changing or dynamic nature of markets. These studies further can be divided into two groups based on the type of relation that is tested to determine the efficiency, viz. return predictability and price–volume relationship. Each study is further compared based on the methodology used to test the efficiency. The focus of this paper is to review the literature studying weak-form, time-varying market efficiency with keeping in mind the following objectives:

1. To classify the literature based on the approach to the weak-form of the efficiency
2. To categorize the studies in each approach based on the relationships studied
3. To compare each relationship studied based on the methodology adopted
4. To discover the scope for future research

The important implications of this review are as follows. Firstly, we show that the extant literature has established that there exists a nonlinear relationship between returns and past returns and also nonlinear relationship between price and volume. Secondly, the multifractal nature of the price and volume series implies that the relationship to vary over time, which is the implication of AMH. Thirdly, we discover important research gaps that help understand the relationship between price–volume and efficiency in the context of AMH.

The review of studies in this paper is organized as shown in the Tables 1 and 2. These tables include a few indicative papers for ready reference. Table 1 shows the review matrix for return predictability studies and Table 2 shows the review matrix for price–volume relationship studies.

Table 1. Review matrix for return predictability studies.

	EMH (Classical)	AMH (Adaptive)
Linear autocorrelation	Box test—Q, VR test, AQ, AVR, Wild bootstrap AVR and AR-GARCH (Kim 2009; Rockinger and Urga 2000)	MF-DFA (rolling subsample), Box test, autocorrelation tests, AQ, VR, AVR, wild bootstrap AVR, time-varying AR model, GARCH-M (Sensoy and Tabak 2015; Tiwari et al. 2019)
Nonlinear autocorrelation	GS, Consistent test, Wild bootstrap GS (Gozbasi et al. 2014)	MF-DFA, GS test, Consistent test (Khuntia and Pattanayak 2018; Kim et al. 2011)
Linear long memory	R/S, Spectral Regression (Barkoulas et al. 2000)	MF-DFA, R/S (Hull and McGroarty 2014)
Nonlinear long memory	modified R/S, ESTAR unit root test (Gozbasi et al. 2014)	MF-DFA, Modified R/S analysis (Todea et al. 2009)
Linear unit root	ADF, PP, DF-GLS, NP, KPSS or VR test (Konak and Şeker 2014), (Gupta and Yang 2011)	—

Note: VR = variance ratio, AVR = automatic variance ratio, AQ = automatic portmantau, GS = generalized spectral. R/S = rescaled range, MF-DFA = multifractal detrended fluctuation analysis.

Table 2. Review matrix for price–volume relationship studies.

	EMH (Classical)	AMH (Adaptive)
Linear Contemporaneous	Canonical correlations, linear regression (Chen 2012; He et al. 2014; Lee and Swaminathan 2000)	MF-DFA DCCA (rolling subsample), dependence switching copula model, MF-DFA and MF-DXA (Ferreira 2019; Hasan and Salim 2017)
Nonlinear Contemporaneous	Canonical correlations, nonlinear regression, GARCH (Chordia and Swaminathan 2000; He et al. 2014)	MF-DFA DCCA (rolling subsample), dependence switching copula model, MF-DFA and MF-DXA (Khuntia and Pattanayak 2018)
Linear Causal	MODWT-VAR, causality tests based on quantiles, Granger causality, regression with fixed effects (Balcilar et al. 2017; Chordia and Swaminathan 2000; Gupta et al. 2018; Lin 2013)	MF-DFA DCCA (rolling subsample), dependence switching copula model, MF-DFA and MF-DXA (Stošić et al. 2015)
Nonlinear Causal	Regression with fixed effects, quantile regression, permutation entropy (Caginalp and DeSantis 2017; Hiemstra and Jones 1994; Matilla-García et al. 2014)	——

Note MF-DFA = Multifractal Detrended Fluctuation Analysis, DCCA = Detrended Cross Correlational Analysis, also quoted as DXA, MODWT = Maximum Overlap Discrete Wavelet Transform.

The rest of the paper is organized as follows. Section 2 describes the random nature of price fluctuation and the efficient market hypothesis. Section 3 develops the perspective of adaptive market hypothesis. Section 4 reviews the return predictability studies in both EMH and AMH perspectives. Section 5 reviews the studies covering the price–volume relationship under EMH and AMH perspectives. Section 6 lists the findings and illustrates the research gap followed by the conclusion in Section 7.

2. The Random Nature of Price Fluctuations and Efficient Market Hypothesis

Study on the random nature of price fluctuation can be traced back to Bachelier (1900) who deduced that the mathematical expectation of a potential profit of a speculator to be zero and showed that movement of stock prices is a stochastic process. The random nature of the price changes was further studied and supported by Cowles (1933); Working (1934); Kendall and Hill (1953); Osborne (1959) and Roberts (1967) and challenged by Cootner (1962); and Steiger (1964). However, the term efficient was first introduced by Fama (1965) for the first time in his paper concluding the prices follow a random walk. Fama (1965) further elaborated that in an efficient market the actual price would be a good estimate of its intrinsic or fundamental value. In the same year, Samuelson (1965) explained the efficient market in terms of a martingale rather than a random walk. (Readers are directed to Delcey (2018) for the precise difference between Fama and Samuelson in the theoretical construction of EMH[1].)

Roberts (1967) coined the term efficient market hypothesis (EMH) and also made a distinction between weak and strong form tests. Later, Fama (1970) formally defined efficient markets as

> "a market with great number of rational profit maximizers actively competing, with each trying to predict future market values of individual securities, and where current important information is almost freely available to all participants."

Since then the EMH has been debated and evidence against EMH has been offered by LeRoy (1973, 1976, 1989) pointing out that stock prices follow martingale process and not random walk. Basu (1977) found the use of the P/E ratio to forecast prices while Ball (1978) documented excess returns after public announcements. Jensen (1978) pointed out the existence of arbitrage opportunity while Lucas (1978) indicated that rational investor may behave differently under risk aversion conditions. Grossman and Stiglitz (1980) argued that markets tend to move toward efficiency over time eliminating any price anomalies. Shiller (1981) showed that volatility of the stock prices is higher than calculated based on fundamental information. Banz (1981) documented that small stocks outperform large stocks and LeRoy and Porter (1981) showed excess volatility in the stocks. Kiem (1983) found that the relation between size and excess return is always negative. These studies provide evidence against the tenets of the EMH.

Further evidence against the EMH was shown by Lo and MacKinlay (1988) who used the variance ratio test and rejected the random walk hypothesis.Fama and French (1988) found large negative autocorrelations in the stock returns in longer time horizons, Conrad and Kaul (1988) found time-variation in expected returns, Poterba and Summers (1988) showed positive autocorrelations in short run and negative autocorrelations over the long run, De Long et al. (1990) showed that irrational noise traders earn higher than expected returns.

In the midst of challenges to the EMH theory, Fama (1991) reclassified the empirical tests of market efficiency, renaming the weak form tests of market efficiency as tests for return predictability, semi-strong martingale tests as event studies and tests for strong-form as tests for private information. He conducted tests of return predictability using variables such as dividend-price ratio, earnings–price ratio, the book–to–market ratio among others instead of using the past returns.

The evidence against EMH still continued with De Bondt (1993); Ferson and Harvey (1993); Fama and French (1995); and Pesaran and Timmermann (1995). Fama (1998) termed this evidence as anomalies, anomalies being the chance results. The debate still continued as Shiller (2003) urged to replace EMH with behavioural finance framework and Schwert (2003) presented further anomalies. While Malkiel (2003) made a strong case for the continuation of EMH, he also presented evidence against EMH in the long run trend in 2005 (Malkiel 2005). Timmermann and Granger (2004) found that forecasting patterns are not persistent thereby supporting EMH, while Milionis and Moschos (2000) argued that due to the heteroscedasticity, although the random walk hypothesis is rejected, the weak-form of hypothesis may not be rejected. Brealey et al. (2011) defined a market as efficient when it was not possible to earn a profit higher than the market return. Recently, Gârleanu and Pedersen (2018) proposed a model in which anomalies arise due to the friction between an investor's search cost of finding informed asset manager and asset manager's cost of collecting the information about assets. They term the markets with such

[1] Delcey (2018) classifies the definition of EMH as 'Fama's EMH' and 'Samuelson's EMH'. Fama's EMH is based on the claim that prices reflect economic fundamentals and the prices fluctuate randomly as they converge to fundamental values, while 'Samuelson's EMH' based on the pure random nature of price changes with no regard to fundamental value.

anomalies as efficiently inefficient markets where there is an equilibrium level of inefficiency reflecting this friction between these two costs.

Apart from arguing against or supporting EMH, there are quite a few papers that could be bifurcated into theoretical exploration papers and survey of literature papers. In the first group, Rubinstein (1975) gave a theoretical exploration of prices fully reflect the information and Milionis (2007) provided the statistical definitions and comments on EMH. Beaver (1981) and Cornelius (1993) explored the definition of informational efficiency. Malkiel (1989) wrote an article on the meaning of efficiency, while Gilson and Kraakman (1984) covered the mechanisms of market efficiency. O'Hara (2003) explored the relationship between liquidity and efficiency, Malkiel (2003) commented on the critics of the EMH, and Jarrow and Larsson (2012) explained the meaning of market efficiency. In the second group, one can refer to the survey of the empirical literature on EMH by Andreou et al. (2001) on the review of statistical models. Yen and Lee (2008) provided empirical evidence on EMH. Degutis and Novickytė (2014) reviewed the literature and methodology on EMH. Ţiţan (2015) and Fakhry (2016) did a review of specialized literature of EMH.

The literature on testing the market efficiency in its weak-form is vast and increasing. However, a new perspective based on bounded rationality is developed recently and is covered in the next section.

3. Adaptive Market Hypothesis

Efficient Market Hypothesis presumes that markets are either efficient or inefficient and that degree of market efficiency over time is stable over a period. This all-or-nothing notion of market efficiency set by EMH was criticized by Grossman and Stiglitz (1980). They argued the impossibility of informationally efficient markets, because if markets are efficient then there would not be any incentive for traders to acquire costly information. In the light of the impossibility of perfect efficient markets, Campbell et al. (1997) introduced a notion of relative efficiency, which permits to compare the efficiency of one market to another market. This gave way to research in the area of changing or dynamic market efficiency.

During this period, academics focused on time-varying or evolving efficiency. For example, Emerson et al. (1997) used Kalman filter technique to trace the changing degree of market efficiency over a period. Zalewska-Mitura and Hall (1999) formalized the time-varying autoregressive model to test the time evolving market efficiency. Charles and Darné (2009) highlighted the use of rolling subsamples to capture the effect of structural changes while applying the time-varying auto-regressive models.

Another stream of literature based on behavioural aspects was developed[2] during this period which integrated the behavioural concepts into the modern portfolio theory. This theme was first studied by De Bondt and Thaler (1985) discovering that stock prices overreact implying that markets are inefficient and are dependent on the behavioural aspect of the investors. Daniel et al. (2001) showed that investors are overconfident and have self-attribution bias that goes against the rational behaviour expected from the investor in the EMH paradigm. Shiller (2003) urged to replace EMH with behavioural finance paradigm. Subsequently, Lo (2004) proposed an adaptive market hypothesis (AMH) based on evolutionary principles with the notion of bounded rationality Simon (1955) to coexist with EMH. Recently, Lo (2012) considered that the investor population, who learn from and adapt to the market environment, change over time.

Under the AMH, prices reflect as much information as dictated by the combination of business conditions such as the number of competitors entering and exiting the industry, and the type and magnitude of profit opportunities available (Lo 2004). The AMH is qualitative and abstract in nature, and therefore the formal definition of AMH is not available in the literature. However, concrete

[2] Readers may refer to Emerson et al. (1997); Zalewska-Mitura and Hall (1999); Lo (2004, 2005) to see the development of literature in time-varying market efficiency.

practical implications are derived to test the AMH. These implications are as follows. First, the relation between risk and reward is unlikely to be stable over time, i.e., the relation is time-varying. Second, there will be arbitrage opportunities available in the market from time to time, indicating markets efficiency changes over the period. Third, the changing business conditions change the investment strategies and therefore, there will be a change in the payoffs. Fourth, the participants adapt to the changing market condition in order to survive. The AMH can be inferred by studying these implications in the market.

The following section covers the return predictability studies under both the EMH and AMH perspectives.

4. Return Predictability Studies

The weak form of efficiency tests can be classified as tests of return predictability and tests of profitability of trading strategies (Lim and Brooks 2011). Tests of return predictability include tests of linear serial correlations, unit root tests, low-dimensional chaos, nonlinear serial dependence, and long memory. The tests of profitability of trading strategies include technical trading rules, momentum and contrarian strategies. This paper focuses only on the return predictability studies and the following subsection covers the studies under the tests of return predictability.

4.1. Return Predictability and EMH

It is well known that the weak-form of efficiency considers that price movements are random in nature and therefore cannot be predicted based on the past market information. In other words, the prices do not have a long memory and should not exhibit any pattern that could enable forecasting future prices. The weak-form of efficiency of the market is established by testing the randomness (random walk hypothesis—RWH hereafter) or martingale difference hypothesis (MDH hereafter in this section) in the price series.

Unit Root Tests The RWH is tested using unit root tests such as ADF (Dickey and Fuller 1979), PP (Phillips and Perron 1988), DF-GLS (Elliott et al. 1996), NP (Ng and Perron 2001) and KPSS (Kwiatkowski et al. 1992) to show whether the series is non-stationary (non-stationarity implying RWH) and variance ratio test (Lo 1989; Lo and MacKinlay 1988).

Standard linear models test RWH using unit roots tests such as ADF, PP, KPSS or variance ratio test. Konak and Şeker (2014) test developed markets for the presence of random walk using unit root tests such as ADF and PP and shows that the market is non-stationary and therefore random walk hypothesis is accepted and concludes the existence of weak-form of market efficiency in FTSE 100. Gupta and Yang (2011) study Indian capital market using ADF, PP and KPSS tests and find that all three tests reject weak-form of efficiency for daily and weekly data, but support for quarterly data. Worthington and Higgs (2004) also test the European markets for the random walk using ADF, PP, KPSS, multiple variance ratio (MVR) test and find that European markets, in general, are inefficient.

Autocorrelation Tests The MDH is typically tested in the time-domain using the sample autocorrelations or in the spectral-domain (frequency-domain) using the periodogram. In the time-domain, the serial correlation for MDH is tested using the portmanteau test of Ljung and Box (1978) and variance ratio test by Lo (1989); Lo and MacKinlay (1988). Recent development in techniques has bettered these tests in terms of size and power properties. These tests are automatic portmanteau (AQ) test by Escanciano and Lobato (2009) and the automatic variance ratio (AVR) test by Kim (2009). However, the presence of long memory i.e., long term dependence in asset returns poses challenges for the results obtained through linear models and requires that nonlinear models be developed. In the nonlinear measures, most popular are the generalized spectral (GS) test and the Consistent tests of Domínguez and Lobato (2003). Further, a survey of literature supports the use of Wild Bootstrap AVR in linear dependence and Wild Bootstrap GS in nonlinear dependence.

Rockinger and Urga (2000) test the transition economies (Czech Republic, Hungary, Poland, Russia) for the evolution of efficiency using time–varying AR (1) model with GARCH effects and find that Hungarian markets are efficient and Czech and Polish markets are converging toward efficiency.

The general finding in the literature review of this section is that there is evidence for weak-form efficiency in the US, find European markets in general inefficient, while transition economies and developing countries are moving toward efficiency.

Long-memory models As many studies have found out long memory or long-term dependence in the time series, the application of linear models to such a series is questionable. The presence of long memory indicating long term dependence in the series contradicts the weak form of EMH. The long memory or dependence in the series is tested using the rescaled range (R/S) method in the linearity of series framework, but it fails to address the nonlinear series. Lo (1991) developed a modified R/S method to address this issue and found no evidence to support long memory in US stock returns. Gozbasi et al. (2014) employed nonlinear ESTAR unit root test (developed by Kruse (2011)) and found nonlinear behavior in Borsa Istanbul stock price index series. Using R/S method and the spectral regression method, Cheung and Lai (1995) find no evidence of persistence in several international stock returns series. Barkoulas et al. (2000) test the long memory or fractional dynamics with spectral analysis using ARFIMA and find evidence for long memory in the Greek market. For a summary of methods and review of important studies in both linear and long memory models, readers are directed to Sewell (2012).

Contrary to recent findings using the multifractal analysis, these studies didn't find long memory in the US, Greece, Turkey and many other countries.

4.2. Return Predictability and AMH

One of the stylized facts (refer (Cont 2001)) of financial time series, intermittence, implies the oscillatory and heterogenic fluctuation in the time series. This means that returns display a high degree of variability or fluctuation at any time scale. This fluctuation is found to be multifractal nature, first introduced by Mandelbrot et al. (1997). They claim that the multifractal model of asset returns also explains most of the other stylized facts of financial time series. Standard models like serial correlation tests, runs tests, unit root tests, variance ratio tests cannot capture the multifractal nature of financial time series (Bacry et al. 2001). Therefore, techniques measuring the multifractal nature of time series have emerged in the literature. Two of the most well-known numerical methods to find the multifractal spectrum of time series are the Wavelet Transform Modulus Maxima (WTMM) and Multifractal Detrended Fluctuation Analysis (MF-DFA). MF-DFA is the preferred method showing less bias and giving less false positive results.

Since the AMH implies the fluctuation in the price due to the adaptive nature of its environment and participants, studies employing MF-DFA have mushroomed in this domain. Other commonly used standard techniques are modified R/S analysis, autocorrelation tests, generalized spectral (GS) test, which is a non-parametric test used to determine the existence of linear and nonlinear dependence in a stationary time series. The following discussion reviews the literature in both the modified versions of standard tests and MF-DFA tests to measure the dynamic nature of the market efficiency.

4.2.1. Testing Efficiency with Hurst Exponent

Tiwari et al. (2019) employ MF-DFA based on Hurst exponent to compare the relative efficiency using the long span of data and show that markets are multifractal and mostly long-term persistent. However, they also find even though the efficiency is varying over time, the markets are not weak-form efficient. Hiremath and Narayan (2016) used the Generalised Hurst exponent derived using fixed and rolling windows technique and found that long-range dependence is time-varying, implying that the efficiency of Indian stock markets has evolved over time and is moving toward efficiency. Anagnostidis et al. (2016) tested Eurozone markets for random walk hypothesis (RWH) via the generalized Hurst exponent analysis, in which Hurst exponent was estimated through a rolling window technique. They found significant mean reverting patterns in stock price movements. Sensoy and Tabak (2015) used generalized Hurst exponent and found that stock markets have different time-varying long-term memory. Horta et al. (2014) calculated Hurst exponent with MFDMA i.e., multifractal detrended moving average and found that Hurst exponent exhibit long memory in the crisis period. Wang et al. (2009) investigated the changing Hurst exponent using MF-DFA and found that the Shenzhen stock market was becoming more and more efficient. Cajueiro and Tabak (2004) used Hurst exponent for testing whether markets are becoming more efficient over the period.

A general finding of the literature is that markets are multifractal in nature and efficiency is time-varying and that most popular method is analysing Hurst exponent estimated by MF-DFA method.

4.2.2. Testing Adaptive Efficiency with Modified Standard Tests

Ghazani and Ebrahimi (2019) using automatic portmanteau (AQ) and generalized spectral (GS) test found that the crude oil market conforms with the AMH principle. Khuntia and Pattanayak (2018) used the consistent test of Domínguez and Lobato (2003) and GS of Escanciano and Velasco (2006) to test Martingale Difference Hypothesis and AMH and found that market efficiency evolves with time and validated the AMH in the bitcoin market. They also found that linear and nonlinear dependence evolves with time. Kim et al. (2011) employed automatic variance ratio test, automatic portmanteau test, generalized spectral test and found return predictability to be smaller during economic bubbles than in normal times. They also found evidence that return predictability is associated with stock market volatility and economic fundamentals. Studying the foreign exchange market, Hull and McGroarty (2014) measure the long-term memory using rescaled range methodology and show greater efficiency in returns and volatility for 'advanced' emerging markets. They find evidence against weak-form EMH with persistent market memory, which is consistent with AMH.

Charles et al. (2017) test Martingale difference hypothesis using automatic portmanteau and variance ratio tests and find that returns have been predictable in a number of periods, consistent with the implications of AMH. Lim et al. (2013) used automatic portmanteau Box-Pierce and wild bootstrap automatic variance ratio test and found that periods with significant return autocorrelations can largely be associated with major exogenous events. Theoretically, the documented time–varying nature of predictable patterns is consistent with the adaptive markets hypothesis. Using three bootstrapped versions of the variance ratio test on fixed length moving window, Urquhart and McGroarty (2016) found that return predictability in stock markets does vary over time in a manner consistent with AMH.

Hiremath and Kumari (2014) used both linear and nonlinear tests. Linear tests showed a cyclical pattern in linear dependence suggesting that the Indian stock market switched between periods of efficiency and inefficiency. In contrast, the results from nonlinear tests revealed strong evidence of nonlinearity in returns throughout the sample period with a sign of tapering magnitude of nonlinear dependence in the recent period. Ahmed (2014) employed rolling joint variance ratio test tests, in rolling window procedure and found support for the time-varying market efficiency. Todea et al. (2009) verified that implications of AMH and found that the degree of market efficiency varies through time in a cyclical fashion.

Urquhart and Hudson (2013) conclude that the AMH describes the behaviour of stock returns better than the EMH. Al-Khazali and Mirzaei (2017) using stochastic dominance and mean-variance analysis showed that AMH explanation of calendar anomalies is better than EMH explanation. Tuyon and Ahmad (2016) observed that dynamic stock price behaviour is in line with the bounded-adaptive market efficiency. Noda (2016) used time-varying AR model and found that the degree of market efficiency changed over time.

Using a non-Bayesian time-varying AR model approach, Ito et al. (2016) discovered that the US stock market evolved over time in a cyclical fashion and showed considerable long periodicity. Charfeddine and Khediri (2016) tested the weak-form of market efficiency employing GARCH-M with state space time–varying parameter and rolling technique sample test on the long memory parameter. They found that GCC markets have different degrees of time-varying market efficiency.

Neely et al. (2009) discovered that excess returns declined over time, but at a much lower speed that would be consistent with efficient markets. Zalewska-Mitura and Hall (1999) extended the classical test for autocorrelation of returns by combining a multi-factor model with time-varying coefficients and the GARCH-M approach to investigate evolving market efficiency. Using Monte Carlo simulation, their findings indicate changing levels of inefficiency in developing markets.

Most of the studies using modified standard tests have supported the adaptive nature of the stock market.

4.2.3. Testing Efficiency Using Both Modified-Standard and MF-DFA Methods

Khediri and Charfeddine (2015) tested time–varying market efficiency using wild bootstrap variance ratio tests and DFA technique finding strong evidence of time varying markets efficiency with rapid mean reversion toward market efficiency. Rizvi and Arshad (2017) using MFDFA and MGARCH technique found that Japan improved efficiency over the period. Rodriguez et al. (2014) employed the DFA technique and found the US market efficiency varies over time and time scales.

The majority of these studies in this domain found the multifractal nature of time series and showed that market efficiency evolves over a period and is dynamic in nature and thus are in line with implications of AMH.

5. Price–Volume Relationship Studies

According to Karpoff (1986) and Karpoff (1987), price–volume relationship[3] is important as it helps in understanding the theories of dissemination of information flow into the market. A positive correlation between stock returns and daily trading volume implies that volume does not provide additional information that is not reflected in stock price (Clark 1973; Crouch 1970; Wood et al. 1985). Blume et al. (1994) and Suominen (2001) investigate the information content of volume on financial markets and find that volume carries information that price alone cannot convey to the market. Lamoureux and Lastrapes (1990) argued that ARCH in the price series represents time dependence in the information flow to the market, and the trading volume reflects this information flow. He showed that trading volume has significant explanatory power in predicting the variance of daily returns, but this effect disappears when the volume is included in the variance equation of the ARCH model. Lee and Swaminathan (2000) show that past volume has information in predicting the price and Chordia and Swaminathan (2000) document that trading volume is a significant determinant of the lead-lag patterns observed in stock returns.

Modeling price–volume relationship Several models are built considering the relation between price and volume, for example, asymmetric volume model of Epps (1975), sequential arrival of information (SIA) model of Copeland (1976), mixture of distribution model (MDM) of Clark (1973); Epps and Epps (1976); Tauchen and Pitts (1983); and Harris (1987). MDM and SIA could be tested with agent-based (simulation) methods, but not with the real data from financial markets. Since trading activity is driven by different types of investors receiving, interpreting and forwarding different types of messages, scholars have come up with two different information related hypotheses that try to explain the relation between price and volume. The first hypothesis relates return volatility and trading volume contemporaneously, based on the mixture of distribution hypothesis (MDH in this section) predicted by Clark (1973) and Harris (1987). The second hypothesis does not relate volume and returns volatility contemporaneously, implying there is a causal lead-lag relationship, predicted by the

[3] The price–volume relationship is important for four reasons: (a) to get insights into the structure of financial markets (b) combination of price and volume data is useful in understanding the consequences of event studies (c) to understand speculative prices and (d) it has high impact on future contracts

sequential information arrival hypothesis (SIAH) of Copeland (1976) and Smirlock and Starks (1988). (Refer Wang et al. (2018) for more details)

5.1. Price–Volume Relationship and EMH

Informational efficiency or EMH emphasizes that information should immediately be incorporated into the prices. Therefore, prices should reflect all the information available. The information available for weak-form efficiency is past prices or volume (Rizvi and Arshad 2017). The price and volume series is generated by the market simultaneously. Therefore, any distant relationship (long memory) between the past prices series and volume series indicate that information is not reflected in the price immediately and thus violates the assumption of EMH.

Contemporaneous and Causal Relationship The literature in the contemporaneous and causal relationship can be divided according to the findings of the studies: studies finding contemporaneous, unidirectional causal, and bidirectional causal relationships and no relationship.

Positive correlation was found by Copeland (1976); Harris and Raviv (1993); Chen et al. (2001); Gagnon and Karolyi (2009); He and Wen (2015); Nasiri et al. (2018) whereas Campbell et al. (1993) found negative relationship and Godfrey et al. (1964) find a weak correlation and Azad et al. (2014) find no relationship. Contemporaneous relationship was found by Jennings and Barry (1983); Mahajan and Singh (2008); Chen (2012) and He et al. (2014). Unidirectional causal relationships were found by Moosa and Silvapulle (2000); Mahajan and Singh (2008); Chuang et al. (2009); Chen (2012); He et al. (2014) and Balcilar et al. (2017). Bidirectional causal relationships were found by Chen et al. (2001); Tripathy (2011) and Lin (2013). On the other hand, Saatcioglu and Starks (1998); Lee and Rui (2002) and Gupta et al. (2018) fail to find strong evidence on the causal relationship between price and volume.

Nonlinear causality was found by Llorente et al. (2002); Gündüz and Hatemi-J (2005); Gebka and Wohar (2013); Ciner (2015) and Caginalp and DeSantis (2017) and bidirectional nonlinear causal relationship was found by Hiemstra and Jones (1994); Silvapulle and Choi (1999); Matilla-García et al. (2014).

The review of this section clearly implies the mixed finding on the type of relationship in price volume relationship, although these studies confirm the nonlinear relationship between the price and volume.

The above studies test the relationship between price and volume as a measure of market efficiency. They try to determine whether past volume carries information for the prediction of future prices in line with the assumption of the EMH. This means that these studies do not test the time-varying nature of the price–volume relationship, which is the important implication of the AMH.

The following section focuses on the return predictability and price–volume relationship studies in the context of the AMH.

5.2. Price–Volume Relationship and AMH

Implications of AMH using price–volume relationship has also been tested in the academics in the recent period. Primarily a combination of detrended fluctuation analysis and the detrended cross–correlation analysis (DCCA) is employed to test the relationship between the price and volume in its multifractal nature.

MFDFA-DCCA Approach Ferreira (2019) study Portuguese market and find negative correlations for listed firms. Hasan and Salim (2017) investigate the Indian market for the price–volume cross–correlations and find that cross-correlated price–volume change display low complexity. El Alaoui (2017) find the existence of multifractal price–volume cross-correlations in Moroccan stock market. Ruan et al. (2016) study the time-varying efficiency in the Chinese gold market and find the cross-correlations to be anti-persistent in general. Sukpitak and Hengpunya (2016) find a weak correlation between market efficiency and trading volume in the Thai market. Wang et al. (2013) study Chinese Index Futures market and find that returns and trading volumes are long-range cross-correlated. He and Chen (2011) investigate Chinese market for nonlinear bivariate dependency and show the nonlinear dependency in cross-correlations between price and volume. Podobnik et al. (2009) investigate power-law cross-correlation using DCCA and find no cross-correlation between price and volume.

Other Approaches Wang et al. (2018) used dependence switching copula model and showed asymmetric return-volume dependence. Khuntia and Pattanayak (2018) studied the bitcoin market using Consistent test and GS test. They found that trade volume has explanatory power in the volatility of returns during bearish or bullish markets, but find no effect during the normal period. They documented the long memory in the volatility of return is adaptive.

Stošić et al. (2015) study 13 stock market indices by employing MF-DFA and MF-DXA approach and find that small fluctuations dominate the multifractal behaviour of the volume changes, while large fluctuations dominate price changes. They also found anti-persistent long-term cross-correlations between price and volume changes.

6. Research Gap

Earlier studies confirm the multifractal nature of price–volume relationship but are inconclusive about the exact cross–correlations between price and volume. Some papers show negative, some show weak correlation and some show no cross–correlation between price and volume. A few papers have studied the long-term cross-correlations between price and volume, finding asymmetric relationship. While studies in the classical EMH have confirmed the nonlinear relationship between the price and volume, authors find only one paper studying the nonlinear cross-correlation relationship between price and volume in the AMH domain. From the practitioner's perspective, it will be important to know the behaviour of these cross-correlations under different market conditions. Previous studies have not investigated such a nonlinear cross-correlation between price and volume during bullish/bearish versus normal period. Therefore, it will be interesting to study the nonlinear price–volume cross–correlations under different market conditions. Also, no previous study has established the asymmetric nature of nonlinear price–volume cross–correlation. Further, it would be interesting to investigate whether the nonlinear cross–correlation holds across different measures of sectoral stock indices within a country and/or across different time scales such as day, week, month, quarter, etc.

7. Conclusions

This paper reviews papers in the weak-form of market efficiency in the period between 1900 and 2019. Authors find that the results of the papers either support classical or adaptive nature of markets, indicating the EMH or AMH respectively. Extensive studies in return predictability have been conducted for testing the weak-form of market efficiency under both EMH and AMH. The weak-form of efficiency is also studied by testing the price–volume relationship under EMH, but in its adaptive form, very limited studies have been conducted by testing price–volume relationship. The literature lacks the studies in the price–volume relationship in the AMH domain. The adaptive market efficiency studies have been able to confirm that market efficiency is a dynamic concept and varies over time. This review leads to further scope in investigating the nonlinear cross–correlation between price and volume.

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Review

Stock Investment and Excess Returns: A Critical Review in the Light of the Efficient Market Hypothesis

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Abstract: The expansion of investment strategies and capital markets is altering the significance and empirical rationality of the Efficient Market Hypothesis. The vitality of capital markets is essential for efficiency research. The authors explore here the development and contemporary status of the efficient market hypothesis by emphasizing anomaly/excess returns. Investors often fail to get excess returns; however, thus far, market anomalies have been witnessed and stock prices have diverged from their intrinsic value. This paper presents an analysis of anomaly returns in the presence of the theory of the efficient market. Moreover, the market efficiency progression is reviewed and its present status is explored. Finally, the authors provide enough evidence of a data snooping issue, which violates and challenges the existing proof and creates room for replication studies in modern finance.

Keywords: excess returns; efficient market hypothesis; data snooping; investment and capital markets

1. Introduction

The efficient market hypothesis (EMH) is considered one of the substantial propositions in social sciences. It is captivatingly modest, has great significance for academic theories and professional practices and is surprisingly irrepressible to empirical evidence or refutation. Even after numerous decades of research and hundreds of published articles, researchers have not yet stretched to a consensus about whether markets are efficient or not.

In an informationally efficient market, price fluctuation should be unpredictable if prices are correctly projected, that is, if they completely integrate the information and anticipations of all market participants. Anomaly returns are discovered as a result of an empirical test that relies on the joint null hypothesis to wit that financial markets are informationally efficient, and as a result of a pattern of returns that is also consistent with predefined valuation models. If the mentioned null hypothesis is rejected, we are unable to identify that the rejection is the result of either part of the hypothesis. The rejection of the hypothesis mainly considers that markets are not efficient; such conclusions are not appropriate because these hypothesis rejections could be the result of an incomplete/inappropriate model. This debate is long-standing, i.e., if markets are efficient and estimation models are correctly valuing the stocks, then why do investors have sustained excess returns? In consideration of leading arguments, this study focuses on all possible dimensions that explain the likely reasons for excess returns.

Essentially, financial anomalies are cross-sectional and time series variant returns that are not explained by any theory or paradigm; Kuhn (1970) explained the concept of anomaly, and it can be traced in history with his name. Anomalies are experiential results that seem to be fluctuating with developed theories of asset pricing behaviour. After anomalies are documented in the finance literature, they often seem to disappear, inverse, or weaken. This raises a question as to whether these are opportunities found in the past, but have since been arbitrarily thrown away, or whether they were just statistical abnormalities that fascinated the devotion of academics and practitioners. Robust anomalies, possibly proof of abnormal gains or asset returns, are not fully accounted for. However, theorists have struggled to give ex-post risk-based reasons for many of the anomalies identified in the literature.

According to the EMH, there is no room for excess returns, although later on, different anomalies are found and investors gain excess returns even with the existence of the EMH. Recently, the literature has found a shred of evidence that these anomalies are weak in magnitude, or sometimes their presence was just a falsification when these studies were replicated. Therefore, this narrative review article is an attempt to address this issue and to combine historical literature from every possible dimension to try to make an extensive study of the available evidence for researchers who are interested in doing their research in this particular field. In addition, this narrative review not only explains the existing knowledge of the topic based on the published research, but it is also an attempt to explain the current state of understanding on the topic.

Existing literature does not have much focus on the critique of existing anomalies as there are many anomalies that have been found to be just a falsification. Hence, this review article makes an addition to the historical literature by raising the question on the authentication of existing anomalies based on newly published evidence. While this study will not only help academics and practitioners to find extensive literature on anomalies for their future research, it will also help investors in many ways. For example, the study will help investors to calculate the expected returns on stocks by using different valuation parameters. Secondly, based on varying anomaly characteristics, this research will assist investors to create profitable portfolios in order to gain excess returns. Thirdly, this study will also be valuable for academics, practitioners and investors to authenticate the true existence of past anomalies instead of relying on existing published literature.

There are several hypotheses that motivate us to find, elaborate and criticise all the available evidence in the literature. One primary reason behind this study is the existence of the efficient market hypothesis. Finance literature has tried to criticise this theory from behavioural aspects, i.e., the existence of a fully efficient market is almost impossible in the real world. Second, in the age of digitalisation when markets are more efficient than ever, how are these anomalies still sustained? Third, the number of anomalies in literature has increased tremendously, and raises the question as to whether existing valuations models are appropriate enough. Fourth, as the number of anomalies is growing gradually, will the magnitude of the anomalies persist? Finally, some shreds of evidence have recently been found that suggest that either anomalies have disappeared or their magnitude is weaker and sometimes, it is believed that these anomalies were just a falsification or p-hacked to show significant results for publications. From the given argument, this study explored a new dimension to replicate the existing literature to authenticate its validity.

The rest of the paper is organised as follows. Section 2 describes the efficient market hypothesis and gives a historical view of the EMH and its existence in the modern era. In Section 3, authors explore the historical return parameters and discuss the widely used valuation models for stock returns. Section 4 covers the cross sectional excess returns and all possible reasons for these returns. Section 5 raises questions on the credibility of the existing literature and explores a new dimension for future research. The final section presents the conclusion of the study.

2. The Efficient Market Hypothesis

Economists and academics have broadly acknowledged the efficient market hypothesis (EMH), as defined by Fama in his important survey article "Efficient Capital Markets" (Fama 1970), which states that securities markets are efficient in the reflection of news/information about particular stocks or about the overall market as a whole. The generally accepted view is that the information flow is smooth, and that it is incorporated into the stock market without any delay. Therefore, technical analysis, which is the study of past stock prices in an effort to forecast future prices, and fundamental analysis, which is the exploration of financial information (such as asset values and company earnings) to help investors select "under-priced" stocks, may not permit an investor to realise returns greater than those that could be gained by holding a randomly chosen portfolio of stocks, at least not with comparable risk. List of selected papers for this section are given in Table 1.

Table 1. Selected work on Development of efficient market hypothesis (EMH).

Author	Year	Paper/Book/Thesis Title (Please See References for Details)
Pearson	1905	The Problem of the Random Walk (Pearson 1905)
Keynes	1923	Some Aspects of Commodity Markets (Keynes 1923)
Cowles	1933	Can Stock Market Forecasters Forecast? (Cowles 1933)
G. Kendall and Hill	1953	The Analysis of Economic Time-Series-Part 1: Prices (Kendall and Hill 1953)
Roberts	1959	Stock-Market "Pattern" and Financial Analysis: Methodological suggestions (Roberts 1959)
Alexandar	1961	Price Movements in Speculative Markets: Trends or Random Walks (Alexander 1961)
Alexandar	1964	Price Movements in Speculative Markets: Trends or Random Walks (Alexander 1964)
Fama	1965	The behaviour of Stock-Market Prices (Fama 1965)
Fama	1970	Efficient Capital Markets: A Review of Theory and Empirical Work (Fama 1970)
G. Malkeil	1973	A-Random-Walk-Down-Wall-Street (Malkeil 1973)
Dimson and Mussavin	1999	Three centuries of asset pricing (Dimson and Mussavain 1999)
Shiller	2003	From Efficient Markets Theory to Behavioral Finance (Shiller 2003)
Steiger	2004	Beyond the F test: Effect size confidence intervals and tests of close fit in the analysis of variance and contrast analysis (Steiger 2004)
Durlauf and Blume	2008	The New Palgrave Dictionary of Economics (Durlauf and Blume 2008)
Sewel	2011	A History of the Efficient Market Hypothesis (Sewel 2011)
Verheyden et al.	2013	A Tale of Market Efficiency (Verheyden et al. 2013)

2.1. Early Developments of the Efficient Market Hypothesis

According to Verheyden et al. (2013), with regards to the stock exchanges of Paris, London and New York, stock prices are the smartest reflection of market participants. L. Bachelier is considered to be one of the pioneers of the EMH: in 1900, he published "speculation theory", in which he explored the theory that expected returns for stocks always remained zero (Sewel 2011). The first half of the 20th century demonstrated well the randomness of stock prices, and most economists work under this assumption. (Pearson 1905) was the first scholar who used the concept of "Random Walk", in 1905, but he used it in the field of botany, not in the field of economics and finance. F. MacCauley used the coin-tossing game in 1925 as an example and compared it with stock prices. Later on, (Cowles 1933) observed the trading patterns of different investors with professional expertise and found that even professional investors were unable to predict excess returns; he concluded the same results later on, in 1944, by analysing the data of the U.S. stock market. The famous economist, J.M. Keynes, renowned for his work "Real Economy", gave insights regarding financial markets and asset pricing (Keynes 1923). He argued that investor gains are not associated with their ability to predict excess returns, but related to the level of risk of the investment.

Post-World War 2, an increasing number of studies emerged in support of the EMH. (Kendall and Hill 1953) concluded, through a time series experiment of 22 stocks, that stock returns are random. These results were surprising for many economists at that time (Dimson and Mussavain 1999). Later on, (Roberts 1959) and (Alexander 1961) confirmed these results, once more in favour of the EMH (Sewel 2011). This pattern was not consistent for a longer horizon, as some studies reported inverse results as well; these results, later on, created a foundation for the critics of the EMH. Alexander (1964) found that U.S. stock prices were not consistent with the concept of a random walk and Steiger (2004) found a predictable pattern in stock returns. Thus, after World War 2, studies on the EMH increased significantly, but not all studies concluded in favour of the EMH hypothesis (Malkeil 1973).

According to (Shiller 2003), the EMH gained immense popularity during the 1980s. E. Fama, a U.S. economist, became a classic in this field and his work was pioneering for efficient markets. He claimed that the evidence in favour of the EMH was strong, and that it could be only neglected if it was empirically tested on a large scale (Fama 1965). The work of H. Roberts went in a new direction, where he divided efficient markets into strong and weak forms. Later on, Fama (1970) further extended this division and added a semi-strong form of efficiency. By considering this extension in the division, the flow of information, and its impact on the market price of stocks, market efficiency was divided into three parts. The three basic types of market efficiency are mentioned in Figure 1.

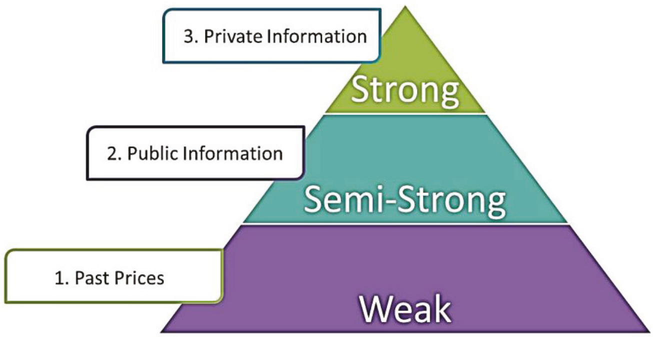


Figure 1. Basic Forms of Market Efficiency.

The three versions of the efficient market hypothesis are varying degrees of the same basic theory. The strong form version of the efficient market hypothesis states that all information (both the information available to the public and any information not publicly known) is completely accounted for in current stock prices, and there is no type of information that can give an investor an advantage on the market. The semi-strong efficiency theory follows the belief that, because all public information is used in the calculation of the current price of a stock, investors cannot utilise either technical or fundamental analysis to gain higher returns in the market. The weak form suggests that the current stock prices reflect all the data of past prices and that no form of technical analysis can be effectively utilised to aid investors in making trading decisions. Advocates for the weak efficiency theory believe that, if fundamental analysis is used, under-valued and over-valued stocks can be determined.

Until 1970, the idea of EMH was prevalent amongst academics but only a little admired by professionals. Malkeil (1973) published the book "A Random Walk Down Wall Street" in 1973, which was considered to be a game changer for this situation. Shiller (2003) said that, after the book was published, the EMH was more fascinating for professionals than academics. "The random walk" concept is directly connected with the efficient market hypothesis, which is used in the literature to elaborate a series of prices, where all subsequent changes occurred randomly. The theory behind the idea of a random walk is that, if the flow of information is unimpeded and stocks instantly absorb the effect of this information, then the price fluctuations tomorrow will be due to the news/information of tomorrow; it will be independent of, or not affected by, any event which occurred on any other day. Therefore, the prices of stocks will reflect all known information and news; even uninformed investors can attain profitable returns by keeping a diversified portfolio, based on the tableau of prices in the market as generously as experts can obtain.

Capital markets are closely related to "cost efficiency"; however, other markets are analysed from a different perspective, such as "allocation efficiency" (Durlauf and Blume 2008). Generally, in an efficient market, the fundamental information of a firm can be observed in their stock prices. In this case, the market value of a company fluctuates in a way very similar to that of the intrinsic value of the company. Therefore, these changes are inconsistent with value and cannot restrain from trading of financial assets. Uneven awareness of investors and volatile transaction costs avoid fundamental changes in the value to reflect the market prices.

Based on EMH, it is not possible to make excess returns from stocks. Therefore, if the market retains a weak form of efficiency, technical analysis yields no excess return. In a semi-strong form of efficiency, stocks not only reflect the historical prices, but reveal all publicly available information as well. Finally, in the strong form of an efficient market, stock prices reflect all information, not just limited to publicly available information.

2.2. Modern Era of Efficient Market Hypothesis and Its Critics

Entering into the 21st century, the intellectual dominance of the efficient market hypothesis was not as universally accepted, as many economists believed that stock prices were partially predictable, which began a new era of discussion; that returns on a stock can be predicted, as well as sustained. It is understood that a new generation of economists began to believe that there exist some behavioural and psychological aspects which enable the prediction of stock prices. Lo and MacKinlay (1990) found that "too many" consecutive transfers in the same direction permitted them to reject the hypothesis that stock prices could be described as true random walks. There were many predictable patterns, which disappeared after some time, and these patterns were a part of the published literature of economics and finance. Schwert (2001) explained two possible explanations for such patterns. One possible reason regarded the researchers, who were always sifting through mountains of data. They focused on those results which challenged the perceived wisdom; they focused on a particular sample or used a specific technique to get significant results, so that they could challenge the efficient market hypothesis. Therefore, it was possible that practitioners would soon realise these predictable patterns, exploit them to some extent, and then render them no longer profitable. List of selected papers for this section are given in Table 2.

Table 2. Selected work on Critics of EMH and Modern state of EMH.

Author	Year	Paper/Book/Thesis Title (Please See References for Details)
French	1980	Stock Returns and the Weekend Effect (French 1980)
Keim	1983	Size-Related Anomalies and Stock Return Seasonality (Keim 1983)
Haugen and Lakonishok	1988	The Incredible January Effect Homewood (Haugen and Lakonishok 1988)
Fama	1988	Market Efficiency, Long-Term Returns, and Behavioral Finance (Fama 1998)
Lakonishok and Smidt	1988	Are Seasonal Anomalies Real? A Ninety-Year Perspective (Lakonishok and Smidt 1988)
M. Poterba and Summers	1988	Mean Reversion in Stock Returns: Evidence and Implications (Poterba and Summers 1988)
Ariel	1990	High Stock Returns Before Holidays: Existence and Evidence on Possible Causes (Ariel 1990)
Lo and MacKinlay	1990	When are Contrarian Profits Due to Stock Market Overreaction? (Lo and MacKinlay 1990)
Hawawini and Keim	1995	On the Predictability of Common Stock Returns (Hawawini and Keim 1995)
Fluck et al.	1997	The Predictability of Stock Returns: A Cross-Sectional Simulation (Fluck et al. 1997)
Shleifer	2000	Inefficient Markets: An Introduction to Behavioral Finance (Shleifer 2000)
Schwert	2001	Stock Volatility In The New Millennium: How Wasky Is NASDAQ? (Schwert 2001)
Malkiel	2003	The Efficient Market Hypothesis and Its Critics. (Malkiel 2003)
Parks R.W. and Zivot	2006	Financial market efficiency and its implications (Parks and Zivot 2006)
Brealy et al	2011	Principles of Corporate Finance (Brealey et al. 2011)
Malkeil	2011	The Efficient-Market Hypothesis and the Financial Crisis (Malkiel 2011)
Bollen, Mao, and Zeng 2011	2011	Twitter mood predicts the stock market (Bollen et al. 2011)
Liu and Zhang	2012	A survey of opinion mining and sentiment analysis (Liu and Zhang 2012)
Mishkin et al.	2012	Financial markets and institutions. Boston: Prentice Hall. (Mishkin and Eakins 2012)
Wang et al.	2019	Effect of Digitalized Rumor Clarification on Stock Markets (Wang et al. 2019)

In terms of the short run—returns measured in terms of days or weeks—one possible argument that challenged the efficient market hypothesis regarded the existence of a positive serial correlation. Many studies that reported negative serial correlation can be found in the literature, as well, where these return reversals were over a more extended period of holding. French (1980) gave the most relevant example, where 25–40% of the deviation in extended holding period returns could be forecasted, in terms of a negative correlation with previous returns. Poterba and Summers (1988) also found mean reversals in the long horizon of stock holding periods. Fluck et al. (1997) developed an investment strategy in which they simulated data for 13 years, from 1980 to the early 1990s. Their sample consisted of stocks that were poor performers in the past 4–5 years; their strategy worked, predicting that stocks which performed poorly in the past 3–5 years would perform better in coming years and, inversely, that those stocks that performed well in previous years would perform poorly in the future.

Some researchers have argued that January is a very unusual month for stock market returns. Equally weighted or value-weighted returns in the first two weeks of this month are comparatively higher than in other periods of the year. According to Keim (1983), return premiums are evident for stocks with low market capitalization. Haugen and Lakonishok (1988) mentioned high January returns in their book, titled "The Incredible January effect". The January effect is not only calendar anomaly; there have been some specific day of the week anomalies found in the literature. For example, Fama (1998) documented that there are significantly higher returns on Monday compared to the rest of the week. A significant difference has also been found in average daily returns amongst countries other than the United States (Hawawini and Keim 1995). A considerable pattern has been observed at the turn of the month (Lakonishok and Smidt 1988), and excess returns have been found around holidays (Ariel 1990).

One general problem with anomalous returns is that they are not dependable from one period to another. These non-random effects, even if we consider them to be reliable, are deficient in magnitude and we cannot exploit them, as the transaction cost may elude its effect.

With technological advancements facilitating vibrant creation, sharing, and collaboration among Web users, the impact of digital media on stock markets has been increasingly prominent. Many studies have investigated the effect of digital media on stock movements (Bollen et al. 2011). Liu and Zhang (2012) analysed the effectiveness of wording in clarification announcements. They found that detailed clarification of information helps to mitigate the impact of rumours, and stock prices tend to return to normal levels after 30 trading days. More notably, digitalised platforms as a governance strategy of regulating authorities have been implemented for a long time. Therefore, richer information releases by digital platforms increase market transparency (Wang et al. 2019).

Brealey et al. (2011) studied many blue-chip stocks and the correlation coefficient of returns over two consecutive days falls between −0.3% and 0.3%. These results give a precise prediction that the current return will not affect the return tomorrow, but one can argue, for a short period, that this period is not enough to capture potential dependencies. Shleifer (2000) explained that technical analysis could be applied to test stock return predictability, but this is not be applicable with a longer horizon. Although technical analysis is widely used for expected returns, it will only be useful for excess returns if there are zero transaction costs (Parks and Zivot 2006). Technical analysis is currently less popular among researchers and academics, but is still widely used by professionals (Mishkin and Eakins 2012).

Active portfolio management and passive portfolio management describe another favourable point for EMH. If an actively managed portfolio failed to perform better than a passively managed portfolio, then it is not lucrative to make use of market information, and the market is efficient. Brealey et al. (2011) found that aggregate excess returns should be zero or negative, which is consistent with the EMH. Malkiel (2003) obtained data from 1991 to 2001 and found that more than 70 percent of mutual funds from the U.S. earned lower returns than their benchmark. Consistent results were obtained when Malkiel (2011) studied an extensive data set from 1970 to 2010 and found that more than 66 percent of U.S. mutual funds yielded fewer returns than the benchmark. Mutual funds that performed well in the short term were unable to perform consistently in a more extended period.

3. Early Valuation Parameters and Models Used to Predict Excess Returns

3.1. Early Valuation Parameters

Initial valuation parameters play a vital role in the prediction of returns, and many researchers have explored this connection. Researchers have claimed that there exist financial ratios, such as price/earnings multiple ratios or dividend yield as a whole market, which have considerable predictive power in attaining excess returns. Researchers have found a strong and long-lasting tendency for small firms to generate more substantial returns than big firms and that value firms tend to out-perform growth firms. List of selected papers for this section are given in Table 3.

Table 3. Selected work on Early Valuation Parameters and Excess Returns.

Author	Year	Paper/Book/Thesis Title (Please See References for Details)
Francis	1960	Price-Earnings Ratios (Francis 1960)
Fama and Schwert	1977	Asset Returns and Inflation (Fama and Schwert 1977)
Ball	1978	Anomalies in relationships between securities' yields and yield-surrogates (Ball 1978; Basu 1983)
Basu	1983	The Relationship Between Earnings' Yield, Market Value and the Returns for NYSE Common Stocks (Ball 1978; Basu 1983)
Keim	1983	Size-Related Anomalies and Stock Return Seasonality (Keim 1983)
Campbel	1987	Stock returns and the term structure (Campbell 1987)
Fama	1988	Market Efficiency, Long-Term Returns, and Behavioral Finance (Fama 1998)
Campbell and Schiller	1988	Stock Prices, Earnings, and Expected Dividends (Campbell and Shiller 1988)
Kahneman and Reipe	1988	Aspects of Investor Psychology (Kahneman and Riepe 1988)
Bagwell and Shoven	1989	Cash Distributions to Shareholders (Bagwell and Shoven 1989)
Fama and French	1993	Common Risk Factors in the Returns on Stocks and Bonds (Fama and French 1993)
Lakonishok et al.	1994	Contrarian Investment, Extrapolation, and Risk (Lakonishok et al. 1994)
Hawawini and Keim	1995	On the Predictability of Common Stock Returns: World wide Evidence (Hawawini and Keim 1995)
Fluck et al.	1997	The Predictability of Stock Returns: A Cross-Sectional Simulation (Fluck et al. 1997)
Fama and French	1997	Multifactor Explanations of asset Pricing Anomalies (Fama and French 1997)
Fama and French	2001	Disappearing dividends: changing "Changing Firm characteristics or lower propensity to pay? (Fama and French 2001)
Schwert	2001	Stock Volatility In The New Millennium: How Wacky Is NASDAQ? (Schwert 2001)
Ball et al.	2019	Earnings, retained earnings, and book-to-market in the cross section of expected returns (Ball et al. 2019)

3.1.1. Dividend Yield and Excess Returns

The dividend yield has the power to predict future returns, and this work, in a statistical way, was first done by Fama (1998) and Campbell and Shiller (1988). Depending on the prediction of the forecasting horizon, around 40 percent of the variance in the future stock returns of the overall stock market are predicted by the initial dividend yield of the total stock index. However, these predictions are not constant in every situation and, later on, many economists contradicted its implications and existence on a different basis. For example, Bagwell and Shoven (1989) and Fama and French (2001) suggested that this pattern was not consistent in the U.S., where one possible argument was that U.S. firms do not have a consistent pattern in the dividend. Company dividend policies, in the 21st century, have been changing, and they are focused more on share re-purchases than on dividend payouts. Therefore, the dividend yield is not as meaningful in recent times as it has been in the past. According to Fluck et al. (1997), this is an important issue, as this phenomenon does not frequently work with individual stocks. Investors who buy a portfolio of individual stocks with the maximum dividend yields in the market will not produce a high rate of return. A prevalent example of this high dividend investment strategy in the U.S. is the so-called "Dogs of Dow" strategy, in which investors buy ten stocks of the Dow Jones Industrial averages with the highest dividend yield. In the past, this strategy worked very well; many "Dogs of Dow" investors aggressively entered into these portfolios and sold them to individual investors. However, these stocks under-performed from 1995 to 1999.

The same type of predictability of the market as a whole, as predicted by dividend yield, can be observed in price/earnings (P/E) patterns as well. Campbell and Shiller (1988) stated that initial P/E ratios described as many as 40 percent of the variance of future returns. They concluded, by considering the P/E ratio, that equity returns in the past were predictable, up to some extent. Several other predictable time series patterns exist in the literature; for example, (Fama and Schwert (1977) argued that stock returns are affected by short-term interest rates and that returns can be predicted through interest rates. Campbell (1987) explained that the term structure of interest rate spreads has considerable importance in the prediction of future stock returns.

3.1.2. Firm Size and Excess Returns

Researchers have found a sturdy and long-lasting tendency for smaller firms to generate more substantial returns than big firms. Keim (1983) found that smaller firms had, on average, one percentage point higher return than big firms, and that this pattern has existed since 1936. Fama and French (1993) used data from 1963 to 1990 and made a portfolio, according to firm size. They divided stocks into deciles by size, the first decile belonging to 10 percent of the smallest firms, and the 10th decile consisting of 10 percent of the biggest firms. The results, as plotted in Figure 2, showed a clear prediction that smaller firms generated, on average, higher monthly returns than big firms.

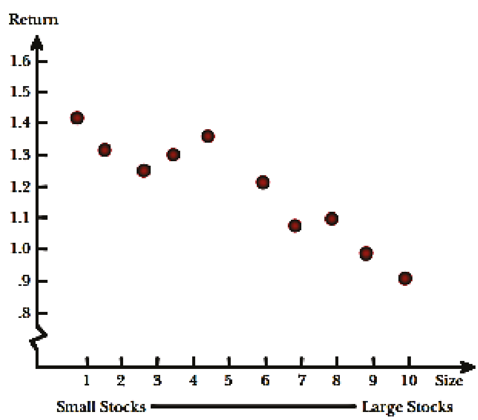


Figure 2. Portfolio for Average Monthly Returns based on Size: 1963–1990.

The critical problem here is the degree to which the higher returns of small companies represent a predictable pattern that will permit investors to make excess risk-adjusted returns. If we consider the Capital Assets Pricing Model as a true model, the value of beta measures the sensitivity/risk of a stock or the extent to which individual stock returns vary with overall market return. Here, beta is a true measure for capturing the systematic risk of the Capital Asset Pricing Model and is considered to be a true statistical measure of risk assessment; in this case, the size effect will be considered to be an anomaly. Fama and French (1993) found that the average relationship between return and beta was flat, instead of upward sloping, which is consistent with the predictions of the Capital Assets Pricing Model.

Furthermore, if the stocks were divided by beta deciles, 10 portfolios constructed on the basis of size would show the same type of relationship, as shown in Figure 2. At the same time, within each size portfolio, the relationship between return and beta continues to be flat. Based on these findings, Fama and French (1993) suggested that the size of beta is a much better proxy for risk than beta itself, and that it should not be taken either as an anomaly or inefficiency.

Although the size factor has gained a lot of attention, questions arose during the mid-1980s. Instead of smaller firms, larger firms gained more risk-adjusted returns. One of the core reasons behind this trend was growing institutionalization in stock markets throughout the world, where managers tended to prefer big firms, due to more liquidity. Survivorship bias mostly affects small firms and some studies in the literature have focused on this issue. In the modern era, it is possible to identify those small firms who have survived and to separate them from those who did not. Therefore, researchers today can easily avoid survivorship bias, which was not possible before.

3.1.3. Value Stocks and Excess Returns

Many studies have suggested that value stocks outperform growth stocks. Stocks with a low price/earnings ratio are recognised as value stocks and these stocks gain higher returns than growth stocks, which are defined as stocks with a high price/earnings ratio. This was first identified by Francis (1960) and, later on, it was tested and confirmed by Ball (1978) and Basu (1983). Kahneman and Riepe (1988) related it to behavioural perspectives, as investors can be over-confident in their ability for the projection of high growth returns and, thus, they overpay for growth stocks. Later on, by using price/cash flow multiples, Hawawini and Keim (1995) obtained the same results. The stock price-to-book value ratio has been found to be a good predictor of future returns, which is a proxy measured as the total value of assets minus total liabilities and difference divided by a total number of outstanding shares. The low magnitude of this proxy is considered to be a hallmark of the so-called "value" in equity stocks and these findings have been consistent with the view of behavioural economists that investors are ready to overpay for "growth" stocks, where expectations will no longer stand with their opinion and expectations. Fama and French (1993) concluded that size and market-to-book ratio have a significant impact and considerable explanatory power in the prediction of expected future returns. Later, Fama and French (1997) concluded that the effect of the Market/Book value holds not only in the U.S., but also has an impact in many other countries.

Subsequent results still provide some questions regarding the efficiency of the market if we accept Capital Assets Pricing Model (CAPM), as has been pointed out by Lakonishok et al. (1994); however, even these findings could not relate to the inefficiency of the market. They argue that CAPM is unable to capture all dimensions of risk. Fama and French (1993) suggested that the market-to-book ratio is a risk factor that should be priced to market, but that the Capital Assets Pricing Model is unable to capture its effect. They also argued that a three-factor model, including size and market/book value risk factors, is an appropriate measure to test different anomalies.

Here, we should keep in mind that every study (or all published literature) is time-dependent, even when these studies or results hold over decades. Ball et al. (2019) predicted that book-to-market strategies work because the retained earnings component of the book value of equity included the accumulation and, hence, the average of past earnings. Schwert (2001) discussed an investment firm "Dimensional fund advisors": this firm starts a mutual fund and selects value firms as an investment by considering the criteria defined by Fama and French (1993). The abnormal return on the portfolio, adjusted for the beta, was negative 0.2 percent from 1993 to 1998. These results, with the absence of abnormal returns, are consistent with those who believe that these findings regarding abnormal "value" returns are just actively managed portfolios by taking only a trending period for their study.

3.2. Excess Returns and Valuation Models

List of selected papers for this section are given in Table 4.

Table 4. Selected work on Excess returns and Valuation Models.

Author	Year	Paper/Book/Thesis Title (Please See References for Details)
Tobin	1958	Estimation of Relationships for Limited Dependent Variables (Tobin 1958)
Markowitz	1959	Portfolio Selection: Efficient Diversification of Investments (Markowitz 1959)
Sharpe	1964	Capital Asset Prices: A Theory of Market Equilibrium under Conditions of Risk (Sharpe 1964)
Lintner	1965	The Valuation of Risk Assets and the Selection of Risky Investment in Stock Portfolios and Capital Budgets (Lintner 1965)
Black et al.	1972	The Capital Asset Pricing Model: Some Empirical Tests (Black et al. 1972)
Fama and Macbeth	1973	Risk, Return, and Equilibrium: Empirical Tests. (Fama and MacBeth 1973)
Basu	1977	Investment Performance of Common Stocks in Relation to their Price-Earning Ratios: A Test of the Efficient Market Hypothesis (Basu 1977)
Banz	1981	The Relationship between Return and Market Value of Common Stocks (Banz 1981)
Bandari	1988	Debt/Equity Ratio and Expected Common Stock Returns: Empirical Evidence (Bhandari 1988)
Fama and French	1992	The Cross-Section of Expected Stock Returns (Fama and French 1992)
Fama and French	1993	Common Risk Factors in the Returns on Stocks and Bonds. (Fama and French 1993, 1996)
Fama and French	1995	Size and book-to-market factors in earnings and returns (Fama and French 1995)
Fama and French	1996	Multifactor Explanations of asset Pricing Anomalies (Fama and French 1993, 1996)
Graham and Harvey	2001	The theory and practice of corporate finance: evidence from the field (Graham and Harvey 2001)
Brounen et al.	2004	Corporate Finance in Europe Confronting Theory with Practice (Brounen et al. 2004)
Fama and French	2004	The Capital Asset Pricing Model: Theory and Evidence (Fama and French 2004)
Degutis and Novickeyte	2014	The Efficient Market Hypothesis: A Critical Review of Literature and Methodology (Degutis and Novickytė 2014)
Liu and Zhang	2014	A neoclassical interpretation of momentum (Mclean and Pontiff 2016; Liu and Zhang 2014)
Mclean and Pontiff	2016	Does Academic Research Destroy Stock Return Predictability? (Mclean and Pontiff 2016; Liu and Zhang 2014)
Rasheed et al.	2016	CAPM and Idiosyncratic Risk using Two-Pass Model: Evidence from the Karachi Stock Market (Rasheed et al. 2016)
Jianu, Jianu, and Țurlea	2017	Measuring the company's real performance by physical capital maintenance (Jianu et al. 2017)

3.2.1. Capital Assets Pricing Model

CAPM has faced much criticism from financial scholars, yet it is still the most widely used asset pricing model in financial research (Rasheed et al. 2016). "Anomaly Returns", in the context of financial economics, refer to the rejection of or relation to deficiencies in the asset pricing model (Linnainmaa and Roberts 2016). The EMH was also closely linked with the Capital Asset Pricing Model and the substitution theory of securities (Degutis and Novickytė 2014). The CAPM has been widely used to measure risk in testing the efficient market hypothesis since it emerged. Therefore, it is necessary to discuss CAPM and its origination, as it is not only used for risk valuation of the efficient market hypothesis; it is also used to test the different anomalies and returns. Jianu et al. (2017) created a model, based on physical capital maintenance, that measured the real performance of a company to obtain better information for investors.

Humans are always pursuing betterment, so that they can do their tasks more efficiently and more actively. This phenomenon is applicable in every field of life, even for researchers. Capital Assets Pricing Model (CAPM) has been used to measure the cost of equity and overall portfolio performance since 1970.

CAPM is an extension of the work of Tobin (1958) and Markowitz (1959), with the additional assumptions that: (i) Selection of investment portfolio is dependent upon expected return and variance of return for a single period; (ii) Estimates should be the same for all assets, in the measurement of mean, variance and covariance; (iii) There is no transaction cost for investment in the capital market; (iv) Assets should be divisible; (v) Short sales should not be regulated and have no restrictions at all; (vi) Investors should have an open opportunity to borrow or lend an unlimited amount of money. Black et al. (1972) showed some deviation in the model.

The CAPM equation, also called the security market line, is given by:

$$E(R_{\mathrm{i}}) = R_{\mathrm{F}} + \beta i(E(Rm) - R_{\mathrm{F}}), \quad (1)$$

where $E(R_{\mathrm{i}})$. is the expected return of stock or cost of equity, R_{F} is the Risk free rate of return, $E(Rm)$ is the expected rate of return of the market portfolio and market, and beta β_i is the measure of systematic risk of asset i, which is defined by $\frac{cov(R_{\mathrm{i}},Rm)}{\mathrm{var}(Rm)}$. Equation (1) explains that the expected return is directly related to the systematic risk or covariance of an asset, which means that high risk-taking investors should have high expected returns and vice versa. If CAPM is a true predictor, then the expected return can be predicted with the knowledge of βi (risk), R_{F} (rate of return), and Rm (market return). The market βi is a measure of slope, calculated in the regression of the excess return $R_{\mathrm{i}} - R_{\mathrm{F}}$ on the excess return of the market $Rm - R_{\mathrm{F}}$. The market beta of a market portfolio is equal to Equation (1), which can be written as:

$$E(R_{\mathrm{i}}) - R_{\mathrm{F}} = \beta i(E(Rm) - R_{\mathrm{F}}). \quad (2)$$

Equation (2) is the basis of quantitative estimation. Here, we can easily identify that, if the value of market beta β_i is zero, there will be no excess return and, if the value of market beta βi is equal to 1, the excess returns will be equal to the market risk premium.

Fama and French (1993) criticised CAPM, in that it is unable to give a true valuation of stock return and works only on the three-factor model. As indicated by the better measure of Fama and French (1993), one must expect that people will tend to shift towards a better measure, but survey results stated that about 73.5% of Chief Financial Officerss in the U.S. relied, to some extent, on CAPM in the estimation of the cost of equity (Graham and Harvey 2001). Brounen et al. (2004) worked on the same type of study, where they carried out a survey of 313 European firms, and found that around 45% of CFOs relied on CAPM while valuing the cost of equity. Here, a question arose: why are practitioners not shifting towards the three-factor model of Fama and French (2004)? There could be multiple reasons for this. For example, at the start of a period, practitioners may not be completely aware of the three-factor model; it might not be cost effective, as it requires more data and information for the valuation of the additional factors; or, maybe, practitioners think that the three-factor model is not always helpful, as the three-factor model is not still better than CAPM when we study the literature in detail.

CAPM was developed by Sharpe (1964) and Lintner (1965). If CAPM is considered as a valid predictor, then it can be beneficial in the elucidation of financial issues related to capital budgeting, portfolio selection, cost-benefit analysis and similar economic issues, which require risk and return relationships. Some empirical studies, such as by Black et al. (1972) and Fama and MacBeth (1973), have provided support for CAPM. CAPM says that the expected return of each stock varies due to its market beta, because every asset has a different value of beta. Black et al. (1972) tested whether the time series and cross-sectional regression of excess returns on market beta were zero or not. Therefore, as CAPM explained that the differences in expected return for multiple securities are due to distinctive beta for each security, different variables add nothing to the explanation of the expected returns. With this explanation of CAPM, there may be a new empirical way to test CAPM: by adding security-specific factors that are unrelated to the value of market beta, do these factors explain the cross-section of returns or not?

For this reason, Fama and MacBeth (1973) added two additional variables, with monthly returns, in the estimation of the cross-sectional regression; these additional variables were squared market beta and the variance from returns regressed on the market. The purpose behind using the squared market beta was to see whether there was a linear relationship between expected return and market beta. The reason behind taking variance was to see whether beta was the only measure of risk that is required to test expected returns.

3.2.2. Three-Factor Model of Fama and French

During the period from 1980 to 1990, CAPM was heavily criticised, due to the discovery of several anomalies. These anomalies provided a challenge for CAPM: to prove that market beta was sufficient to explain expected stock returns. Some of the renowned anomalies discovered during this period (e.g., leverage, a book-to-market value of equity ratio, earnings-to-price ratio, and so on (Basu 1977)) found that, when stocks were sorted according to earnings-to-price ratio, stock returns of high E/P ratio were higher than the prediction of CAPM. Banz (1981) found the size effect and observed that stocks with low market value earned higher returns than the predictions of CAPM, which meant that small stocks have a higher beta and higher expected returns than those captured by CAPM. (Bhandari 1988) argued that leverage has a positive relationship with expected stock returns and that the proxy of leverage is the book value of the debt-to-market value of equity. Figure 3a shows an average excess return of the FF 25 (Fama and French portfolios ranked on size and book-to-market) against the average excess return one would expect given beta. Empirically observed excess returns have no apparent relationship to the CAPM-predicted excess returns. Figure 3b shows actual excess returns and CAPM expected excess returns against the estimated betas of the FF 25. Again, the CAPM did not explain the returns well. Furthermore, a closer review specifies that small-growth and small-value portfolios severely mismatch CAPM.

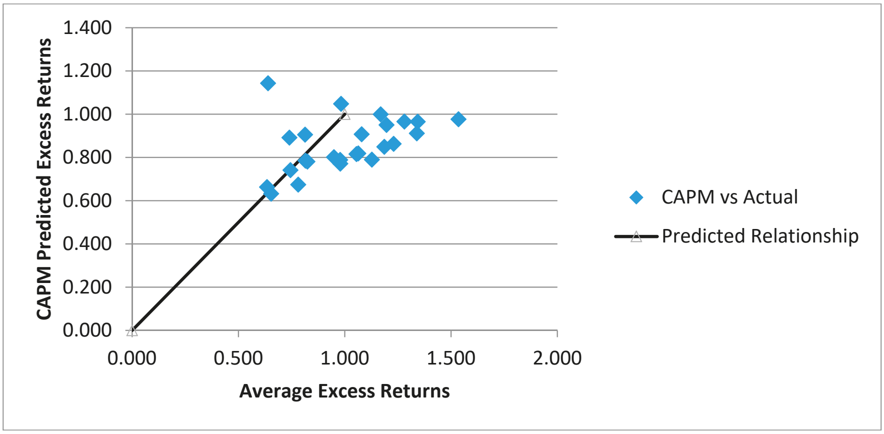
Fama and French (1992) stated the different findings of prior studies and found that stocks with a high book-to-market ratio had higher expected returns than those measured by the market beta. The above results led to a prediction about the explanatory power of other factors for expected returns. Later, these findings led Fama and French (1993) to challenge the explanatory power of market beta.

They confirmed that size, debt-equity, book-to-market equity ratio and earning-price ratio have significant explanatory power to average stock returns, and also confirmed that market beta could not solely explain the average returns. Using these findings, Fama and French (1993, 1996) proposed a three-factor model. The Fama and French three-factor model captures portfolio performance sorted by size and book-to-market equity ratio, according to the following equation:

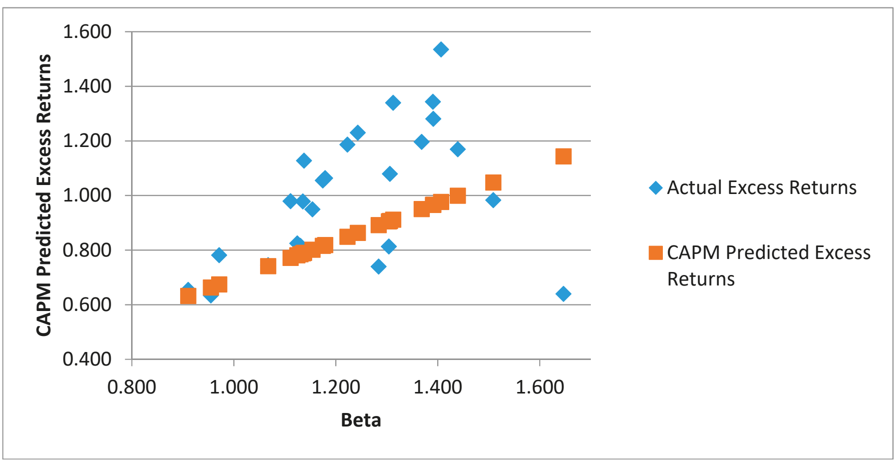
$$E(R_{\mathrm{i}}) - R_{\mathrm{F}} = \beta_{\mathrm{i}}(E(Rm) - R_{\mathrm{F}}) + \beta_{\mathrm{i}}E(SMB) + \beta_{\mathrm{i}}E(HML) \tag{3}$$

where *SMB* (small minus big) is the difference of returns between small and big stocks, *HML* (high minus low) is a difference of returns between high Book-to-market value ratio and low book-to-market value ratio stocks, and β_{i} is the sensitivity of each particular factor of the stated variable. Fama and French argued that, if asset pricing is rational, then both factors are proxies for valuing risk. They also found an average monthly correlation between market betas and the two other stated variables. As a result, all correlation values were less than 0.15 and these values were based on the average monthly returns of individual stocks. Fama and French (1995) found that weak firms with persistent low earnings have a positive slope of *HML* and high values of Book value of Equity/Market value of Equity, while strong firms with high earnings have a negative slope of *HML* and low BE/ME ratio. Here, it is observed that "loser stocks" (low long term returns) tend towards positive slopes for both *SMB* and *HML*, and will gain higher average future returns; vice versa for "winner stocks" (high long term returns).

Fama and French interpreted the three-factor model as evidence of risk premium or distress premium, but did not give an explanation regarding the question "why are distress premiums priced?" Mclean and Pontiff (2016) and Liu and Zhang (2014) argued that the inclusion of distress premium in the three-factor model is either due to survivor bias or data-snooping. However, the model was also unable to explain the momentum effect, as in the situation (discussed in earlier arguments) regarding long-term winner stocks and long-term loser stocks. Hence, the Fama and French three-factor model only captures and predicts short-term return reversals and a continuation of this short-term phenomenon into longer horizons is missing and left unexplained. Anomalies are the reason for the foundation of new valuation models. As new anomalies are discovered, existing models are shown to be unable to capture these variations.



(**a**)



(**b**)

Figure 3. (**a**) Fama and French (FF) 25 (portfolios ranked on size and book-to-market): average excess return (U.S. stocks 1963–2015) to the FF 25 against the average excess return one would expect, given market beta. (b) Fama and French 25 (portfolios ranked on size and book-to-market): actual excess returns (U.S. stocks 1963–2015) and Capital Assets Pricing Model (CAPM)-expected excess returns against estimated betas.

4. Reasons behind Cross-Sectional Excess Returns

List of selected papers for this section are given in Table 5.

Table 5. Selected work on Reasons behind Cross Sectional Excess returns.

Author	Year	Paper/Book/Thesis Title (Please See References for Details)
Ball and Brown	1968	An empirical evaluation of accounting income numbers (Ball and Brown 1968)
Blume and Husic	1973	Price, Beta, and Exchange Listing (Blume and Husic 1973)
Fama	1989	Market Efficiency, Long-Term Returns, and Behavioral Finance (Fama 1998)
Daniel et al.	1988	Investor Psychology and Security Market Under- and Overreactions (Daniel et al. 1988, 2001)
Fama and French	1991	Efficient capital markets: II (Fama and French 1991; Fama 1998)
Fama	1998	Market efficiency, long-term returns, and behavioral finance (Fama and French 1991; Fama 1998)
Barberis et al.	1998	A model of investor sentiment (Barberis et al. 1998),
Daniel et al.	2001	Overconfidence, Arbitrage, and Equilibrium Asset Pricing (Daniel et al. 1988, 2001)
Barberis and Thaler	2003	A Survey of Behavioral Finance (Barberis and Thaler 2003)
Nagel	2005	Short sales, institutional investors and the cross-section of stock returns (Nagel 2005)
Frazzini and Lamont	2006	The earnings announcement premium and trading volume (Frazzini and Lamont 2006)
Wu et al.	2010	The q-Theory Approach to Understanding the Accrual Anomaly (Wu et al. 2010)
Savor and Wilson	2013	How Much Do Investors Care About Macroeconomic Risk? Evidence from Scheduled Economic Announcements (Savor and Wilsony 2013)
Liu and Zhang	2014	A neoclassical interpretation of momentum (Liu and Zhang 2014)
Savor and Wilson	2016	Earnings Announcements and Systematic Risk (Savor and Wilson 2016)
Harvey et al.	2016	The Cross-Section of Expected Returns
Engelberg et al.	2016	Anomalies and News (Engelberg et al. 2016)
Jianu and Jianu	2018	The share price and investment: Current footprints for future oil and gas industry performance (Jianu and Jianu 2018)
Donangelo et al.	2019	The cross-section of labor leverage and equity returns (Donangelo et al. 2019)
Favilukis et al.	2019	The Elephant in the Room: the Impact of Labor Obligations on Credit Market (Favilukis et al. 2019)

The literature has shown many observable firm-specific characteristics which can be used to predict cross-sectional returns (Fama 1998; Nagel 2005; Mclean and Pontiff 2016). By using the Ohlson share price model for a sample of 51 listed companies on the London Stock Exchange, it was proven that investments in long-term assets influence the share price, in the case of companies that have recorded losses (Jianu and Jianu 2018). If we go back to the findings of Ball and Brown (1968) and Blume and Husic (1973), even four decades after their conclusions, academics still disagree on the reasons behind these patterns. Donangelo et al. (2019) and Favilukis et al. (2019) argued that labour leverage may play an important role in shaping the cross-sectional variation of equity returns. Research findings show that these patterns could be explained by the three possible reasons. First, cross-sectional differences of risk are the reason behind predictability, as can be observed from the discount rate (Fama and French 1991; Fama 1998). Cross-sectional predictability is expected, because return variances are used to value stocks and they are a reflection of changes in the prevailing discount rates. The second explanation belongs to the behavioural aspect of finance, that mispricing is the core reason for return predictabilities (Barberis and Thaler 2003). Therefore, marginal investors may lead towards biased expectations regarding cash flows, which might cause the creation of correlation between anomaly variables and these mistakes, which are, in turn, related to a cross-section of stocks. Updated information also changes the belief of investors; it corrects the stock prices and creates predictability of returns. The last explanation for return prediction is data mining. Fama (1998) argued that academics have tested thousands of variables and it is not important if some of them predict returns in their samples, even if none of the research does in reality.

These three explanations have different predictions, in each case, such as how news arrival will affect the predictability of a cross-sectional return. Therefore, the risk-based model cannot predict the cross-sectional return difference on a particular day; however, at the same time, the behavioural model will predict a high excess return at the time of a particular event and correct this erroneous expectation, as it is based on biased expectations.

4.1. Risk Differences Approach

It has been made evident that stock returns are unconditionally higher on the earning announcement date (Frazzini and Lamont 2006). Engelberg et al. (2016) found that long anomaly (short anomaly) returns were higher (lower) on earning announcement days, by controlling for the fact that returns are higher on a particular earning announcement news date. Anomalies do not perform well on macro-economic news announcement days, but it is not easy to align this with the fact that an anomaly return represents compensation for consumption risk, as it is expected to be higher on these possible announcement days (Savor and Wilsony 2013). Savor and Wilson (2016) found a model that could value and identify the reasons for higher returns on earning announcement days. According to their model, the premium on an earning announcement day occurs because rational investment agents infer market information of earnings from each earning announcement; therefore, the value of beta is higher for the announcing company. In contrast, they did not include the implications of unexpected higher returns on unexpected news days for the Dow Jones. They were also unable to explain the relationship between anomaly variables and analyst forecast error.

A higher risk premium was implied for investment-based models on the day of announcement of earnings in studies by Wu et al. (2010) and Liu and Zhang (2014), where an argument against the investment model where "returns of the simplest investment model are equivalent to the return on assets (ROA)" was posed, as these returns become known to investors at announcement of earnings. These models are not capable of capturing such variations and making predictions related to non-earning announcements or earning forecast errors by analysts. Hence, these investment-oriented models are still risk-based and unable to perform well for anomaly variables, during macro-economic news announcements or when market returns are high.

4.2. Behavioural Bias and Mispricing

Excess returns may be attributed to the behavioural bias of investors, as well. Many models have been developed to capture these biased behavioural anomalies, and some prominent models are based on these biased expectations (Barberis et al. 1998), (Daniel et al. 1988, 2001). These models capture variations that price to structural anomalies, where long-term reversals are due to biased expectations of investors towards expected future cash flows. These prices are adjusted and rectified on the public announcement of updated news. To explain this intuition, Engelberg et al. (2016) incorporated a simple agent-based model, in which they captured the biased expectations of the agent towards expected future cash flows and these expectations were rectified on arrival of cash flow news publicly. They found that firms whose agents had overly optimistic (pessimistic) expectations for expected cash flows had negative (positive) returns on the announcement of news. Their findings regarding the earning announcement day and return on news day were consistent with intuition in the literature.

Engelberg et al. (2016) examined earnings forecasts of sell-side analysts and assessed the impact of biased expectations. They found that, if the analysts had biased expectations towards anomaly stocks, their projections would be more optimistic towards the short side of anomaly stocks or anomaly portfolios, and more pessimistic towards stocks on the long side of anomaly portfolios.

4.3. Data Mining

Although the above results for the earnings announcement and news days are inconsistent with risk-based explanations, it could be consistent with data mining explanations (Engelberg et al. 2016). Harvey et al. (2016) argued that factors identified from theory should have fewer hurdles than factors discovered from empirical evidence. Economic theories are always based on some underlying economic principles; thus, there is little space for data mining.

Hundreds of anomalies have been discovered and documented in recent decades; data mining is one of the concerns that have become acute. Harvey et al. (2016) introduced a multiple testing mechanism to derive different thresholds of significance levels capturing the data mining of anomaly literature. The cut-off for this threshold continually increased as more anomalies were affected by data mining; a more recent factor is that the value of the t-statistic should be higher than three. Hence, the anomaly literature has been found to be affected by widespread p-hacking, which creates a more considerable space to test and verify the anomaly literature.

5. Replication: A Futuristic Approach

List of selected papers for this section are given in Table 6.

Table 6. Selected work on Replication: A Futuristic Approach.

Author	Year	Paper/Book/Thesis Title (Please See References for Details)
Dewald et al.	1986	Replication in Empirical Economics (Dewald et al. 1986)
Lo and Mackinlay	1990	When are Contrarian Profits Due to Stock Market Overreaction? (Lo and MacKinlay 1990)
Fama	1998	Market efficiency, long-term returns, and behavioral finance (Fama 1998)
Mccullough and Vinod	2003	Verifying the Solution from a Nonlinear Solver: A Case Study (Mccullough and Vinod 2003)
Schwert	2003	Anomalies and Market Efficiency (Schwert 2003)
Conrad et al.	2003	Value versus Glamour (Conrad et al. 2003)
Ioannidis	2005	Why Most Published Research Findings Are False (Ioannidis 2005)
Harvey et al.	2016	The Cross-Section of Expected Returns (Harvey et al. 2016)
Mclean and Pontiff	2016	Does Academic Research Destroy Stock Return Predictability? (Mclean and Pontiff 2016)
Baker	2016	Is there a Reproducibility Crisis? (Baker 2016)
Brodeur et al.	2016	Star Wars: The Empirics Strike Back. (Brodeur et al. 2016)
Ben-David et al.	2017	Exchange Traded Funds (Etfs) (Ben-David et al. 2017)
Coy	2017	Lies, damn lies, and financial statistics (Coy 2017)
Harvey	2017	Presidential Address: The Scientific Outlook in Financial Economics (Harvey 2017)
Yan and Zheng	2017	Fundamental Analysis and the Cross-Section of Stock Returns: A Data-Mining Approach (Yan and Zheng 2017)

Several studies have been found in the literature, some of which are in favour of EMH, and most of which are in support of predicted returns. Both types contradict each other and economists are yet to be unified on a single view. Therefore, some arguments and studies have brought forward a new dimension to solve this mystery, initiating further debate in the financial economics literature. For example, Harvey et al. (2016) mentioned that the reliability of factor identification from a theory is more authentic than the discovery of factors by empirical testing. Therefore, this argument creates a basis for replication of all historically discovered anomalies, in order to test the reliability of these anomaly variables.

Academics from finance and economics have consistently warned against the dangers of data mining. The basis of future research is dependent upon the success and failure of past investigations (Lo and MacKinlay 1990). Therefore, the issue of data snooping does not affect some of the studies, which becomes more severe as these all studies have been performed in a single large data set. Furthermore, when this extensive data was scrutinised, more spurious outcomes emerged. As Fama (1998) mentioned, most of the anomalies disappeared when tested with value-weighted portfolios; earlier, it was tested through equal weighted portfolios. Conrad et al. (2003) argued that data snooping can be observed in more than one half of the in-sample relationships between average return and firm characteristics. Schwert (2003) found that, as anomalies became a part of literature, they seemed to weaken, reverse, or disappear with time.

Mclean and Pontiff (2016) accounted for 97 different anomalies to test, out of the sample, and found that the average high-minus-low returns reduced when these anomalies were tested for after publications. Harvey et al. (2016) documented two primary reasons related to publications that may provide a reason for the high frequency of false discoveries. First, it is tough to publish an article in a top journal with negative results. Second, it is challenging to publish a replicated study in economics and finance journals, primarily when you deal with a subtle type of research. However, in many fields of natural sciences, replicated studies are published frequently in many top journals. As a result, academics from the finance and economics fields tend to focus more on discovering new factors, instead of rigorously proving and verifying existing published factors.

Harvey (2017) found that publication biases are due to complex agency problems. Editors are more concerned with gaining citation-based impact factor and, for more citations, they prefer to publish research articles with more significant results. In this scenario, authors (most of the time) do not let research papers with weak or negative findings go for submission. More disconcertingly, authors (sometimes) go for p-hacking, to make their results more favourable for publication. Due to this situation, the authors will get a surprisingly significant and embarrassingly large magnitude of false results, which cannot be replicated. For this situation, Harvey provides a remedy, in the form of the Bayesian p-value, which incorporates economic plausibility of the underlying hypothesis as a part of the inference.

Yan and Zheng (2017) formulated more than 18,000 fundamental signals, capturing the effect of data mining by using the bootstrap approach. They incorporated almost all published variables and factors that were tried, but not reported, in the published literature. This approach was only suited to variables which are based on past return data, such as accounting variables.

The literature of anomalies provides a basis for scientific research of the asset management industry. Exchange traded funds, which are factor-based, grew tremendously from the mid-1990s to 2016. These funds had a value of more than 1.35 trillion dollars in the U.S. stock market and accounted for around 10% of total stocks traded in U.S. markets (Ben-David et al. 2017). With the growing importance of factor investigation, the financial press media questioned the reliability of the underlying investigated factor. Coy (2017) wrote: "Most investors have a vague sense they're being ripped off. Here's how it happens." Researchers have more interest in creating a twist-for-prize anomaly. The subtle variation in data seems like it is the right forum for money-making. Adverse outcomes of research are put aside and positive results are submitted to a journal.

At present, finance is the only field that pursues replication of existing empirical studies seriously. The famous study of Dewald et al. (1986) replicated studies published in the 'Journal of Money, Credit and Banking', and observed inevitable errors. However, their research suggested that the existing results could not be reproduced. Dewald et al. wrote: "The replication of research is an essential component of scientific methodology. Only through replication of the results of others can scientists unify the disparate findings of various researchers' indiscipline into a fit, consistent, coherent body of knowledge" (p. 600). Different software gives different results for the same data set and Mccullough and Vinod (2003) found the same pattern while testing non-linear maximization routines. They also observed that many published studies in the 'American Economic Review' failed to give the same results when tested with different software. (Brodeur et al. 2016) tested more than 5000 statistical tests of published papers in the 'Quarterly Journal of Economics', the 'American Economic Review' and the 'Journal of Political Economy' and found a series of a troubling patterns in test statistics. The features were related to sizeable under-representation of the p-value, high p-values, and other humps related to slightly below p-value from 5 percent. These findings made evident that academics have been p-hacking to make their results significant, in order to make them more powerful for publication and ignore that results with insignificant values do not help them in publications. Papers affected by these two situations of p-hacking can rarely be found in theoretical model-based articles, articles with old tenured authors and articles with randomised control trials.

Ioannidis (2005) argued that there were large possibilities for false results when studies used small datasets. 'The Economist' reported several cases belonging to different fields of study, including Biosciences, Psychology and many other areas, where the success rate for replication of results is meagre. Baker (2016) published an article in 'Nature', where he surveyed 1576 scientists and reported that more than 80% scientists believe that the reproducibility issue for results in the published scientific literature is a dilemma for research outcomes. Reduced usage of statistical tools, publication pressure and selective reporting are three critical issues for this crisis.

Therefore, researchers believe that they should focus more on the reliability of factors obtained from empirical testing, criticizing factors based on strong theory. A new dimension of finance belongs to the replication of all those published studies, which contradict the well-established theories.

6. Conclusions and Limitations

With the existence of stock markets, investors will make mistakes by their collective judgement. It can be assured that some market participants are not rational. Consequently, excess returns in stock markets and irregularities in the pricing of stocks can be found over time, which also persist for shorter periods of time. Undoubtedly, markets can never be completely efficient, because there is no benefit or incentive for professionals to float information in the market, such that it is quickly reflected into stock prices.

The efficient market hypothesis is divided into two parts: First, inefficient markets: stock returns remain random. Second, investors cannot attain excess returns with the existence of an efficient market. The EMH was considered to be an absolute truth and found much attention during the 1980s. Many studies have concluded that markets are inefficient, and the reality of EMH now exists on relative terms. The EMH is unable to capture excess variation in stock prices, asset bubbles, seasonality effects, and the overreactions of investors, and so on. Conversely, returns from stocks were found to be random, and market participants are unable to gain consistent excess returns. Evidence of cross-sectional predictable patterns challenged the existing well-established asset pricing paradigm. Indeed, researchers should focus more on such a type of model, by additionally considering the importance of behavioural aspects.

In modern times, published literature on anomalous returns has gained much attention from academics and researchers. Therefore, in light of the anomaly literature, markets are no more efficient and investors can predict and gain excess returns by using the available room of these anomalies. Based on replication of the existing anomaly literature, a new dimension emerged, where many past studies were found to be falsified and a new discussion started on the current state of markets and reality of these anomalies.

Moreover, researchers must admit that the existing evidence regarding anomalies is not a constitutional proof and the established paradigms are wrong. The issue of data snooping, found in many types of research, gives an alarming indication regarding the reliability of these studies. Data snooping affects all aspects of return procedures, averages and variations with other anomalies and factors. Future research can gain advantage from new historical samples to obtain more insight into asset prices.

The limitations of the study are as follows: much work in the literature has been analytical, case studies and simulation-based. We identified several factors from the existing literature; however, more empirical studies will be needed for validation. The findings of this article are based on a review of more than 90 papers; however, it is still possible that some important papers might not have been included. As this paper was a qualitative analysis of studies within focused themes, personal biases might have occurred.

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Review

Improved Covariance Matrix Estimation for Portfolio Risk Measurement: A Review

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Abstract: The literature on portfolio selection and risk measurement has considerably advanced in recent years. The aim of the present paper is to trace the development of the literature and identify areas that require further research. This paper provides a literature review of the characteristics of financial data, commonly used models of portfolio selection, and portfolio risk measurement. In the summary of the characteristics of financial data, we summarize the literature on fat tail and dependence characteristic of financial data. In the portfolio selection model part, we cover three models: mean-variance model, global minimum variance (GMV) model and factor model. In the portfolio risk measurement part, we first classify risk measurement methods into two categories: moment-based risk measurement and moment-based and quantile-based risk measurement. Moment-based risk measurement includes time-varying covariance matrix and shrinkage estimation, while moment-based and quantile-based risk measurement includes semi-variance, VaR and CVaR.

Keywords: portfolio selection; risk measure; fat tail; Copula; shrinkage; semi-variance; CVaR

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1. Introduction

This paper is motivated by three stylized facts about the operation of real-world financial markets. First, as real-world financial data are asymmetric and fat-tailed, the return series cannot be approximated by normal distribution. Second, financial time series are marked by volatility clustering and last, dependence structure of multivariate distribution is required to model such data and the model needs to be flexible enough to accommodate different types of financial data. Given these characteristics of financial data, many portfolio selection and risk measurement models have been developed to account for such data. Interestingly, we have not come across literature that reviews these developments in recent years. The present research would help fills this important gap. Accordingly, the aim of this paper is to review of development of the literature in the above areas and identify the directions for future research.

As already stated, financial data are known to exhibit some unique characteristics such as fat tails (leptokurtosis), volatility clustering and possible asymmetry. When the tails of distribution have a higher density than that expected under conditions of normality, it is known as fat tailed data distribution. It is 'a distribution that has an exponential decay (as in the normal) or a finite endpoint is considered thin tailed, while a power decay of the density function in the tails is considered a fat tailed distribution' (LeBaron and Samanta 2004, p. 1). As financial data typically exhibit asymmetry and fat tails, the Gaussian distribution cannot adequately represent it. Consequently, alternative parametric distributions that can account for skewness and fat tails have been suggested in the literature. Over the years, the fat tail phenomenon and the various methods used to capture the characteristics of the fat tail of financial data has generated considerable interest among researchers. Similarly, complex dependency patterns such as asymmetry or dependence in the extremes are found in the financial data. The full characteristics of such data cannot be adequately captured by multivariate Gaussian distributions given that it cannot model extreme events. The multivariate Student's *t* and its skewed version could be valid alternatives but also have some disadvantages as outlined by Bauwens and Laurent (2005) and others. Consequently, for such data increasingly the copula approach is being used. It not only can describe the dependence characteristics but also can be combined with other distributions such as Student *t* distribution to describe fat tails.

We proceed as follows: Section 2 provides an overview of the above characteristics of financial data, Section 3 reviews the literature on portfolio selection models, Section 4 reviews the literature on factor models, Section 5 is devoted to portfolio risk measurement literature review and Section 6 provides directions for future research and conclusions of the study.

2. Fat tail of Financial Data and Data Dependence

In this section, we review the literature on fat tails and data dependence.

2.1. The Concept of Fat Tails

Mandelbrot (1963) first introduced the concept of fat tails in mathematical finance to describe cotton price changes. It was followed by many econometric studies devoted to the quest for suitable classes of models that capture the essential statistical properties of stock and stock index returns, for example, Heyde et al. (2001), McAleer (2005), Liu and Heyde (2008) and Tsay (2010), among many others.

The fat tail distribution may have more than one definition, as there is no universal definition for the term *tail* in the first place. It generally refers to a probability distribution with a tail that looks fatter than usual or the normal distribution. A good example may be the Student *t* distribution which is a fat tailed distribution and exhibits tails that are fatter than the normal. It is also a leptokurtic distribution which has excess positive kurtosis as illustrated in Figure 1.

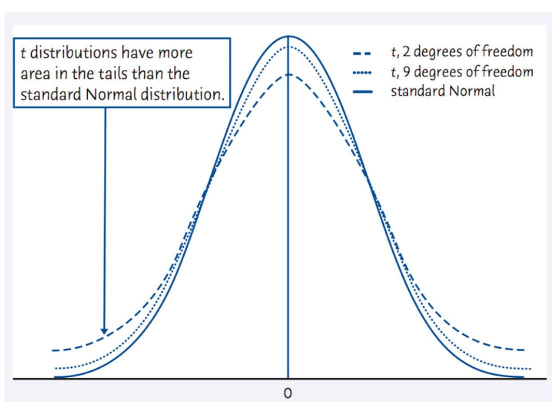

Figure 1. Student *t* distribution is leptokurtic and has a fatter tail when compared to a standard normal distribution.

Some researchers consider that a fat tail distribution refers to a subclass of heavy tailed distributions that exhibit power law decay behavior as well as infinite variance. One example may be a distribution X defined with a fat right tail by $P(X > x) \sim x^{-\alpha}$ as $x \to \infty$, where P is the probability for the cumulative distribution, $\alpha > 0$ is a (small) constant and referred to as the tail index, and the tilde notation "~" is used to mean that there exists some finite value of x above which the probability distribution follows the right-hand side of the expression, that is, asymptotically the tail of the distribution decays like a power law (for more, see e.g., Kausky and Cooke (2009). It may be noted that a Student *t* distribution can be considered to be fat tailed by rewriting its cumulative or density function form, and it has finite variance if the degrees of freedom is larger than 2. In addition, a fat-tailed distribution is heavy tailed, although not every heavy tailed distribution has a fat tail. For example, the Weibull distribution is heavy-tailed but not fat-tailed.

Empirically, we present two figures as an example for real-world data. The real data is the daily Tableau Software close price data from 15 March 2018 to 14 March 2019 collected via Yahoo! Finance at https://au.finance.yahoo.com/quote/DATA/history?p=DATA. Figure 2 shows its time series plots, with the upper panel for the simple returns and lower panel for the log returns. Figure 3 compares the empirical Tableau densities with normal densities and shows that the Tableau data reveals obviously a fat tail and high peak.

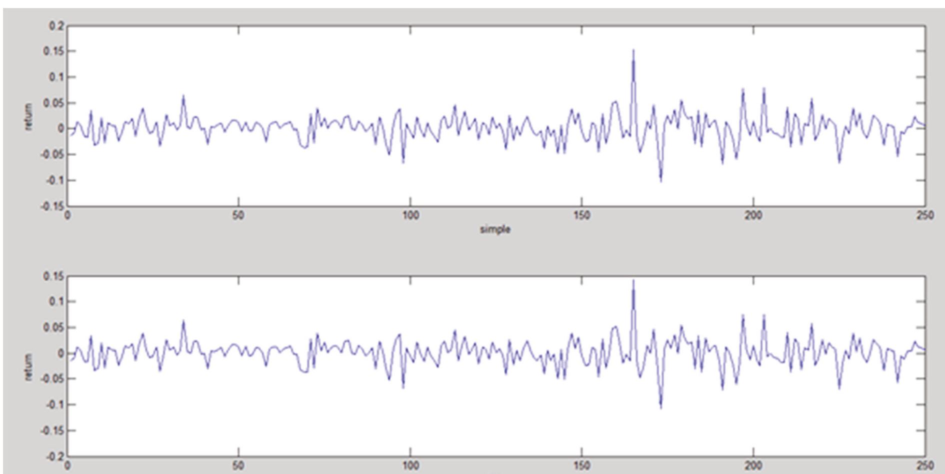

Figure 2. Time series plots of daily returns of Tableau data.

The initial studies that followed the seminal work of Mandelbrot (1963) used the stable Pareto distribution to simulate the fat tail of such data. Fama (1965), Fama and Roll (1968) also used stable Pareto distribution to study the fat tail characteristics of financial data. Such distributions have many properties exhibited by normal distribution such as closeness under summation. However, Upton and Shannon (1979) as well as Friedman and Vandersteel (1982) claimed that a stable Pareto distribution was inappropriate for simulating the fat tail shape of financial data because the return was more peaked and had fatter tails. Ghose and Kroner (1995) found that the GARCH model and the stability model had something in common, which meant that many of the discoveries of the stable distributions with fat tail in finance were caused by temporary volatility aggregation.

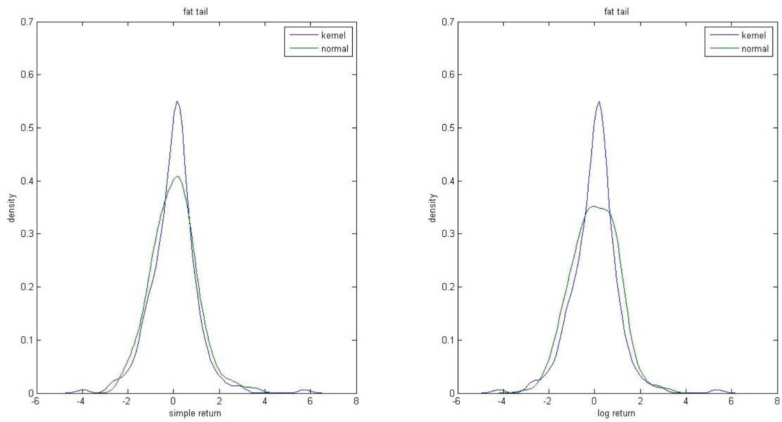

Figure 3. A comparison of simple return and log return of daily Yahoo finance densities (blue) with normal densities (green). The above figure compares the empirical Tableau densities with normal densities and shows that the Tableau data reveals obviously a fat tail and high peak.

Subsequently, Sornette et al. (2000) introduced a multivariate fat tailed asset return distribution and depicted accurately the high-order cumulants of wealth changes in arbitrary portfolios. A computational technique of functional integrals and Feynman diagrams borrowed from particle physics was used. Most of the empirical applications of the stochastic volatility (SV) model assume that the conditional distribution of returns, given the latent volatility process, is normal. Liesenfeld and Jung (2000) used German stock data to compare stochastic volatility model based on conditional normal distribution and conditional fat tail distribution. These conditional fat tail distributions were mainly Student t distributions and generalized error distributions. Cont (2001) presented a set of stylized empirical facts (including fat tail) emerging from the statistical analysis of price variations in various types of financial markets and analyzed how these stylized empirical facts invalidated many of the common statistical approaches. Chib et al. (2002) discussed a class of generalized stochastic volatility models defined by the horizontal effects of fat tails, fluctuations, observational and evolutionary equations, and the covariate effects of the jumping part of the observational equation and provided two Markov Chain Monte Carlo (MCMC) fitting algorithms for the above models. In addition, simulation-based inference in generalized models of stochastic volatility was considered.

Zhou (2002) used the multivariate normal mixture model to characterize the fat tail characteristics of market risk factors, examined the relationship between risk and return, and established an asset pricing model with fat tail characteristics excluding options. This model provided a new perspective to study asset pricing. Wong et al. (2009) proposed Student t mixture autoregressive model which is also able to capture serial correlations, time-varying means and volatilities, and the shape of the conditional distributions can be time varied from short-tailed to long-tailed, or from unimodal to multimodal. Also, Chen and Yu (2013) proposed a novel nonlinear VaR method to model the risk of option portfolio under fat tailed market risk factors. Multivariate mixture of normal distributions was used to depict the heavy-tailed market risk factors.

Glasserman (2004) used multivariate t distribution to characterize the risk factors of fat tailed market, and indirectly obtained an expression of closed moment generating function. This expression reflects the change of portfolio value when the fat tailed problem was transformed into thin tailed problem. On this basis, the moment generating function was obtained by using the structure of multivariate t distribution. Albanese et al. (2004) used multivariate t distribution to characterize the fat tail of market risk factors. First, the matrix transformation of option portfolio value was derived from Delta-Gamma-Theta model. Thereafter, the density function of option portfolio value was discretized. Finally, the approximate VaR value was calculated by Fourier inverse transformation and linear interpolation. This new method does not assume that the characteristic function for the return model is known explicitly. Considering the difference between multivariate normal distribution and multivariate *t* distribution in the description of market risk factors, Albanese and Campolieti (2006) proposed the probability density function for calculating the change of option portfolio value and the Monte Carlo simulation method for estimating the multivariate VaR at a given confidence level and explored the relationship between a normal distribution and a fat tail distribution. Like Glasserman (2004), Siven et al. (2009) deduced the closed expression of moment generating function in the case of multivariate *t* distribution and compared Fourier-Inversion method with Monte Carlo simulation method. The results showed that the Fourier-inversion method was much quicker than Monte Carlo simulation method and that Fourier-Inversion was a good way to calculate option VaR. Asai (2008) studied two models for describing fat tail and volatility dependence: autoregressive stochastic volatility model with Student *t* distribution (ARSV-T) and multifactor stochastic volatility (MFSV) model, and the results showed that ARSV-T model provided a better fit than MFSV model based on Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC).

Asai (2009) compared stochastic volatility models defined by normal distribution and other fat tailed distributions, such as Student *t* distribution and generalized error distribution. Delatola and Griffin (2013) proposed a Bayesian semiparametric stochastic volatility model, and this model allowed the distribution of returns to be fat tail and allowed the correlation between returns and fluctuations. Abanto-Valle et al. (2015) proposed a stochastic volatility model which assumed that the return followed the biased Student *t* distribution. This model could flexibly control the skewness and the fat tail distribution of the return condition. Meanwhile, an effective MCMC algorithm was given to estimate and predict the parameters. Lafosse and Rodríguez (2018) combined stochastic volatility model with *GH Skew* Student *t* distribution to characterize the skewness and fat tail of financial data and showed the evidence of asymmetries and heavy tails of daily stocks returns data. Gunay and Khaki (2018) noted that capturing conditional distributions, fat tails and price spikes was the key to measuring risk and accurately simulating and predicting the volatility of energy futures. These researchers tried to model the volatility of energy futures under different distributions.

2.2. The Dependence of Financial Data

Financial data are usually interdependent. They also exhibit a tendency of volatility clustering, that is, temporal dependence, in which large financial returns are followed by large financial returns. The interdependence of financial data has been extensively researched in various fields of finance, for example, following the US stock market crash of 1987, the contagion spread to the UK and other developed countries (King and Wadhwani 1990). To model the non-linear dependence in data, following Engle (1982), many ARCH-type models have been proposed. However, assumption of iid in such models makes their use inappropriate to model non-linear dependence in a univariate series or simultaneous dependence in two or more timeseries. Copula comes to rescue here. Some important publications are listed in the following table.

Copula proposed by Sklar (1959) can identify the dependency structure, capture the potential nonlinear correlation, and fit the dependency of financial data well, which makes it a good choice to measure correlation (Embrechts 1999). Copula refers to "functions that join or couple multivariate distribution functions to their one-dimensional marginal distribution functions" (Nelsen 1999, p. 1). The copula decomposes an n-dimensional distribution function in to the marginal distribution functions and the dependence part. It is the latter that the copula describes. In Table 1 below some key research work on copula has been included.

Table 1. Selected work on Copula.

Author	Year	Paper/Book/Thesis Title (Please See References for Details)
Sklar	1959	Fonctions derépartitionàn dimensions et leurs marges
Joe	1997	Multivariate Models and Dependence Concepts
Embrechts	1999	An Introduction to Copulas
Mashal and Zeevi	2002	Beyond correlation: Extreme co-movements between financial assets
Van den Goorbergh et al.	2005	Bivariate option pricing using dynamic copula models
Kole et al.	2007	Selecting Copulas for risk management
Hafner and Reznikova	2010	Efficient estimation of a semiparametric dynamic copula model

"Modern risk management calls for an understanding of stochastic dependence going beyond simple linear correlation" (Embrechts et al. 2001). These researchers emphasized the necessity to use Copula to simulate multivariate correlations in financial data given its stochastic dependence and pitfalls. Mashal and Zeevi (2002) showed that Student *t* Copula had an advantage over other multivariate Copulas in fitting financial data. Kole et al. (2007) used goodness-of-fit test for *t*, Gaussian and Gumbel Copula in risk management of linear assets and found that *t* Copula had more advantages than Gaussian and Gumbel Copula. Sak et al. (2010) used a flexible and accurate model, such as *t* Copula dependency structure and generalized hyperbolic distribution, to simulate logarithmic returns. They also calculated the tail probability of the current asset portfolio.

Studies have shown evidence of two types of asymmetries in the joint distribution of stock returns: skewness in the distribution of individual stock returns and an asymmetry in the dependence between stocks. Patton (2004) showed that the rotational Gumbel Copula function was superior than the normal and the Student *t* Copula, in describing the asymmetric dependency structure of two stock indexes. Trivedi and Zimmer (2006) considered the use of the copula approach for a model with three jointly determined outcomes. The model could handle the discrete case in which outcomes include a mixture of dichotomous choices and discrete count data. They applied this technique to study self-selection and interdependence between health insurance and health care demand among married couples. Hu (2006) proposed a hybrid Copula+ model to capture different types of dependent structures, in which the marginal distribution of each market asset was estimated by nonparametric method and the mixed Copula was estimated by quasi-maximum likelihood method. Patton (2006) extended the Copula theory to allow conditional variables, analyzed two important exchange rates using different forms of Copula-GARCH model, and used them to construct a flexible model of conditional dependency structure of these exchange rates. Liu and Luger (2009) adapted and examined an iterative (fixed-point) algorithm for the maximum-likelihood estimation of copula-based models that circumvents the need to compute second-order derivatives of the full-likelihood function. The algorithm exploits the natural decomposition of a potentially complicated likelihood function: the first part is a working likelihood that only involves the parameters of the marginals and the residual part is used to update estimates from the first part.

Van den Goorbergh et al. (2005) studied the price problem of Binary Options with correlations between assets and used the parameter Copula family with multiple alternative Gaussian dependency structures to fit the correlation. The relationship was assumed to be a function of asset volatility and it changed with time. Since then, time-varying Copula model has been extensively studied. Bartram et al. (2007) used the time-varying Copula model to study the effect of the introduction of the euro on the dependence between 17 European stock markets from 1994 to 2003. The time-varying Copula model used the GJR-GARCH-T model to realize the marginal distribution and Gauss Copula to realize the joint distribution. These could capture the time-varying nonlinear correlations. The correct modeling of non-Gaussian dependences is a key issue in the analysis of multivariate time series, Giacomini et al. (2009) used copula functions with adaptively estimated time-varying parameters for modeling the distribution of returns and applied it to the portfolio VaR. Hafner and Reznikova (2010) proposed a new semiparametric dynamic Copula model in which the marginal of Copula was assigned as a parameter GARCH-type process while the dependent parameters of Copula could change with time in a nonparametric manner. Negative extreme changes were common in international stock markets, Garcia and Tsafack (2011) pointed out the limitations of some common methods and proposed a regime-switching Copula model, which included a normal system with symmetric dependencies and an asymmetric dependency. The system was applied to allow changes in the market between the international stock and bond markets. Hafner and Manner (2012) proposed a dynamic Copula model in which dependent parameters followed an autoregressive process. Since this kind of model includes Gaussian Copula with stochastic correlation process, it can be regarded as a generalization of multivariate stochastic volatility model. Mendes and Marques (2012) found that the dependency structure between assets was not only linear but also used robust estimation of dual Copula model to fit logarithmic returns. Chen and Tu (2013) used four different types of time-varying Copula to fit the index futures and spot returns by relaxing the traditional normal joint distribution hypothesis and improved the hedging portfolio VaR. Creal and Tsay (2015) constructed a series of Copula families with time-varying dependent parameters by writing Copula as a factor model with random loads.

The Vine Copula (Joe 1997) has great advantages in describing the relationship between multiple financial assets and is widely used in financial risk management. Maugis and Guegan (2010) compared the Vine Copula method with several traditional GARCH models and concluded that the Vine Copula method could give better portfolio VaR prediction. As distinct from the existing Vine Copula structure strategy, Diβmann et al. (2013) proposed automatic Copula selection and estimation technology based on graph theory. It enabled flexible modeling of complex dependencies, that is, even those with larger dimensions. So and Yeung (2014) discussed the construction+ of Vine Copula structure and studied the relationship between financial markets and Vine Copula theory. Geidosch and Fischer (2016) confirmed the advantages of Vine Copulas over traditional Copula in simulating the dependent structure of credit portfolios. Aiming to measure risk and finding the optimal weights of portfolios containing three financial instruments, Pastpipatkul et al. (2018) used C-D vine Copulas method to establish the dependence relationship of each pair of financial instruments and used Monte Carlo simulation technology to generate simulation data to calculate risk value (VaR) and expected shortfall.

3. Portfolio Selection: A Review of Common Models

A commonly used model for portfolio selection is the mean-variance model, in which, the optimal portfolio weight depends on the mean and covariance matrix of asset returns. Usually, the available portfolio weights are obtained by using sample mean and sample covariance matrix to replace the true mean and covariance matrices of asset returns respectively. However, the estimation of sample means, and covariance usually involves errors and the estimation errors in sample mean are much larger than those in sample covariance. This makes the mean-variance model more sensitive to estimation errors. Therefore, the global minimum variance models whose optimal portfolio weight only depends on the covariance matrix is used. Furthermore, for the measurement of portfolio risk, the factor model is commonly used to estimate covariance matrix.

Accordingly, the literature on portfolio selection has developed in three strands: the traditional mean-variance model and the newer, global minimum variance model and the factor model.

3.1. Mean-Variance Model

In the traditional mean-variance model proposed by Markowitz (1952), the return of financial assets is represented by a random variable with Gaussian distribution. The assumption of normal (Gaussian) distribution means that the return of assets depends only on the mean and variance. Markowitz (1959) extended the mean-variance model in a pioneering book on portfolio selection. Merton (1972) studied the application of the mean-variance model allowing short-sale in portfolio selection. Over the years, many studies have used the above models. Some groundbreaking articles are summarized in Table 2 below.

Table 2. Selected works on Portfolio Selection.

Author	Year	Paper/Book/Thesis Title (Please See References for Details)
Markowitz	1952	Portfolio Selection
Samuelson	1969	Lifetime portfolio selection by dynamic stochastic programming
Merton	1969	Life time portfolio selection under uncertainty: The continuous-time case
Pogue	1970	An extension of the Markowitz portfolio selection model to include variable transactions' costs, short sales, leverage policies and taxes
Merton	1972	An analytic derivation of the efficient portfolio frontier
Fernández and Gómez	2007	Portfolio selection using neural networks

Markowitz's traditional mean-variance model is a static model in which investors can only make investment decisions at the beginning of the investment period and then wait until the end of the investment period. Based on this, the mean-variance model was later extended to the multi-period case. Samuelson (1969) proposed a discrete time multi-period consumption-investment model to maximize the end-of-term expected utility for investors. Grauer and Hakansson (1993) compared the effects of mean-variance asymptotic and quadratic asymptotic in a discrete time dynamic investment model. Yi et al. (2008) used the mean-variance model to consider the discrete time portfolio optimization of asset liability management under uncertain investment level and deduced the analytical optimal strategy by using embedding technology. Wu and Li (2011) studied the discrete time mean-variance portfolio model with regime switching under the assumption of stochastic cash flow.

Merton (1969, 1971) studied the maximized expected return of continuous time model under a given planning period, which is a pioneering work of continuous time research. Karatzas et al. (1987) considered a generalized consumption-investment model with a single member, which aimed to maximize the linear combination of the total expected discount utility and the end-of-term wealth utility from the consumption over a continuous investment period. Li and Ng (2000) firstly used embedding technology to solve the problem of inseparability and constructed a framework with mean-variance model in a discrete case. Xie et al. (2008) used the stochastic optimal linear-quadratic control technique to obtain the optimal dynamic strategy for continuous time mean-variance portfolio selection in incomplete markets. Using dynamic programming and embedding techniques, the closed form optimal strategy and efficient frontier were derived. Xu and Wu (2014) studied the continuous time mean-variance portfolio selection problem with inflation in incomplete markets and obtained the efficient bounds of dynamic optimal strategy and mean-variance model. Wu and Chen (2015) studied the time-consistent multi-period mean-variance portfolio selection problem under the assumption that risk aversion was dynamically dependent on market conditions.

Pogue (1970) first gave a description of the mean-variance portfolio problem in the presence of transaction costs. Davis and Norman (1990) further explored the portfolio selection problem under proportional transaction costs. Dumas and Luciano (1991), Morton and Pliska (1995) studied portfolio selection with proportional transaction costs and fixed transaction costs, respectively. Yoshimoto (1996) first assumed that the transaction cost was a V-shaped function, and then obtained the optimal portfolio strategy. Oksendal and Sulem (2002) studied the optimal consumption and portfolio under fixed and proportional transaction costs, with the objective of maximizing cumulative consumption expected utility within the scope of planning. Xue et al. (2006) constructed a mean-variance portfolio selection model with concave transaction costs to capture real market conditions. The authors provide a branch and bound algorithm as a solution. Dai and Zhong (2008) proposed a numerical penalty method to solve the continuous time portfolio selection problem with proportional transaction costs. Peng et al. (2011) studied portfolio optimization with quadratic transaction costs in the framework of the mean-variance model. Wang and Liu (2013) studied the multi-period mean-variance portfolio selection problem with fixed and proportional transaction costs and defined the indirect utility function to solve the problem by using dynamic programming and Lagrange multiplier. Liagkouras and

Metaxiotis (2018) proposed a new multi-period fuzzy portfolio optimization algorithm for multistage mean-variance fuzzy portfolio optimization with transaction costs.

To make the model more practical, different constraints were introduced in the mean-variance model. Fernández and Gómez (2007) generalized the standard mean-variance model including cardinality and boundary constraints, and the constraints guaranteed investment in a given set of different assets and limited the amount of capital invested in each asset. Soleimani et al. (2009) proposed a portfolio selection model based on mean-variance model framework, which included cardinality constraints, minimum trading lot sizes and market (sector) capitalization. Castellano and Cerqueti (2014) studied the mean-variance optimal portfolio selection problem for risky assets with low-frequency trading and low liquidity. To simulate the dynamics of illiquid assets, pure-jump processes were introduced, which enabled the development of portfolio selection models in mixed discrete/continuous time settings.

Simaan (2014) provided a framework that allowed performance comparisons of within and out of sample between mean-variance portfolios and portfolios that maximize expected utility. To develop the best market timing strategy, Gao et al. (2015) considered the mean-variance dynamic portfolio selection problem with management cost time constraints. Lioui and Poncet (2016) proposed a new portfolio decomposition formula to reveal the economics of investor portfolio selection according to the mean-variance criterion and noted that the number of components of the dynamic portfolio strategy could be reduced to two: the first was to hedge the risk of discounted bonds maturing within the investor's time limit without preference, while the second was to hedge against time variation in pseudo relative risk tolerance.

3.2. Global Minimum Variance Model

The global minimum variance model (GMV) is a specific optimal portfolio with minimum variance on the effective boundary. Haugen and Baker (1991) used the GMV model to verify whether the capitalization weighted (cap weights) portfolio was an efficient investment as claimed by sponsors of such plans. These researchers found that even assuming informationally efficient capital market and that all investors rationally optimized the relationship between risk and expected return, the portfolio of cap weights was not efficient except under extreme restrictive conditions. Chopra and Ziemba (1993) promoted the use of GMV in finance and pointed out that the error in expected returns was 10 times than the error in variance and covariance. Chan et al. (1999) focused on the GMV portfolio and emphasized that the GMV portfolio performed better than the Markowitz mean-variance model. Jagannathan and Ma (2003) pointed out that the weight of the GMV portfolio should be more stable than that of the standard mean-variance model because the estimation error of the covariance was smaller than that of the mean. Kempf and Memmel (2006) noted that the GMV portfolio could provide better out-of-sample results than the tangent portfolio theory and studied the distribution of portfolio weights under the GMV model. Demiguel and Nogales (2009) claimed that GMV model relied only on covariance matrices and were insensitive to estimation errors. These studies have led to the popularity of GMV in portfolios selection.

Traditional GMV only solves the portfolio weights from the perspective of optimization, but many scholars are interested in the distribution and nature of the portfolio weights of GMV. Under the assumption of normal distribution, Okhrin and Schmid (2006) derived the multivariate density function of GMV portfolio. Clarke et al. (2006) noted that the stock weights on the left of the effective boundary under the minimum variance model were independent of the expected safe return. At this point, the portfolio could be obtained only by using the covariance matrix of stocks without involving the equilibrium expectation or the active forecast return. Bodnar and Schmid (2008) discussed portfolio weights in GMV model under the assumption that returns followed a matrix elliptical contoured distribution. Assuming that securities returns were neither normal nor independent, they found that the stochastic nature of the portfolio in GMV model did not depend on the mean vector and the assumption of the distribution of securities returns. Bodnar and Schmid (2009) derived the variance and expected return of sample GMV portfolio distribution. Frahm (2010) derived a small sample hypothesis test for global and local minimum variance portfolios and calculated the exact distribution of portfolio weight estimation. At the same time, the first two moments of the estimation of portfolio expected return were given. On the assumption that the conditional distribution of logarithmic returns was normal, Bodnar et al. (2017) considered the weight estimation problem of the optimal portfolio from the perspective of Bayes and obtained the posterior distribution of the weight of GMV portfolio by using the standard prior of mean vector and covariance matrix.

Following the research on distribution and nature of the portfolio weights of GMV, parameter uncertainties, Glombek (2014) analyzed the mean, variance, weight and Sharpe ratio estimators of excess returns of GMV portfolio under consistent and asymptotic distributions, discussed the problem of high-dimensional assumptions and demonstrated the applicability of this method. Maillet et al. (2015) proposed a robust approach to mitigate the effects of parameter uncertainties for a decision maker using GMV strategy to optimize portfolio selection. Based on Taylor's robust M-estimator and Ledoit-Wolf shrinkage estimator, Yang et al. (2015) proposed a hybrid covariance matrix estimator under the GMV model for portfolios, with outliers of financial data, fat tailed distribution of sample data and obtained a consistent estimate of portfolio risk by minimizing the optimum linear shrinkage strength using random matrix theory. Bodnar et al. (2017) analyzed the GMV portfolio model under the Bayesian framework, adding the prior beliefs of investors to the investment decision. Carroll et al. (2017) evaluated the performance of GMV portfolio strategy and equal weight portfolio strategy under time-varying conditions between assets. They found that conditional correlation is more important than conditional variance in portfolio performance. The also found that frequent asset rebalancing does not help improve portfolio performance. Bodnar et al. (2018) estimated the GMV portfolio in high-dimensional case by using the results of random matrix theory, gave a shrinkage estimator in the sense of non-distribution assumption and minimizing the variance of samples, and obtained the asymptotic properties of the estimator under the assumption of the existence of fourth-order moments.

The mean-variance models are highly data intensive. Consequently, search was on for models that can capture enough of reality but are simpler. This led to the development of factor models.

4. Factor Model

The literature on factor models has evolved in two stages: single factor models and multi-factor models.

A factor model that is linear in form posits that the return of an asset can be expressed by the following equation:

$$r = a + b_1 f_1 + \cdots + b_k f_k + e,$$

where r is the return of an asset, a, $b_1, \ldots, b_k$ are the parameters, e is the error term. We call it a single factor model when $k = 1$, and we call it a multi-factor model when $k \geq 2$.

4.1. Single Factor Models

The factor models have drawn attention of researchers, after Sharpe (1963) used, the factor model to estimate the covariance matrix. Geweke (1977) used dynamic factors to analyze the economic time series data and found that the results supported the methodology.

Geweke and Singleton (1981) proposed the theory of identification, estimation and inference in the dynamic confirmatory factor model of economic time series data and pointed out that the dynamic confirmatory factor model could accommodate the important characteristics of prior constraints in the parameter matrix. Watson and Engle (1983) studied the problem of specification and estimation of the dynamic unobserved component model and provided the method of estimating unknown parameters based on score method and EM algorithm by maximizing the likelihood function. Diebold and Nerlove (1989) identified and estimated the univariate ARCH model, and then used the results of the univariate ARCH model to propose the multivariate latent variable ARCH model. Engle et al. (1990) suggested the use of Factor-ARCH model as a concise structure of conditional covariance matrix of asset excess returns, which made it possible to study the dynamic relationship between asset risk premium and volatility in multivariate systems. Through a variety of diagnostic tests and compared with the previous empirical results, it was shown that the Factor-ARCH model was better as compared to other models given that it had the advantage of stability over time. Lanne and Saikkonen (2007) proposed a multivariate generalized orthogonal factor GARCH model and gave a program to test the correctness of the number of factors. Also, a mixture of Gaussian distributions was considered, and it was found that some parameters of the conditional covariance matrix that were not identifiable under normality could be identified when the mixture specification was used. Cardinali (2012) used orthogonal factors to model the structure of conditional covariance matrices. The advantage of this approach was that the estimated factors could be simulated using a univariate GARCH process, and the model could be extended to multivariate cases.

4.2. Multi-Factor Models

Litterman and Scheinkman (1991) empirically determined the common factors of treasury bond returns based on past securities. The analysis showed that most of the fluctuations of fixed income securities return could be explained by three factors, and the three-factor model was particularly useful for hedging. Chen and Scott (1993) considered that it was necessary to establish a formal theoretical structure model for bonds and other different types of interest rate options. Based on this, a multi-factor equilibrium model was proposed to estimate the parameters driving the interest rate change process and to determine the number of factors necessary to characterize the interest rate structure model. Duffie and Kan (1996) proposed a consistent and arbitrage-free multifactor model of the term structure of interest rates. The model assumed that the returns on a fixed maturity date followed a parametric multivariate Markov diffusive process with stochastic volatility parameters and provided the necessary and sufficient condition for numerical algorithm and the stochastic affine representation of the model. Fama and French (1993) proposed that the return on excess assets could be explained by three factors: sensitivity to market excess returns, market capitalization and book price ratio. Campbell (1996) noted that adding human capital to common factors could improve the performance of multi-factor asset pricing model in predictability of returns. Chan et al. (1999) found that the market, size and stock market value can capture the common structure of the return covariance matrix and found that the use of three factor model for the minimum variance portfolio model was adequate. Stock and Watson (2002) studied predictions with multiple predictors, observations, and a single time series, and noted that a small number of principal component estimators could be used for prediction when data followed an approximate factor model. Bai (2003) used principal component estimator to establish the inference theory of large-dimensional factor model and derived the finite distribution of convergence rate and factor, factor load and common component. Han (2006) studied the effects of time-varying expected return and volatility on asset allocation in a high-dimensional context, and proposed a dynamic factor multivariate stochastic volatility model, which allowed the first two moments of many assets returns to change with time. Adrian and Franzoni (2009) used conditional CAPM models to allow unobserved changes in risk load factors over time. Based on the assumption that investors could rationally learn the long-term level of the load factor from the observed returns, Kalman filter was used to simulate conditional beta. Fan et al. (2013) used the multifactor model to estimate the covariance matrix in the high-dimensional case. Jungbacker et al. (2014) studied the dynamic factor model and showed how to use cubic spline function to smoothly limit the factor load. Hou et al. (2015) put forward a new four factor model by combining market and scale with investment and profitability. Jungbacker and Koopman (2015) presented a new method of dynamic factor model based on likelihood analysis. These researchers used linear dynamic stochastic processes to simulate latent factors and autoregressive processes with correlations to determine the singular perturbation sequence. The method was found to be effective in estimating the factors and maximum likelihood parameters. Fama and French (2015) added profitability and investment to the three-factor model and constructed a five-factor model to reveal several abnormal phenomena of average returns. Fama and French (2016) used five-factor model to explain the abnormal phenomenon of average returns. Chiah et al. (2016) confirmed that the five-factor model was superior to the multifactor model in explaining the changes of asset returns in global asset market. Stambaugh and Yuan (2017) proposed a four-factor model that combined the two mispricing factors with market and size factors. They found that the ability of the model to account for many anomalies is much better than the earlier models.

Fama and French (2017) used international data to test the five-factor model. The global three factor and five factor models did not perform well in the test of regional portfolio. Therefore, local variables were used to establish the model that is, the factors and returns to be explained came from the same region. Kubota and Takehara (2018) used five factor model (Fama and French 2015) to test whether the model could well explain the pricing structure of Japanese long-term data stocks. They found that the original version of the five-factor model was not the best benchmark pricing model for Japanese data from 1978 to 2014. Roy and Shijin (2018) proposed a balanced six factor asset pricing model, which explained the change of asset returns by adding human capital to the five-factor model and tested the six-factor asset pricing model with four different portfolios. Tu and Chen (2018) developed a new factor-augmented model for calculating the value at risk (VaR) of bond portfolios based on the Nelson-Siegel structural framework and tested whether the information contained in macroeconomic variables and financial stress shocks could enhance the accuracy of VaR prediction.

5. Portfolio Risk Measure

Several methods are available for the measurement of portfolio risk and we divide them into (a) moment-based risk measurement and (b) moment-based and quantile-based risk measurement. The moment-based methods include time-varying covariance matrix and the shrinkage estimation use the covariance matrix in the risk measurement. The semi-variance method calculates the risk below the target value, and the target can be regarded as a quantile. VaR is based on quantile measures of risk, while CVaR is a measure of risk based on the idea of VaR quantile and mean value. Therefore, semi-variance, VaR and CVaR are risk measures based on moments and quantiles.

5.1. Moment-Based Risk Measurement

5.1.1. Time-Varying Covariance Matrix

Some groundbreaking publications are summarized in Table 3 below.

Table 3. Selected work on Correlation/Covariance and GARCH.

Author	**Year**	**Paper/Book/Thesis Title (Please See References for Details)**
Engle	1982	Autoregressive conditional heteroscedasticity and estimates of UK inflation
Engle et al.	1984	Combining competing forecasts of inflation using a bivariate ARCH model
Bollerslev	1986	Generalized autoregressive conditional heteroscedasticity
Bollerslev et al.	1988	A capital asset pricing model with time-varying covariances
Bollerslev	1990	Modelling the coherence in short-run nominal exchange rates: A multivariate generalized ARCH model
Engle and Kroner	1995	Multivariate simultaneous generalized ARCH
Tse and Tsui	2002	A multivariate generalized autoregressive conditional heteroscedasticity model with time-varying correlations
Engle	2002	Dynamic conditional correlation: A simple class of multivariate generalized autoregressive conditional heteroskedasticity models
McAleer et al.	2008	Generalized autoregressive conditional correlation

Engle (1982) introduced the autoregressive conditional heteroscedasticity (ARCH) family model and used it to estimate the means and variances of inflation in the U.K. The ARCH effect is found to be significant and the estimated variances increased substantially during the chaotic 1970s. Bollerslev (1986) extended the ARCH family model to the Generalized autoregressive conditional heteroskedasticity (GARCH). To capture the dynamic changes of financial markets, time-varying dynamic covariance matrix has been widely used in portfolio investment. Since the GARCH model can successfully describe one-dimensional time-varying variance, many researchers have tried to extend the time-varying variance to the multivariate case by using the multivariate GARCH model.

Bollerslev et al. (1988) used multivariate GARCH (MGARCH) model to estimate the earnings of bills, bonds and stocks. The expected return of bills, bonds and stocks was proportional to the return of each diversified or market portfolio. The results showed that conditional covariance varied greatly over time and this time-varying factor was an important determinant of time-varying risk premium. Kroner and Claessens (1991) used similar technologies to get a series of optimal dynamic hedge funds. Lien and Luo (1994) assessed the multi-period hedging ratio of currency futures in the framework of MGARCH.

Engle et al. (1984) provided a necessary condition for the conditional covariance matrix in the two-dimensional ARCH model to be a positive definite. However, it was not feasible to extend the necessary condition of positive definite conditional covariance to a more generalized model. Bollerslev (1990) suggested that the constant conditional correlations (CCC) MGARCH model could overcome the difficulty of positive definite. Because of the simplicity of calculation, constant conditional correlations MGARCH model has been widely used in practice, but some researchers find that some assumptions of constant correlations MGARCH model are not supported by financial data in practice. Engle and Kroner (1995) gave the formulas and the theoretical results of estimations for multivariate GARCH models in simultaneous equations, proposed a new parameterization method (BEKK) for multivariate ARCH processes, and discussed the equivalent relations of various ARCH parameterizations. At the same time, the sufficiency constraints for the conditional covariance matrix to guarantee positive definiteness were proposed, and the 'sufficient and necessary conditions' for the stability of covariance were given.

Bera et al. (1997) pointed out that the BEKK model proposed by Engle and Kroner (1995) did not perform well in estimating the optimal hedging ratio. Also, Lien et al. (2002) pointed out that BEKK was difficult to converge in estimating the conditional variance structure of spot and futures prices. Tsui and Yu (1999) used the dual GARCH model to study stock returns in two emerging markets, Shanghai and Shenzhen of China, and the information matrix test statistic did not support the hypothesis of the constant conditional correlation of stock returns. Tse (2000) introduced the Lagrange Multiplier test to the multivariate GARCH model with constant correlation assumption and this test verified the limitations of the multivariate GARCH model with constant correlation. The data of stock market returns in China was used to draw a conclusion that the correlation was time-varying.

The fact that the correlation is time-varying has been accepted by many scholars. Tse and Tsui (2002) proposed a MGARCH model with time-varying correlation. The conditional covariance matrix could be decomposed into conditional variance matrix and conditional correlation coefficient matrix. Each conditional variance term was assumed to follow a unitary GARCH model, and the conditional correlation coefficient matrix followed a similar autoregressive moving average. At the same time, Engle (2002) proposed a new family of multivariate GARCH models, a dynamic conditional correlation (DCC) model to estimate time-varying correlations.

MGARCH model settings are usually determined by practical considerations such as easy estimation, which often leads to serious losses in general. The deficiencies and developments on the DCC and BEKK models have been extensively reviewed by McAleer (2019a, 2019b). Alexander (2001) proposed an orthogonal GARCH model in which the time-varying covariance matrix was derived from a small number of uncorrelated factors. Weide (2002) proposed a new MGARCH model: the covariance matrix with many parameters could be parameterized with considerable degrees of freedom and the estimation of parameters was still feasible. This model could be regarded as a natural generalization of O-GARCH model and nested in a more general BEKK model. To avoid the difficulty of convergence, the unconditional information was used to make the number of parameters estimated by conditional information more than half. Vrontos et al. (2003) proposed a new parameter method for MGARCH with time-varying covariance: the covariance matrix guaranteed positive definiteness and the number of parameters of the method was relatively small, which could be easily applied to high-dimensional time series data model. The parameter estimation of multivariate model was realized by classical Bayesian technique, and the maximum likelihood estimation was realized by Fisher scoring method. Ledoit et al. (2003) proposed a new method for estimating the time-varying covariance matrix in the framework of the MGARCH (1,1) model for the diagonal VECH. This method was numerically feasible in dealing with large-scale problems and could generate semi-definite conditional covariance matrix without imposing impractical prior restrictions.

Cappiello et al. (2006) studied the existence of asymmetric conditional second-order moments in international equity and bond yields and analyzed them by the asymmetric version of Engle (2002) dynamic conditional correlation (DCC) model. A large amount of evidence showed that the series of national stock index returns indicated strong asymmetric conditional volatility, while there was little evidence that bond index returns showed such behavior. Mcaleer et al. (2008) established the generalized autoregressive conditional correlation (GARCC) model on the assumption that the normalized residual followed the random coefficient vector autoregressive process. The GARCC model enabled conditional correlation to change over time. GARCC was also more general than Engle (2002) Dynamic Conditional Correlation (DCC) and Tse and Tsui (2002) time-varying correlation model and did not impose excessive restrictions on the parameters of DCC models. At the same time, the structural properties of GARCC model, especially the analytical form of regularity conditions, were deduced, and the asymptotic theory was established. Hafner and Franses (2009) extended Engle (2002)'s DCC model to allow asset-specific correlation sensitivity. This model was useful for investors holding large asset returns. At the same time, they proposed two estimation methods, one based on complete likelihood maximization and the other based on individual correlation estimation. Applying the generalized DCC (GDCC) model to the daily data of stock returns of 39 UK firms on FTSE, they found convincing evidence that the GDCC model was improved on the DCC model and on the constant conditional correlations MGARCH model of Bollerslev (1990). Haas et al. (2009) proposed an asymmetric multivariate extension of a new normal mixed GARCH model, discussed the parameterization and estimation problems, derived the covariance stationarity condition and the existence of the fourth moment, and gave the expression of the dynamic correlation structure of the process.

Diamantopoulos and Vrontos (2010) used multiple Student t error distributions to simulate the fat tail nature of conditional distribution of financial returns data, extended the Vrontos et al. (2003) model, and then proposed a Student t full factor multivariate GARCH model. Combined with the reduction parameterization of covariance matrix in the full factor multivariate GARCH model, the model could be applied to high dimensional problems. Ausin and Lopes (2010) argued that the conditional ellipsoid joint distribution of MGARCH model required strong symmetry, and financial data did not satisfy this assumption in many cases. Therefore, they proposed a time-varying correlation Copula GARCH model to deal with portfolio selection problems. Wei et al. (2010) used a greater number of linear and nonlinear GARCH class models (see McCulloch (1985); Polasek et al. (2007) to capture the volatility features of two crude oil markets and found that the nonlinear GARCH-class models exhibited greater forecasting accuracy than the linear ones. Christoffersen et al. (2012) combined the DCC model with partial t Copula to study the conditional correlation of emerging stock market indices in 33 developed countries. Santos and Moura (2014) proposed a new method for conditional covariance matrix estimation based on flexible dynamic multivariate GARCH model.

Klein and Walther (2016) incorporated an Expectation-Maximization algorithm for parameter estimation of the mixture memory GARCH (MMGARCH) and found MMGARCH was also able to cover asymmetric and long memory effects. Also, for variance forecasting and Value-at-Risk prediction, they found MMGARCH performed better due to its dynamic approach in varying the volatility level and memory of the process. Conrad and Mammen (2016) established the asymptotic theory of quasi-maximum likelihood estimator for the parametric GARCH-in-Mean model. The asymptotic behavior was based on the study of fluctuations of the parametric process of the model. Although time-varying GARCH-M models are commonly used in econometrics and finance, the recursive nature of conditional variance makes likelihood analysis computationally infeasible. Therefore, Anyfantaki and Demos (2016) suggested using Markov Chain Monte Carlo algorithm, which allowed classical estimators to be computed by simulating EM algorithm or only using simulated Bayes in O(T) operations (T is sample size), and derived the theoretical dynamic properties of time-varying parameter EGARCH (1,1)-M. Dias (2017) proposed an estimation strategy for stochastic time-varying risk premium parameters in time-varying GARCH-in-mean model, and Monte Carlo study showed that the algorithm had good finite sample properties.

Although time-varying covariance matrix performs well in capturing the dynamic change of finance markets, sample covariance matrix is used to replace the truly unknown covariance matrix in practice and there is estimation error in sample covariance matrix. Therefore, shrinkage estimation is introduced to reduce estimation error in sample covariance matrix.

5.1.2. Shrinkage Estimation

Jobson and Korkie (1980) used James-Stein estimator in mean-variance portfolio to demonstrate that the estimator provides more reasonable results than the traditional estimators. Jorion (1985) revealed the disadvantages of replacing expected returns with corresponding sample estimate without considering the inherent uncertainty in these parameter values. On this basis, Stein's method of estimating initial returns was studied. By shrinking the sample average to a common mean, it was found that the out-of-sample performance of the optimal portfolio increased significantly. Frost and Savarino (1986) studied the portfolio selection problem by maximizing expected returns, based on the forecasting distribution of securities returns under the Bayesian framework, and found that the method could improve the performance of portfolio by reducing the priori information of estimation error. Jorion (1991) compared the active investment strategies of expected return under three alternative models: historical sample mean, shrinkage or Bayesian estimation and CAPM-based estimation and found that exchange risk is not factored in to stock prices despite its significance. Like Jorion (1991), Grauer and Hakansson (1995) compared the investment strategies and returns of the three estimated dynamic investment models. Mori (2004) studied the performance of mean-variance model on the optimal portfolio weights of proportional estimator and Stein estimator when the parameters were unknown. Kan and Zhou (2007) discussed the problem of investing in riskless assets and tangent portfolio funds and proposed a combination of sample tangent portfolio and sample global minimum variance portfolio. Okhrin and Schmid (2007) provided a comparison between the exact and asymptotic distributions of portfolio weight estimates and a sensitivity analysis of asset return moments. At the same time, considering the shrinkage estimation of several types of moments, the portfolio weights and its corresponding estimators were compared based on moment estimation.

The use of linear shrinkage to estimate covariance matrix has also attracted wide attention among researchers. Ledoit and Wolf (2003, 2004) used a linear combination of sample covariance matrices and a target matrix to estimate the covariance matrix, where the target matrix could be the identity matrix, or the covariance matrix estimated by the one factor model and applied this method to the portfolio selection problem. Bai and Shi (2011) summarized the methods commonly used in high-dimensional covariance matrix estimation, including shrinkage, observable and implicit factors, Bayesian method and random matrix theory. Yang et al. (2014) proposed a hybrid covariance matrix estimation method based on robust M estimation and Ledoit and Wolf (2004) shrinkage estimation. Ikeda and Kubokawa (2016) considered a class of general weighted estimators, including the linear combination of sample covariance matrices and the model-based estimators and the linear shrinkage estimators without special factors under the factor model.

On the other hand, the optimal portfolio is directly dependent on the inverse of the covariance matrix. Accordingly, the direct shrinkage of the inverse covariance matrix is also a good strategy. Stevens (1998) dealt with portfolio optimization problems by primitively constructing several direct characteristics of the inverse covariance matrix. Kourtis et al. (2012) used the linear combination of the inverse covariance matrix and the target matrix to estimate the inverse covariance matrix, where the target matrix could be the identity matrix, the inverse of the covariance matrix estimated by the one factor model and the linear combination of the former two and applied this method to the portfolio selection problem. Bodnar et al. (2016) gave an explicit stochastic representation of the weights of mean-variance portfolios by using the linear transformation distribution of the inverse covariance matrix.

Bickel and Levina (2008a) discussed the regularization of covariance matrices with n observation samples and p variables by hard threshold method. Under the conditions that: the true covariance matrix was sparse in a proper sense, the variables were Gaussian or sub-Gaussian distribution, (Log p)/n approached zero and the explicit rate could be obtained, then the threshold estimation was consistent. Bickel and Levina (2008b) studied the estimation of banded and tapered sample covariance matrix and the banded inverse covariance matrix. Rothman et al. (2009) proposed a new generalized threshold algorithm combining shrinkage and threshold and studied the generalized threshold of sample covariance matrix in high-dimensional case. The generalized threshold of the covariance matrix has good theoretical properties and almost no computational burden. At the same time, an explicit convergence rate can be obtained in the operator norm, showing the tradeoff between sparsity, dimensionality and sample size of the real model. It was found that the generalized threshold is consistent in a large class of models if the dimension p and sample size n satisfy log (p/n) approaching zero. Konno (2009) considered the estimation of large-dimensional covariance matrices for multivariate real normal and complex normal distributions when the dimensions of variables were larger than the number of samples. For real and complex cases, the Stein-Haff equations and eigen structures of singular Wishart matrices were respectively, provided. By using these techniques, unbiased risk estimates for some classes of global covariance matrices under real and complex invariant quadratic loss functions were obtained. Chen et al. (2010) considered the shrinkage method in a high-dimensional case and, proposed a covariance estimation method based on minimizing mean square error in Gaussian samples. Firstly, under the condition of sufficiency of statistics, Rao-Blackwell theory was used to propose a new method, RBLW estimator, which was superior to Ledoit-Wolf method under mean square error. Secondly, the iterative method of the clairvoyant shrinkage estimator was proposed to reduce estimation error. At the same time, the convergence of the iterative method was established, the closed-form expression of the limit was determined, and this method was an Oracle approximate contraction (OAS) estimator. Fisher and Sun (2011) used the convex combination of the sample covariance matrix and the well-conditioned target matrix to estimate the covariance matrix and introduced a new set optimal convex combination estimates of three commonly used target matrix. Cai and Liu (2011) considered the estimation of sparse covariance matrix using the threshold step of single element change. The estimator is completely data-driven and has good data and theoretical results. Moreover, the estimator adaptively achieves the optimal convergence rate on a large class of sparse covariance matrices under spectral norm. Ledoit and Wolf (2012) further studied the linear shrinkage of Ledoit and Wolf (2004) by nonlinear transformation of sample eigenvalues and extended the nonlinear shrinkage method to the precision matrix. Fan et al. (2013) proposed the principal orthogonal complement thresholding method (POET) to discuss the estimation of high-dimensional covariance with conditional sparse structure and fast divergent eigenvalues. By assuming the sparse error covariance matrix in the approximate factor model, some cross-sectional correlations were allowed even after the common but unobservable factors were excluded. The POET estimator included sample covariance matrix, factor covariance matrix, threshold estimator and adaptive threshold estimator. At the same time, the convergence rates of sparse residual covariance matrix and conditional sparse covariance matrix under different norms were studied. With the increase of dimension, the sample covariance matrix becomes ill-conditioned and even singular. A commonly used method to estimate covariance matrix is Stein-type type compression estimation when the dimension is high. Touloumis (2015) proposed a new family of nonparametric Stein-type shrinkage covariance estimators, which were convex linear combinations of sample covariance matrices and predefined reversible target matrices. Under the Frobenius norm, the optimal shrinkage strength for defining the optimal convex linear combination depended on the unobserved covariance matrix and must be estimated from the data. At the same time, a simple and effective estimation process was proposed, which could obtain the nonparametric uniform estimator of the optimal contraction intensity for three commonly used target matrices. Zhang and Zhang (2018) combined the advantages of shrinkage estimation, vine copula structure and Black-Litterman model that could satisfy three investment objectives: estimation sensitivity, asymmetric risks appreciation, and portfolio stability.

5.2. Moment-Based and Quantile-Based Risk Measurement

5.2.1. VaR and CVaR

Some important articles are summarized in Table 4 below.

Table 4. Selected work on Portfolio Selection and VaR/CVaR.

Author	Year	Paper/Book/Thesis Title (Please See References for Details)
Baumol	1952	The transactions demand for cash: An inventory theoretic approach
Goldfarb and Iyengar	2003	Robust portfolio selection problems
McKay and Keefer	1996	VaR Is a Dangerous Technique
Artzner et al.	1997	Thinking coherently
Pflug	2000	Some remarks on the value-at-risk and the conditional value-at-risk
Uryasev	2000	Optimization of Conditional Value-at-Risk
Chen and Yang	2017	Multiperiod portfolio investment using stochastic programming with conditional value at risk
Zhang and Gao	2017	Portfolio selection based on a benchmark process with dynamic value-at-risk constraints

With the in-depth study of portfolio optimization theory and financial data, VaR attracted increasing attention in risk measurement. Baumol (1952) put forward the idea of VaR and used it to study the choice of securities. After Morgan (1996)'s risk measurement system, VaR has gained more attention (see Beder 1995; Jorion 1996). The basic principle recommended by the Basel Committee on Banking Supervision in 2001 states that VaR is a key indicator of risk (Szegö 2002). Goldfarb and Iyengar (2003) considered the robust VaR portfolio selection problem under the assumption of normal distribution and the objective of these robust formulations was to systematically combat the sensitivity of the optimal portfolio to statistical and modeling errors in the estimates of the relevant market parameters. Ghaoui et al. (2003) studied the portfolio selection problem with the worst case VaR when some of the distributed information was known. VaR is also used in insurance contracts. Wang et al. (2005) designed an optimal insurance contract by maximizing the expected final wealth of the insured under VaR constraints. Wang et al. (2005), Huang (2006) established an insurance contract under the risk constraint of VaR assuming that the insured was risk-averse. Giot (2005) used GARCH model and Riskmetrics model with residuals following normal distribution and Student t distribution to study VaR of three stocks traded on NYSE in 15 and 30 min. Chin (2008) compared the power of VaR under quantile and nonlinear time-varying volatility, proposed a simple Pareto distribution to explain the fat tail property in the empirical distribution of return, and implemented the measure of non-parametric quantile estimation of VaR using interpolation method. Batten et al. (2014) used the modified version of the multifractal model of asset returns (MMAR) with a series of asset returns data characterized by second. Considering the fat tail of financial data, long-term dependence and inconsistency with the MMAR scale, the out-of-sample VaR prediction was derived, and the difference between this method and GARCH (1,1) position scale VaR model was compared. Zhao and Xiao (2016) proposed an optimal portfolio selection model with VaR constraints and the asset price process was modeled by a non-generalized statistical mechanics rather than a classical Wiener process. This model could describe the characteristics of fat tails of returns. Also, a Hamilton Jacobi Bell equation was obtained by using the dynamic programming principle and the closed form solution of logarithmic utility was obtained by Lagrange multiplier method. Jang and Park (2016) incorporated VaR constraints into the wealth and fuzziness of fund management and provided an optimal portfolio selection model for fund managers who divided assets into risk and risk-free. Chang et al. (2016) used the Granularity Adjustment (GA) method to calculate VaR in portfolio credit risk model and used Monte Carlo simulation to study the impact of concentrated risk on risk value. Naimy (2016) used CDS portfolio data from March 2013 to November 2015 in the United States, Europe and Asia to study the accuracy of VaR by measuring risk under the Delta normal and historical methods. Based on the VaR calculation method of portfolio composed of options and bonds, Wang et al. (2017) proposed a Monte Carlo simulation method to allow jump diffusion in underlying assets and provided a layout suitable for various models, including non-parametric and semi-parametric structures.

Several nonlinear VaR models for the calculation of option portfolio VaR have also been extensively studied. These models concentrate on relaxing the assumption that the change of option portfolio value is linear with the change of market risk factors while maintaining the computational feasibility. They improve the correlation between market risk factors and option portfolio value, including quadratic and linear terms, and are called Delta-Gamma-Theta-Normal VaR models. Morgan (1996) calculated the VaR value of option portfolio using the method of Johnson distribution transformation. Hardle et al. (2002) evaluated the accuracy and speed of computational methods for nonlinear VaR, including Johnson transformation, Cornish-Fisher, Monte Carlo and Fourier-Inversion methods. Data experiments showed that Johnson transformation and Cornish-Fisher method were faster but inexact, and Monte Carlo method was accurate but inefficient. Accordingly, the Fourier-Inversion method was found to be the best choice. Castellacci and Siclari (2003) used the Cornish-Fisher method to calculate the first-order moments of the distribution of portfolio value changes. Cui et al. (2013) studied Delta-Normal and Delta-Gamma-Theta-Normal VaR as well as parametric VaR asymptotic methods for nonlinear portfolios and discussed their computational effectiveness.

The widespread use of VaR has led many researchers to expand it to multidimensional case. However, there are many definitions of multidimensional quantile that make it difficult to generalize one-dimensional VaR to multivariate and still maintain many good properties of one-dimensional VaR (see Serfling 2002; Hallin et al. 2010; Fraiman and Pateiro-López 2012). In addition, McKay and Keefer (1996) believed that VaR may be ineffective in portfolio selection. Artzner et al. (1997) pointed out that VaR did not have subadditivity and convexity. Basak and Shapiro (2001) noted VaR-based optimal decisions had greater losses than expected expectation-based optimal decisions. Miller and Liu (2006) argued that under the current general assumption of joint normal distribution, there were many deviations in the VaR model of portfolio due to model set up errors.

Fortunately, Artzner et al. (1997) and Embrechts et al. (1999) explained that CVaR could be a reasonable alternative to VaR. Pflug (2000) proved that CVaR was a coherent risk measure and emphasized several properties of CVaR, such as convexity and monotonicity. Uryasev (2000) provided a comprehensive description of CVaR. Assuming the distribution was ellipsoid and the VaR was computable, Embrechts et al. (2001) showed the result of CVaR under the restricted condition was consistent with that of VaR. Rockafellar and Uryasev (2002) argued that CVaR was superior to VaR as a risk measure and gave the properties of CVaR under the distribution of financial losses involving prudent behavior. Gaivoronski and Pflug (2005) gave a method to calculate the minimum VaR portfolio under specific returns. By removing local outliers and smoothing VaR, the VaR's efficient boundaries were calculated. At the same time, the differences of VaR, CVaR and standard deviation as risk measures were compared. Kibzun and Kuznetsov (2006) compared the standards of VaR and CVaR and identified the links between them. Topaloglou et al. (2008) used CVaR as a risk measure to solve the international portfolio selection problem under the stochastic programming model. Huang et al. (2010) considered the relatively robust CVaR model when the potential distribution of asset returns belonged to a particular set. Under the worst case of uncertain distribution, the possible optimal decision was given according to the realization of each distribution. Mainik and Schaanning (2012) compared two possible concepts of CVaR available in the current literature, studied their general dependency consistency, and presented their performance in several stochastic models. Nguyen and Samorodnitsky (2013) proposed a multivariate tail estimator involving CVaR sequential statistical tests. Bernardino et al. (2014) constructed two multivariate CVaRs at the level of multivariate distribution functions and provided new risk measures based on Copula structure and random ordering of marginal distributions. Wang and Huang (2016) endogenously formulated the best form of insurance contract to maximize the expected utility of insurance under VaR and CVaR constraints. Date and Bustreo (2016) studied how to approximate VaR and CVAR using new heuristic methods when the net return of portfolio investment may be a nonlinear function of non-Gaussian risk factors. Chen and Yang (2017) used CVaR as a risk measure to propose portfolio stochastic programming and stage wise portfolio stochastic programming based on the stock investment data. Zhang and Gao (2017) used the dynamic CVaR risk-constrained benchmarking process to deal with the dynamic portfolio problem. Using the dynamic programming technique, they derived the corresponding Hamilton Jacoby Bellman equation and obtained the optimal portfolio strategy by Lagrange multiplier method. Li et al. (2018) proposed a hybrid intelligent algorithm using genetic algorithm design and adaptive penalty function, Simulated Annealing Back Propagation neural network and fuzzy simulation technic to solve the fuzzy mean CVaR efficient portfolio model. At the same time, in order to further improve the computing speed, MPI technology was used to parallelize the hybrid intelligent algorithm.

For both the VaR and CVaR, a probability level of cumulative loss needs to be specified (Benninga and Wiener 1998). Furthermore, (i) the optimal portfolios with the VaR constraints are sensitive to the confidence level selected (Campbell et al. 2001), (ii) the CVaR model requires either an assumption about the asset returns distribution or a substantial amount of return observations below the target return (Boasson et al. 2011). Comparison with VaR and CVaR, semi-variance is a good substitution for measuring the one-sided risk.

5.2.2. Semi-Variance

Some groundbreaking articles are summarized in Table 5 below.

Table 5. Selected work on Portfolio Selection and Semi variance.

Author	Year	Paper/Book/Thesis Title (Please See References for Details)
Roy	1952	Safety First and the Holding of Assets
Markowitz	1959	Portfolio selection: Efficient diversification of investments
Bawa and Lindenberg	1977	Capital market equilibrium in a mean-lower partial moment framework
Bawa	1978	Safety-first, stochastic dominance, and optimal portfolio choice
Chen et al.	1991	A Method for Approximating Semivariance in Project Portfolio Analysis
Hamza and Janssen	1998	The mean-semivariances approach to realistic portfolio optimization subject to transaction costs
Ballestero	2005	Mean-semivariance efficient frontier: A downside risk model for portfolio selection
Huang	2008	Mean-semi variance models for fuzzy portfolio selection
Sayilgan and Mut	2010	Uses of Variance and Lower Partial Moment Measures for Portfolio Optimization

Roy (1952) proposed the concept of downside risk and defined it as a risk below the target value. Markowitz (1959) proposed a well-known mean-semi-variance model to estimate the weights of portfolio. Hogan and Warren (1972) pointed out the advantage of using the mean-semi-variance criterion in portfolio selection over the mean-variance model. Stone (1973) gave two interrelated three-parameter risk measures, in which the semi-variance was a special case. Hogan and Warren (1974) compared the difference between mean-variance model and mean-semi-variance model. Porter (1974) analyzed the relationship between stochastic dominance and mean-semi-variance model. Jahankhani (1976) empirically verified the relationship between return and risk in the mean-variance model and mean-semi-variance asset pricing model. Bawa and Lindenberg (1977) extended the semi-variance to the generalized lower partial moment framework, developed a Capital Asset Pricing Model (CAPM) using a mean-lower partial moment framework and derive explicitly formulae for the equilibrium values of risky assets that hold for arbitrary probability distributions. Fishburn (1977) applied the downside risk to the utility function model. Bawa (1978) extended the downside risk to higher order and showed its usability. Nantell and Price (1979) calculated variance and semi-variance by means of the distribution of prior portfolio returns and found that asset market portfolio prices with semi-variance were higher than variance at a certain risk level. Choobineh and Branting (1986) provided a simple form of semi-variance approximation by using mean, variance, critical value and cumulative probability below the critical value. Lee and Rao (1988) proposed a new asset pricing model in the framework of mean lower partial moment, which used semi-variance and semi-deviation to measure risk. Lewis (1990) used semi-variance as a measure of risk, applied it to the capital market and utility theory, and explained its advantages and disadvantages. Chen et al. (1991) proposed a set of linear regression models to approximate the semi-variance of the total returns of items with independent distribution. Chow et al. (1992) pointed out that in the absence of prior knowledge about the parametric structure of asset return distribution and the form of investor preference function, variance may no longer be an appropriate risk measure. They used various risk-return measures independent of distribution to test the efficiency and decentralization effect of international portfolio investment and found that semi-variance could effectively and conveniently identify risks. Tse et al. (1993) put forward an optimal strategy for personal investment using downside risk and proposed a model for accurate calculation of failure probability under the assumption of Brown's motion process. Markowitz (1993) transformed the mean-semi-variance portfolio optimization problem into the mean-variance optimization problem and used the critical line algorithm to obtain the optimal solution. Josephy and Aczel (1993) proposed an unbiased, consistent and effective estimators for the semi-variance.

With the deepening of risk research, the downside risk has attracted more and more attention (Rom and Ferguson 1994). Kaplan and Alldredge (1997) used a specific risk-based index, which could maintain a certain level of risk in different periods of time, to make a series of trade-offs between risk and return and studied its properties and performance in the case of semi-variance. Hamza and Janssen (1998) took transaction cost into consideration and applied the mean-semi-variance model to the portfolio selection problem, introduced a series of binary variables and separable constraints, and finally solved the portfolio optimization problem using separable techniques. Grootveld and Hallerbach (1999) analyzed the similarities and differences of using variance and downside risk as risk measures from empirical data and theory. Costa and Nabholz (2002) considered different computational forms of mean and semi-variance with errors and formulated robust mean-semi-variance portfolio selection problems based on linear matrix inequality optimization problems. Estrada (2004) noted that semi-variance was supported by theoretical facts and practical considerations and was a feasible measure of risk, and that the mean-semi-variance behavior criterion was perfectly consistent with the expected utility and the average compound return utility. Ballestero (2005) defined semi-variance as a weighted sum of squares deviating from the objective value of return on assets and applied it to portfolio selection. Jin et al. (2006) proved that no matter the market conditions and the distribution of stock returns, the effective strategy of mean-semi-variance in a single period could always be realized. They also established the realizability of the mean-semi-variance model under the condition of no arbitrage and extended it to the general downside risk measurement problem. Sira (2006) described the significant differences in portfolio outcomes using variance and semi-variance to measure risk and emphasized that using semi-variance as a risk measure could lead to more robust and effective boundaries. Chabaane et al. (2006) used a group of hedge funds with significant deviations from normal to consider the portfolio problem by maximizing expected return under the constraints of standard deviation, semi-variance, VaR and CVaR. However, if the asset return data do not follow the normal distribution, the mean-semi-variance model may produce inefficient portfolios. Consequently, Eldomiaty (2007) proposed the mean-semi-deviation model to measure the average loss rate. Huang (2008) proposed two fuzzy mean-semi-variance models and proved the properties of semi-variance in the case of fuzzy variables. Sayilgan and Mut (2010) regarded the portfolio problem as a multi-objective optimization, used the semi-variance and the lower partial moment as the risk measurement, and took genetic algorithm to solve the multi-objective optimization to achieve Pareto efficient portfolio. Cumova and Nawrocki (2011) transformed the exogenous asymmetric matrix into a symmetric matrix and proved that there was indeed a closed form of solution. On this basis, the critical line algorithm could be used to solve the mean semi-variance problem. Assuming investment capital and net cash flow as fuzzy variables, Zhang et al. (2011) proposed the reliability return index and the reliability risk index by using the expected value of credibility and the lower semi-variance of the fuzzy variables and gave the comprehensive risk return index for selecting the optimal investment strategy. Zhang et al. (2012) proposed a probabilistic mean-semi-variance entropy model to deal with multi-period portfolio selection under fuzzy returns. Metaxiotis and Liagkouras (2012) used a multi-objective evolutionary algorithm to solve the constrained mean-semi-variance portfolio optimization problem. Alimi et al. (2012) used fuzzy programming technology to solve multi-objective fuzzy mean semi-variance portfolio optimization model. Brito et al. (2016) proposed a flexible approach to portfolio selection using skewness/semi-variance bio-objective optimization framework, which allowed investors to analyze the effective balance between biases and semi-variables. Salah et al. (2016) noted that estimating portfolio risk by conditional variance or conditional semi-variance could obtain information about the future development of different asset returns and help investors to obtain more effective portfolio. Chen et al. (2017) considered that stock returns limited by expert estimates were described as uncertain variables and then verified three properties of semi-variances of uncertain variables. Based on the concept of semi-variances of uncertain variables, the mean-semi-variance models of two types uncertain portfolio selection were proposed.

The semi-variance is also used in the multi-period case. Bi et al. (2013) discussed the continuous time mean-semi-variance portfolio selection problem with probability distorted by nonlinear transformation, provided 'necessary and sufficient' conditions for the existence of feasibility and optimal strategy, and gave the general form of the solution when the optimal solution existed. Zhang (2015) considered the multi-period portfolio selection problem in a fuzzy investment environment, in which the return and risk of assets were characterized by probability mean and semi-variance, respectively. At the same time, based on the possibility theory, a new multi-period possible portfolio selection model was proposed, which includes risk control, transaction cost, borrowing constraints, threshold constraints and cardinality constraints. Liu and Zhang (2015) considered the multi-period fuzzy portfolio optimization problem with the shortest trading lot. Based on the possibility theory, a mean-semi-variance portfolio selection model was proposed to maximize the final wealth and minimize the cumulative risk within the entire investment level. Najafi and Mushakhian (2015) proposed a multi-stage stochastic mean-semi-variance CVaR model to deal with portfolio optimization problems. The parameters of semi-variance and CVaR were controlled at a certain confidence level. Huang et al. (2016) took the correlation between items and time sequence into account to propose a new mean-variance and mean-semi-variance model. Chen et al. (2018) took securities returns as uncertain variables to establish a multi-period mean-semi-variance portfolio optimization model with realistic constraints: transaction costs, cardinality and boundary constraints. Furthermore, if the security return was zigzag uncertain variable, they gave the equivalent deterministic form of mean-semi-variance model and proposed a modified imperialist competitive algorithm to solve the corresponding optimization problems.

6. Conclusions

In finance literature, the issues of portfolio selection, and risk measurement have always attracted attention of researchers globally. Accordingly, the present paper set out to review the development of related literature in the above areas and to identify the directions for future research. The study focused on three themes: (a) a review of literature on stylized facts that is, fat tails, volatility clustering and dependence structure of returns data, thereafter (b) a review of literature on portfolio selection and finally on (c) portfolio risk measurement. The objective was not only to trace the historical development but also identify possible research issues for future research.

The two important models for portfolio selection are the mean-variance model and global minimum variance model. The portfolio risk is measured by the covariance matrix in these models. From the literature review of these two models, we stressed that the covariance matrix estimation is important because the optimal portfolio weights rely on the covariance matrix. Accordingly, one of our focuses is on the estimation of covariance matrix. However, the estimation error in the covariance matrix estimation of asset returns is so large that the portfolio weights are likely inefficient. Therefore, the shrinkage methods are adopted to cope the estimation error in the estimation of covariance matrix. The shrinkage methods include Stein-type shrinkage methods and linear shrinkage methods. In linear shrinkage methods, we find that the factor model can be used to estimate the covariance matrix and the estimation is used as the target matrix. Consequently, the factor model is also included in the present paper. Also, to reflect the rapid changes of financial markets, we consider that the time-varying structure of covariance matrix is effective, and we take it as one useful improvement of the estimation of covariance matrix.

In addition to the covariance matrix to measure risk of portfolio, VaR and CVaR is another approach from the quantile perspective. Furthermore, many researchers think the risk is not symmetric and the risk should be the downside risk which measures the risk of falling below a target value. If the investor cares more about the loss, the downside risk measure could be a good solution.

The fat tail feature of financial data has received considerable attention in the relevant literature and many studies are based on the multivariate t distribution. In the presence of fat tails, the risk measure becomes more difficult to examine and the dependence of financial data is more important because co-movements exacerbate negative portfolio returns. Consequently, the Copula method has become a popular tool to describe the dependence structure of financial data appropriately.

However, there are many interesting questions that remain unsolved. For instance, in the stein-type shrinkage estimation of covariance matrix for portfolio selection problem, could we give an explicit shrinkage parameters selection method with maximizing investors' utility? How to measure the asymmetric relationship of asset returns and apply it to portfolio selection problems?

One of the co-authors of this paper, Sun et al. (2018) have derived the Stein-type shrinkage strategy for optimal portfolio selection using the Cholesky decomposition of the covariance matrix under the mean-variance framework. The Stein-type shrinkage strategy is applied to simulation experiments and an empirical study to test its feasibility. Their proposed method works well in the simulation study and in the empirical analysis; however, there still exist interesting questions. For future work, the assumption of $n > p$ may be replaced by $p > n$ for high dimensional cases, where n is the sample size and p is the number of variables. A reasonable statistical loss function with a different objective function may be studied to take advantage of the proposed approach. In addition, the assumption of the normal distribution can be extended to elliptically symmetric or skewed distributions and take robustness into consideration as well.

Please note that in the minimum variance model, the covariance matrix plays an important role because it measures the risk and relationship of asset returns simultaneously under the normality assumption. However, as discussed earlier, the distribution of asset returns is non-normal and has an obvious fat tail nature. In addition, the risk is one-sided. Hence it should be beneficial to study further and use a better tool to replace the covariance matrix, by involving the semi variance and distance correlation as discussed by e.g., Huang et al. (2016) and Sun et al. (2019).

Similarly, studies are required to examine the extent to which investment managers in the real-world incorporate the findings from the academic literature in practice.

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Review

Factors, Outcome, and the Solutions of Supply Chain Finance: Review and the Future Directions

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Abstract: In the current highly competitive and fast-changing business environment, in which the optimisation of all resources matters, creating an efficient supply chain is crucial. Earlier studies on supply chains have focussed on aligning product/services and information flows while neglecting the financial aspects. Due to this, in recent times, importance has been given to align financial flows with the other components of the supply chain. The interest in supply chain finance rose after the financial crisis when the bank loans declined considerably, as the need for better management and the optimisation of working capital became obvious. This paper reviews the articles on supply chain finance based on three themes—factors, outcomes, and solutions—while at the same time providing directions for future research on supply chain finance. This article is unique, as it investigates the factors affecting supply chains according to the existing literature. It also sheds light on the outcome of the supply chain without limiting the discussion only to the benefits. Further, it addresses the question: what are the solutions constituting supply chain finance?

Keywords: supply chain management; supply chain finance; working capital; factors; outcomes; solutions; optimisation

1. Introduction

In the modern fast-changing business environment, competitive pressures have become more acute. To maintain a competitive advantage and be on top of the game, focus and attention have been given to make supply chains more effective and efficient, in contrast to competing as a single company. A lot of academic research studies have been devoted to improving the physical flow of goods or services and the informational flow of the supply chain. However, the financial aspect of the supply chain has been heretofore neglected (Lamoureux and Evans 2011; Bailey and Francis 2008; Pfohl and Gomm 2009; Caniato et al. 2016). If the supply chain is to be more efficient and the companies are expected to maintain a competitive advantage or even to compete, all the components of the supply chain need to be given proper attention.

Supply chain finance (SCF) became more critical after the financial crisis of September 2008, when the loans from banks and financial institutions receded very drastically. Considerably, other alternative forms of financing, especially trade credit from suppliers, became more demanding. However, an extension of trade credit is subjected to the bargaining power whereby weaker suppliers will be forced to increase the payment period or forcibly delay the repayment (Fabbri and Klapper 2016). This can create risk or disruption in the supply chain (Boissay and Gropp 2007; Coricelli and Masten 2004; Raddatz 2010; Caniato et al. 2016). Therefore, there is a need for the better management and optimisation of working capital in the supply chain which SCF endeavours. SCF has also been touted to improve the accessibility of funds to small and medium enterprises (SMEs). Besides, it also assists with viewing working capital management from the supply chain perspective, rather than a single entity perspective. However, although most of the works on SCF deal with working capital, it is important to note that it is not limited to optimising short-term financial flow; it may also cover long-term financing. SCF can create win–win situations for the supply chain (SC) partners. A lot of academic research works have come up in the last few years that address this area of supply chain.

According to Xu et al. (2018), the research on supply chain finance (SCF) can be traced back to the 1970s; for example, Budin and Eapen (1970) worked on the net cash flow that is generated in business operations during a cash-planning period, and the effect of such changes on the policies relating to trade credit and inventories. Haley and Higgins (1973) studied the relationship between trade credit policy and inventory policy. However, the formalisation of the definition of SCF occurred only during the 21st century. According to Pfohl and Gomm (2009), Stemmler and Seuring (2003) were amongst the first ones to use the term SCF where they spoke of the control and optimisation of financial flows induced by logistics. Hofmann (2005) defined SCF as "located at the intersection of logistics, supply chain management, and finance" and as "an approach for two or more organisations in a supply chain, including external service providers, to jointly create value by planning, steering, and controlling the flow of financial resources on an inter-organisational level".

Pfohl and Gomm (2009) defined SCF as the inter-company optimisation of financing and the integration of financing processes with customers, suppliers, and service providers to increase the value of all of the participating companies. Gomm (2010) defined it as "optimising the financial structure and cash flow within the supply chain". The researcher also stated that the objective of SCF is to optimise financing across borders to decrease the cost of capital and increase the speed of cash flows. Further, SCF is defined as "the use of financing and risk mitigation practices and techniques to optimise the management of the working capital and liquidity invested in supply chain processes and transactions" (Global Supply Chain Finance Forum n.d.; Babich and Kouvelis 2018). Thus, this definition added a dimension of risk mitigation to supply chain finance.

It can be seen that the main aim of supply chain finance is to optimise the inter-organisational flow of funds (Hofmann 2005) preferably through the solutions implemented by financial institutions (Camerinelli 2009) or technology service providers (Lamoureux and Evans 2011). The ultimate aim is to align financial flows with other components of the supply chain, i.e., physical and information flow, within the supply chain, improving cash flow from a supply chain perspective (Wuttke et al. 2013b).

As the interest on the SCF grew in the 21st century both in academics and practice, research and contributions to SCF increased. However, there have been differences in the approach to SCF, and thus there emerged different perspectives to the definition of SCF. Gelsomino et al. (2016b) showed that the SCF literature lacked a single definition, and there are two main perspectives to a SCF: financial-oriented perspective, and supply chain-oriented perspective. There is another perspective to SCF, which is called the 'buyer driven-oriented perspective', which mainly focusses on 'reverse factoring', and can be considered as a subset of the 'finance-oriented perspective'. The finance-oriented perspective considers SCF to be a set of (innovative) financial solutions and concentrates on short-term financing and particularly on the financing solutions relating to receivables and payables. The role of financial institutions or banks concerning SCF solutions is mandatory in this perspective. The 'supply chain-oriented perspective' of SCF includes, within the SCF framework, the optimisation of the inventories along the chain (or at least between the customer and the supplier) to reduce the working capital. Therefore, the need for financing or working capital shifts to the player with a better availability of cash and/or a lower financing cost. Further, it does not limit SCF to only short-term financing, and there is no mandatory role of financial institutions and banks in SCF solutions. Thus, it can be said that the 'supply chain perspective' of SCF has a broader view of SCF than the 'finance-oriented perspective'.

There have been literature review articles relating to supply chain finance, e.g., Gelsomino et al. (2016b) and Xu et al. (2018). Gelsomino et al. (2016b) did a review of the existing literature based on three themes, i.e., concept and definitions, expected benefits, and SCF initiatives in place. Although the expected benefits have been touched on by Gelsomino et al. (2016b), the outcome or consequences of SCF do not just pertain to benefits as evident from the literature; as such, the current researchers felt the need to explore the outcome. Xu et al. (2018) performed a bibliometric analysis of the SCF literature. They provided bibliometric information on the published articles relating to SCF, including the identification of four research clusters of SCF. However, they did not touch upon the main focus of this current article, i.e., the factors, outcomes, and solutions of SCF. By focusing on three themes—the factors, outcomes, and solutions of SCF—this paper will contribute to the existing literature.

2. Methodology

This paper is more oriented towards a structured literature review, as it focusses on the systematic method, meaning a detailed plan of the path and steps undertaken to select, scan, and analyse the literature to reduce biases and improve transparency (Tranfield et al. 2003; Hofmann and Bosshard 2017). A structured literature review is generally applied to close the research–practice gap (Touboulic and Walker 2015; Hofmann and Bosshard 2017) and for developing the propositions and future research directions. This article adapts the procedures used by Denyer and Tranfield (2009) and Hofmann and Bosshard (2017), as shown in Figure 1.

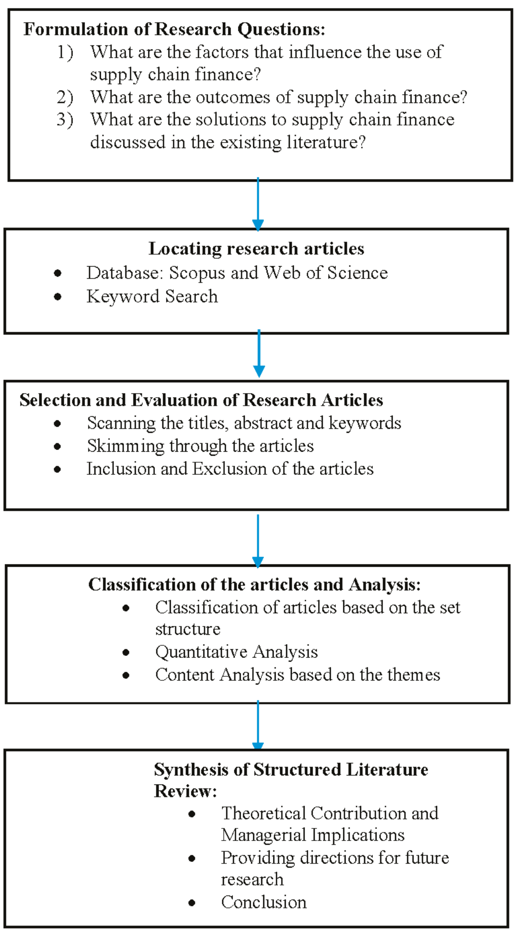

Figure 1. Literature review procedure (adapted with permission from Hofmann and Bosshard 2017).

3. Formulation of Research Questions

This literature review is motivated by the following three research questions:

RQ1: What are the factors that influence the use of supply chain finance?

RQ2: What are the outcomes of supply chain finance?

RQ3: What are the solutions to supply chain finance that have been discussed in the existing literature?

The article aims to answer these three research questions, and the researchers believe that answering these questions will lead to the contribution of this article to the supply chain finance literature. Therefore, the paper focuses on the three themes, i.e., the factors, outcomes, and solutions of supply chain finance.

4. Locating the Research Articles

Articles were searched from the scientific research databases of Scopus and Web of Science using a string of keywords, i.e., "Supply Chain Finance" OR "Supply Chain Financing" OR "Financial Supply Chain" OR "Financial Value Chain". From the search results, conference proceedings were removed. Scopus produced a result of 182 articles and Web of Science produced a result of 45 search results. This review article concentrated specifically on three themes:

a. Factors influencing supply chain finance
b. The outcome of supply chain finance
c. Solutions of supply chain

First of all, the abstract of the articles was read; then, the body of the articles was also carefully read, and only those articles fitting to the themes were selected for final review. The majority of the articles in the Web of Science were overlapping with that of Scopus. It is understandable that the Web of Science indexed a lesser number of journals, and most of them are listed in Scopus as well. Finally, 70 articles were considered for the review. The process of the identification, screening, derivation of eligibility documents, and final inclusion of the documents for review is given in Figure 2.

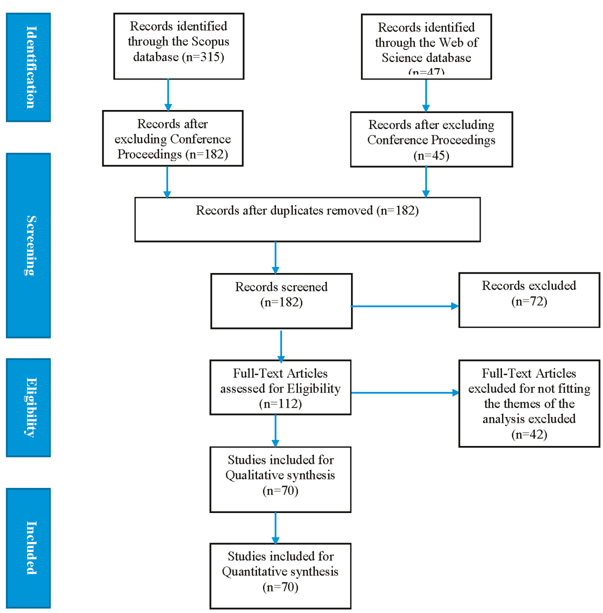

Figure 2. Procedure for locating, screening, and selecting documents.

5. Classification of the Articles

The classification of selected and collected literature is done as per the format shown in Table 1. Initially, the findings of the articles reviewed were grouped in the head 'findings'. However, whether the findings were related to 'factors' or/and 'outcomes' was further analysed. Thus, separate heads for 'factors' and 'outcomes' were created. The rest of the heads under which categorisation was done are shown in Table 1, which was completed using Microsoft Excel.

Table 1. Categorisation of the articles.

Category	Information
Author(s)	Contributor(s) to the article
Source	Journal or book in which the considered article was published
Year	Year in which the article was published
Volume and issue	Volume and issue of the articles reviewed
Country	Country of the corresponding author's affiliation
Keywords	Keywords stated by the articles to help with visibility
Objectives of the paper	Aims/objectives/research questions of the paper
Methodologies	Methodologies used in the study. If multiple methodologies were used, then all of the methodologies were recorded in the first round. Then, for the final categorisation, only the main methodology was considered.
Findings	Findings/results/outcomes of the paper
Factors	Forces or factors that are discussed explicitly or implicitly to influence supply chain finance
Outcome	The consequences or outcome of supply chain finance, whether positive or negative and discussed explicitly or implicitly in the literature
Solutions	Various instruments or initiatives or modes that help facilitate supply chain finance
Limitations and gaps	Limitations/gaps/future directions mentioned in the paper or that can be observed in the paper

6. Synthesis of Structure Literature Review

This article does not claim to cover the entire literature on the supply chain finance exhaustively; instead, based on the articles reviewed, it provides a snapshot of the supply chain finance regarding three themes: factors, outcomes, and solutions. Also based on the analysis and review, it provides a path for future research work.

7. Results and Findings

7.1. Methodologies

Figure 3 shows most of the published articles have followed an analytical modelling methodology (37 articles), followed by case studies (15 articles). These two methodologies make up 74% of the total articles reviewed.

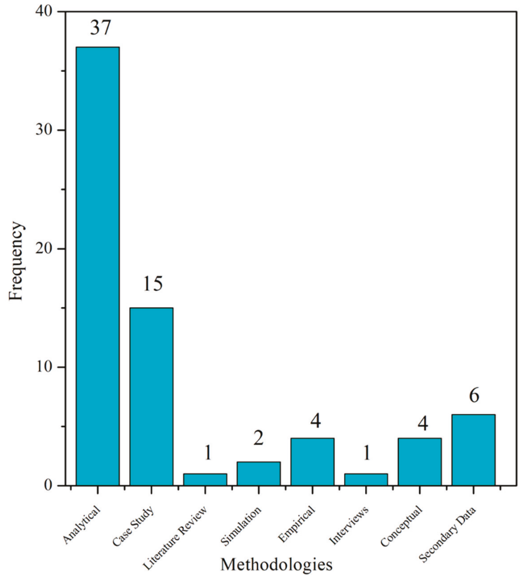

Figure 3. Methodologies of the reviewed articles.

7.2. Year of Publication

Figure 4 shows that the years with the highest numbers of published articles were in 2018 (13 articles), 2017 (13 papers), and 2016 (12 papers). It is expected that by the end of 2018, the number of publications in 2018 will exceed that of the previous year. The number of publications has increased considerably in the last four years, showing that supply chain finance has been of high academic interest.

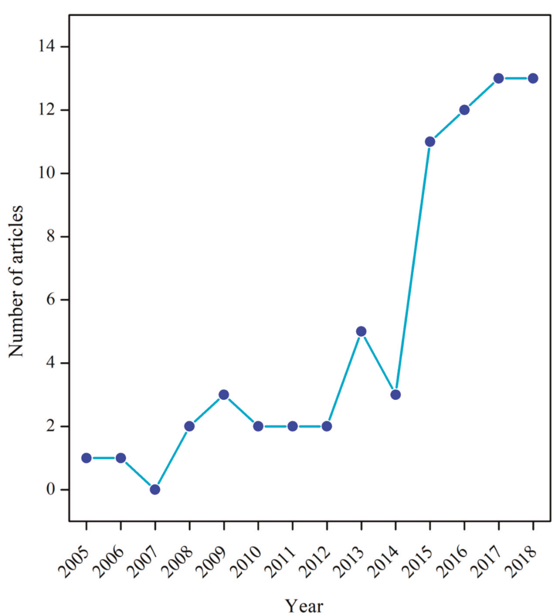

Figure 4. Number of articles per year.

7.3. Source of Publication and Top Cited Papers

The highest number of reviewed articles is found in International Journal of Physical Distribution and Logistics Management (six papers), followed by International Journal of Production Economics (three papers), Revista de la Facultad de Ingeniería U.C.V (three papers), Supply Chain Forum (three papers), Sustainability (three papers), Applied Stochastic Models in Business and Entity (two papers), The European Journal of Operations Research (two papers), The International Journal of Applied Business and Economic Research (two papers), The International Journal of Logistics Research and Applications (two papers), The International Journal of Production Research (two papers), The International Journal of Simulation: Systems, Science, and Technology (two papers), Manufacturing and Service Operations Management (two papers), and Supply Chain Management (two papers). These articles cover 50% of the total articles reviewed, showing how diverse the sources of the publications have been. Table 2 shows the distribution of the sources of articles in terms of the 'Name of the Journal' and the number of articles reviewed.

Table 3 also provides the top 10 cited papers from both Scopus and Web of Science.

Table 2. Distribution of reviewed articles by sources of publication.

Name of the Journal	No. of Articles
International Journal of Physical Distribution and Logistics Management	6
International Journal of Production Economics	4
Revista de la Facultad de Ingeniería	3
Supply Chain Forum	3
Sustainability	3
Applied Stochastic Models in Business and Industry	2
European Journal of Operational Research	2
International Journal of Applied Business and Economic Research	2
International Journal of Logistics Research and Applications	2
International Journal of Production Research	2
International Journal of Simulation: Systems, Science, and Technology	2
Manufacturing and Service Operations Management	2
Supply Chain Management	2
Advances in Transportation Studies	1
Agro Food Industry Hi-Tech	1
Amfiteatru Economic	1
Asian Journal of Law and Society	1
Asia-Pacific Journal of Operational Research	1
Boletin Tecnico/Technical Bulletin	1
Business Process Management Journal	1
International Federation for Information Processing (IFIP)	1
International Journal of Integrated Supply Management	1
International Journal of Islamic and Middle Eastern Finance and Management	1
International Journal of Logistics Systems and Management	1
International Journal of Operations and Production Management	1
International Journal of Revenue Management	1
International Journal of Services, Technology, and Management	1
Journal of Applied Accounting Research	1
Journal of Business Logistics	1
Journal of Corporate Finance	1
Journal of Cases on Information Technology	1
Journal of Industrial and Management Optimization	1
Journal of Management Information Systems	1
Journal of Purchasing and Supply Management	1
Journal of Modelling in Management	1
Journal of Supply Chain Management	1
Journal of the Operational Research Society	1
Journal of Shanghai Jiaotong University (Science)	1
Logistics and Supply Chain Innovation: Bridging the Gap between Theory and Practice	1

Table 2. *Cont.*

Name of the Journal	No. of Articles
Logistics Research	1
Management Science	1
Omega	1
Metallurgical and Mining Industry	1
OR Spectrum	1
Research Journal of Applied Sciences, Engineering, and Technology	1
Research Journal of Applied Sciences, Engineering, and Technology	1
Shenzhen Daxue Xuebao (Ligong Ban)/Journal of Shenzhen University Science and Engineering	1
Xitong Gongcheng Lilun yu Shijian/System Engineering Theory and Practice	1

Table 3. Top 10 cited papers from Scopus and Web of Science.

Scopus		Web of Science	
Author(s)	**Times Cited**	**Author(s)**	**Times Cited**
Pfohl and Gomm (2009)	63	Raghavan and Mishra (2011)	37
Randall and Farris (2009)	63	Wuttke et al. (2013a)	35
Raghavan and Mishra (2011)	58	Shang et al. (2009)	20
Wuttke et al. (2013a)	43	Johnson (2008)	20
Wuttke et al. (2013b)	34	Yan and Sun (2013)	17
Gomm (2010)	31	Wuttke et al. (2016)	8
Johnson (2008)	30	Van der Vliet et al. (2015)	7
More and Basu (2013)	29	Yan et al. (2014)	7
Fairchild (2005)	26	Yan and Sun (2015)	6
Shang et al. (2009)	25	Chen et al. (2017)	5

7.4. Country

Figure 5 depicts the contributing countries to the supply chain finance literature. The highest contribution has come from China (29 articles), followed by Germany (eight articles), the United States of America (USA) (eight articles), and Switzerland (five articles). China alone has contributed about 40% of the total reviewed papers. In comparison, all of the above-mentioned countries—i.e., China, Germany, the USA, and Switzerland—contributed 77% of the total articles reviewed. Among these countries, there are similarities and differences in the patterns of contribution to the field, e.g., China and Germany's main contributions have come in the form of analytical articles, followed by case studies and conceptual articles. However, in the case of China, around 86% (25 out of 29) of the articles have been analytical, whereas in the case of Germany, it is 50% (four out of eight). With regards to the USA, the majority of the articles have been in the form of studies based on secondary data (five out of eight), and in the case of Switzerland, more articles have been in the form of empirical studies based on surveys. It is interesting to note that there is no article present in the sample that is considered for the review from the regions such as Africa and South America. It can be said that there is still a lack of exploration and studies on supply chain finance in certain parts of the globe.

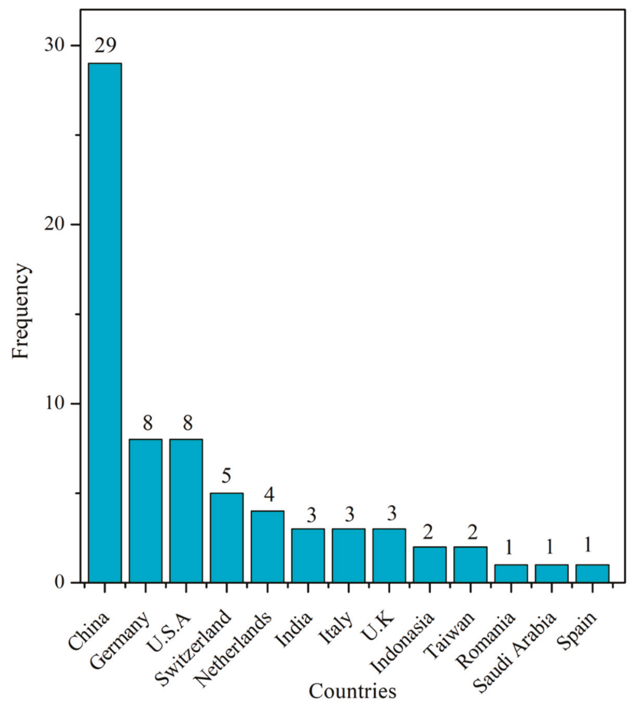

Figure 5. Contributing countries.

7.5. Factors Influencing the Acceptance of Supply Chain Finance

Several researchers discussed the varied number of factors that are expected to affect the acceptance of supply chain finance amongst firms in the supply chain. The most widely discussed factors in the literature are collaboration, the automation of trade process/level of digitalisation, trust, reputation, image or track record, bargaining power, coordination, financing cost, information sharing, cooperation, availability of external financing, financial attractiveness, supply chain integration, credit rating, dependence, objectives, information visibility, workforce, and joint decision making.

Collaboration is one of the important factors that have been widely discussed as having an effect on the use of SCF (Fairchild 2005; Pfohl and Gomm 2009; Wuttke et al. 2013a, 2013b; Popa 2013; Silvestro and Lustrato 2014; Wandfluh et al. 2016; Caniato et al. 2016; Protopappa-Sieke and Seifert 2017; Zhang 2016; Blackman and Holland 2006). It is clearly understood that SCF is a collaborative form of financing, and thus, collaboration as a factor plays an important role in its use and successful adoption. Not only inter-firm collaboration, but intra-firm collaboration as well, i.e., between departments of the organisation, is found to be essential for SCF (Wandfluh et al. 2016; Caniato et al. 2016). Trust is an integral part of supply chain financing, and several researchers have stressed that trust is essential (Randall and Farris 2009; Wuttke et al. 2013b; Liebl et al. 2016; Martin 2017; Blackman and Holland 2006; Karyani et al. 2015; Ta et al. 2018). Martin (2017) stated that trust exists when there is honesty and benevolence. The parties involved in the supply chain need to maintain trustworthiness, and Ta et al. (2018) mentioned that changes in the trustworthiness can play a crucial role in maintaining a relationship. It is important for the SC partners to maintain openness (Randall and Farris 2009) and fairness (Chen et al. 2017). In line with this, several articles also stressed reputation, image, or track record (Iacono et al. 2015; Liebl et al. 2016; Chen 2016; Zheng and Zhang 2017). While Iacono et al. (2015) showed the importance of a bank's track record in reverse factoring, Liebl et al. (2016) stated that buyers extend reverse factoring to the suppliers with a proper track record. Chen (2016), while working on the supply chain financing and the function and role of logistics enterprises, pointed out the need for the focal company to have a good reputation, i.e., the logistics company in this case. Zheng and Zhang (2017) viewed the SCF for Business to Business (B2B) cross-border e-commerce business, and demonstrated that reputation is essential. The higher the reputation, image, or track record, the better the trustworthiness and facilitation of SCF will be. Besides, the SC partners need to maintain cooperation (Jiang et al. 2016; Zheng and Zhang 2017; Yu and Zhu 2018) and coordination (Shang et al. 2009; Silvestro and Lustrato 2014; Gomm 2010; Yu and Ma 2015), as well as share risk, reward (Randall and Farris 2009), and information (Silvestro and Lustrato 2014; Wandfluh et al. 2016; Jiang et al. 2016; Ding et al. 2017); and jointly make decisions (Raghavan and Mishra 2011; Wuttke et al. 2013b). Carnovale and Yeniyurt (2015) demonstrated that the supply chain network is crucial for the firm's performance, and a well-connected network is associated with better performance.

Power is defined as "the ability of one firm to influence the actions and intentions of another" (Maloni and Benton 2000; Martin 2017), and it also plays a role in SCF, which several articles have highlighted (Wuttke et al. 2013b; Caniato et al. 2016; Wuttke et al. 2016; Protopappa-Sieke and Seifert 2017; Chen et al. 2017). In the literature, power has been mostly associated with the bargaining power of the buyer (focal company), as the buyer has been assumed to be a larger enterprise to their supplier. Caniato et al. (2016) used a term called "financial attractiveness" to refer to the bargaining power of the focal company to the financial institutions, which help in offering SCF solutions to their supplier, as in the case of reverse factoring. If the bargaining power of the focal firm, which is the buying firm in this case, is high, the buyer tends to reduce the purchase prices, whereas if it is low, then the buyer will try to improve the relationship with key suppliers. Similarly, the dependence of one firm on another, which is the reciprocal of power, influences the supply chain financing (Wuttke et al. 2013a; Martin 2017). Wuttke et al. (2013a) goes further, and divided dependence into 'pooled dependence' and 'dispersion of dependence'.

Caniato et al. (2016) mentioned that there is a plurality of objectives behind adopting SCF, i.e., improving the adopter's financial performance and securing the supply chain, and these objectives play a crucial role in SCF adoption. Other studies by Iacono et al. (2015), Liebl et al. (2016), and Zhou et al. (2018) also confirmed the influence of objectives on SCF.

The level of automation of trade processes or the level of digitalisation is another important factor that the literature stressed (Fairchild 2005; Wuttke et al. 2013b; Gomm 2010; Caniato et al. 2016; Chen 2016; Blackman and Holland 2006; Zhou et al. 2018). The automation of trade processes may occur in various ways, e.g., electronic invoicing, reconciliation databases, electronic payment systems, trade platforms, and forecasting platforms, among others. These technologies or automation may be offered by banks or financial service providers (Silvestro and Lustrato 2014), or it may need the involvement of another party in the supply chain financing, i.e., a technology service provider (TSP) (Martin and Hofmann 2017). TSP may act as a bridge between the funders and buyers, as well as the sellers. Due to the significance of technologies and vast opportunities arising out of it, Fintechs are also starting to get involved in SCF (Tsai and Peng 2017). Although for the traditional SCF solutions, a higher level of automation may not be needed, for innovative SCF solutions, a higher level of automation may be required. The visibility of information across the trade process and the supply chain is desirable. In supply chain financing, the same is desired (Silvestro and Lustrato 2014; Jiang et al. 2016), and the level of automation can increase the visibility.

The studies of Yan and Sun (2013) and Martin (2017) highlighted that the availability of external financing affects the supply chain partners' participation in SCF, and the easier accessibility of external financing may reduce the use of SCF.

The frequency and volume of transactions matter in supply chain finance, as the transactions need to be financially attractive, especially for the financial service provider. However, the same may hold true for the buyer as well, e.g., in the case of reverse factoring, where the buyer may be motivated to use reverse factoring only for those suppliers with an attractive enough volume of receivables (Pellegrino et al. 2018; Hofmann and Zumsteg 2015; Iacono et al. 2015).

Supply chain integration has also been discussed as an influence on supply chain financing. Wuttke et al. (2013a) considered it as an umbrella that includes the joint decision, joint investment, real-time sharing of operational information, regular meetings, engagement in collaborative planning, and sharing cost information, among others. Not only should the supply chain partners be integrated upstream and downstream, but SC integration should also exist among financial service providers (FSPs) as well.

The talent, skill, and expertise of the workforce may also affect supply chain financing. Jiang et al. (2016) input it in a factor called 'basic condition', which consisted of personnel quality, and other factors similar to this concept include innovation ability, technical ability, quality, and financial condition.

Yan and Sun (2013) performed several analytical methodologies such as the Stackelberg game, coordination analysis, and numerical analysis, and showed that an "appropriate financing scheme/solution" matters, and influences the retailer's decision to order.

The literature has discussed several factors influencing SCF. However, it may be possible to classify them into broader groups based on similar characteristics. It is understandable that many of these factors will be overlapping between categories, but for simplification and clearer understanding, classification of the factors is desirable. Table 4 shows the categorisation of these factors into five categories, i.e., operational factors, financial factors, relationship factors, and informational factors.

Table 4. Categorisation of factors.

Operational Factors	Financial Factors	Relationship Factors	Technological Factors	Informational Factors
Coordination	Financial attractiveness	Collaboration	Automation of trade process/level of digitalisation	Information sharing
Frequency and volume of transactions	Financing cost	Trust		Information visibility
Objectives	Availability of external financing	Bargaining power		Reputation/image
Workforce	Credit rating	Cooperation		
	Appropriate financing scheme/solutions	Dependence		
		Joint decision making		
		Shared risk and reward		
		Supply chain network		

7.6. The Outcome of Supply Chain Financing

One of the benefits of SCF that the literature has widely highlighted is the reduction of cost of financing (Van der Vliet et al. 2015; Iacono et al. 2015; Gelsomino et al. 2016b; Zheng and Zhang 2017; Ding et al. 2017; Babich and Kouvelis 2018; Yu and Zhu 2018; Yang et al. 2018). It helps to facilitate offering finance at a lower cost to the SC partners, who generally are not privileged to receive capital at lower cost. It leads to financial service providers extending finance at lower interest rates. Supply chain finance not only facilitates a lower cost of financing, it also helps reduce the overall cost in the supply chain, e.g., cost of producing and delivering goods/services (Blackman and Holland 2006; Iacono et al. 2015; Gelsomino et al. 2016b; Jiang et al. 2016; Liu and Wen 2017; Babich and Kouvelis 2018). SCF has been widely touted to offer solutions to the problems faced by SMEs in availing finance; the literature on SCF revealed that SCF improves the accessibility to funds, particularly for smaller SC partners (Suayb Gundogdu 2010; Wang et al. 2012; Yan and Sun 2015; Hofmann and Zumsteg 2015;

Liu and Wen 2017; Ding et al. 2017; Chen and Wen 2017; Zheng and Zhang 2017; Li et al. 2011). The major problems in approaching working capital optimisation from a single-company perspective involve larger enterprises exercising their bargaining power and optimising the working capital at the expense of other enterprises in the supply chain, which can cause cash flow risk and disruptions in the supply chain. SCF, on the other hand, helps reduce cash flow risk (Wuttke et al. 2013b; Jiang et al. 2016; Martin 2017; Yan and Sun 2015; Gelsomino et al. 2016b; Liu and Wen 2017) and disruptions in the supply chain (Blackman and Holland 2006; Wuttke et al. 2013b; Jiang et al. 2016). It helps unlock and improve the working capital position, e.g., in factoring, reverse factoring, inventor financing, or warehouse financing, a supplier can avail the needed funds before the payment period. Although financial institutions may need to offer to fund at lower rates, SCF ensures an increase in transactions (Hofmann and Zumsteg 2015; Jiang et al. 2016), and helps increase revenue and income for FSPs (Iacono et al. 2015; Zheng and Zhang 2017). Several articles discussed the ability of SCF to enhance the profitability of the individual enterprises as well as that of the supply chain (Wang et al. 2012; Hofmann and Zumsteg 2015; Yan and Sun 2015; Grüter and Wuttke 2017; Bi et al. 2018a; Yu and Zhu 2018; Zhou et al. 2016). There are also other articles that merely touched on the benefits as improving the financial performance (Gomm 2010; Yan et al. 2014; Shi and Wang 2015; Caniato et al. 2016; Carnovale and Yeniyurt (2015); Zhang 2016; Liu and Wen 2017). It is understandable that all of the above-discussed points contribute to the overall financial performance. Pfohl and Gomm (2009) stated that SCF affects the firms by influencing three areas: volume, cost, and duration. The solutions will affect one or more of the dimension(s), and some of the solutions will have a greater effect than the other (also see Gelsomino et al. 2016b).

The visibility of information in the chain is essential for the efficiency and effectiveness of the chain, and SCF aids in reducing information asymmetry in the supply chain (Fairchild 2005; Hofmann and Zumsteg 2015; Ding et al. 2017; Gelsomino et al. 2016b; Li 2017; Song et al. 2018). Several researchers are also of the view that supply chain finance also helps reduce financing risk (Wang et al. 2012; Tsai and Peng 2017). While Wang et al. (2012) stated that SCF can reduce the financing risk for the commercial banks, Tsai and Peng (2017) approached the reduction of financing risk from perspective of the larger enterprise offering loans to the suppliers through online SCF platforms. The main reason for the reduction of risk for larger enterprise as per Tsai and Peng (2017) is due to greater familiarity with their suppliers. Although the approach may be different, nevertheless, SCF can help reduce the financing risk for the finance provider.

Supply chain finance also helps to improve the collaboration between functional departments within the firm, as well as that between enterprises (Bi et al. 2018a; Bi et al. 2018b; Yang et al. 2018). It also helps improve the coordination in the supply chain (Huff and Rogers 2015; Bi et al. 2018a; Bi et al. 2018b). In fact, it improves the relationship in the chain by reducing the conflicts and issues and improving collaboration and coordination.

Some of the articles discussed SCF as improving the overall supply chain (Yu and Ma 2015; Protopappa-Sieke and Seifert 2017; Chen et al. 2017). It may be said that SCF offers a win–win situation for all of the supply chain partners. Overall, it can be said that SCF provides both financial and non-financial benefits.

On the other hand, there are also articles that discussed the possible negative effects of SCF. The major issues that could arise from SCF are risk, uncertainty, and vulnerability. Johnson (2008) demonstrated that risk/uncertainty/vulnerability can occur due the leakage of documents, as supply chain partners may be transacting through financial institutions. The researchers also characterised the threat of loss by examining search patterns in peer-to-peer networks, and also showed the linkage between firm visibility and threat activity. Karyani et al. (2015) stated that if there is a congestion of cash flow in one of the perpetrators, it will cause a ripple effect on the other partners of the supply chain as well. Martin (2017) found that suppliers may also face uncertainty on future terms besides being uncertain about buyers to offer them a financing alternative or solutions.

7.7. Supply Chain Finance Solutions

Supply chain finance is not a single solution-based mode of financing. As it is a medium to optimise the flow of funds and cover the supply chain, various solutions or instruments make up the SCF solutions. Table 5 shows various SCF solutions discussed in the literature.

Table 5. Some of the widely discussed solutions in the literature.

Solutions	Definition	Source	Frequency in the Sample
Reverse Factoring	In reverse factoring, the buyer sells the accounts payables and works together with the supplier and the banks to optimise the flow of funds.	Liebl et al. (2016)	7
Accounts Receivables Financing	Accounts receivable financing refers to the act of borrowing from a commercial bank with the accounts receivable that have not yet been received.	Ramezani et al. (2014); Wang (2017)	5
Purchase Order Financing	"Purchase order financing allows banks to offer loans to suppliers by considering the value of purchase orders issued by reputable buyers, and assessing the risk of the supplier delivering the order successfully."	Babich and Kouvelis (2018)	5
Agricultural Supply Chain Finance	A supply chain financing generally of pre-harvest, trade services financing, and post-harvest, which is applied in the agriculture sector.	Suayb Gundogdu (2010); Li et al. (2011); Karyani et al. (2015);	5
Factoring	"Factoring is a type of supplier financing in which firms sell their creditworthy accounts receivable at a discount (generally equal to interest plus service fees), and receive immediate cash."	Klapper (2006)	4
Online SCF Platform	An online platform that facilitates in networking the parties involved in supply chain finance (SCF).	Hofmann and Zumsteg (2015); Martin and Hofmann (2017); Gao et al. (2018)	5
Inventory Financing	A short-term loan from a financial institution to finance inventories.	Caniato et al. (2016)	4
Warehousing Financing	Warehouse financing means that co-operators mortgage their goods in warehouses for pledge loans.	Jiang et al. (2016)	4
Buyer Direct Financing	In buyer direct financing, the buyer (manufacturer) issues both sourcing contracts and loans directly to the suppliers.	Babich and Kouvelis (2018)	4
Vendor-Managed Inventory	"The supplier is given the freedom to plan its own production and decide upon the replenishment schedule as long as the agreed customer service levels are met. This enables suppliers to stabilise their production and to optimise the transportation cost"	Waller et al. (1999); Claassen et al. (2008)	3

Table 5. *Cont.*

Solutions	Definition	Source	Frequency in the Sample
Raw Material Financing	It is a part of inventory financing whereby the funds are given to finance raw materials.	Basu and Nair (2012); More and Basu (2013)	2
Third Party Logistics Financing	A logistics service provider buys goods from a manufacturer and obtains an interim legal ownership before selling them to the manufacturers' customers after a certain time.	Caniato et al. (2016); Song et al. (2016)	2
Dynamic Discounting	"Dynamic Discounting (DD) utilises trade process visibility granted by an information and communication technology (ICT) platform to allow the dynamic settlement of invoices in a buyer–supplier relationship."	Gelsomino et al. (2016a)	2
Early Payment Discount Program	A programme in which the supplier offers a cash discount to encourage the buyer to pay quickly.	Ho et al. (2008)	2
Buy Back Guarantee	"It refers to a kind of supply chain financing [in which] the bank helps the capital-constrained retailer settle the payment, based on the core supplier's buyback guarantee."	Chen et al. (2017)	2
Credit Guarantee	"A credit guarantee where the deep-pocket manufacturer represents a promise of timely payment for the retailer with high default risks in the supply chain."	Yan et al. (2014, 2017)	2
Bank Guarantee	A bank guarantee is a promise from the debtor's bank that the liabilities of the debtor will be met in the event of failure to repay.	Martin and Hofmann (2017)	1
Manufacturer Collateral	"The manufacturer assumed to be the core enterprise of a chain, provides her retailer with collateral to help him borrow from the bank at a low-interest rate."	Bi et al. (2018a)	1
Supplier's Subsidy	The supplier allows the retailer a delay in payment, and provides a subsidy contract to alleviate its problems if it is profitable.	Bi et al. (2018a)	1
Pre-selling	In a preselling program, firms offer to sell their products, possibly at a discounted wholesale price, long before the selling season.	Xiao and Zhang (2018)	1
Trade Credit	Trade credit is a short-term loan between firms that are tied in both timing and value to the exchange of goods between them. It occurs when there is a delay between the delivery of goods or the provision of services by a supplier and their payment.	Ferris (1981); and García-Teruel and Martínez-Solano (2010)	1

Reverse factoring is the most widely discussed solution in the supply chain literature (Liebl et al. 2016; Lekkakos and Serrano 2016; Caniato et al. 2016; Iacono et al. 2015; Grüter and Wuttke 2017; Popa 2013; de Goeij et al. 2016). In fact, there are some articles that considered reverse factoring to be SCF. Gelsomino et al. (2016b) put it as 'buyer-driven perspective', which is a subset of the financial-oriented perspective of SCF. Besides, there are other solutions mentioned, such as payables discounting (Silvestro and Lustrato 2014), approved payables financing (Martin 2017), and payables extension finance (Basu and Nair 2012; More and Basu 2013), which in substance are similar to reverse factoring, i.e., based on payables.

Several articles also focused on 'accounts receivables financing', which is the mode of financing in which enterprises use receivables as the underlying asset (Basu and Nair 2012; Popa 2013; More and Basu 2013; Silvestro and Lustrato 2014; Wang 2017). Two forms of accounts receivables financing are evident from the literature, i.e., accounts receivables pledging and accounts receivables factoring. Although factoring may be a part of accounts receivables financing, various articles touched on factoring specifically as the mode of financing (Caniato et al. 2016; Tang et al. 2018; Martin and Hofmann 2017; Yu and Ma 2015).

The suppliers may avail of financing using the 'purchase orders' before the repayment period from the buyers. This form of financing is known as 'purchase order financing' (Basu and Nair 2012; More and Basu 2013; Silvestro and Lustrato 2014; Tang et al. 2018; Babich and Kouvelis 2018).

Supply chain finance may also be used to finance the agricultural supply chain, and is known as 'agricultural supply chain finance'. Karyani et al. (2015) and Karyani et al. (2016) categorised it into 'pre-harvest financing' and 'trade services financing'. Suayb Gundogdu (2010), while studying the Islamic structured trade finance on cotton production, grouped the financing modes into pre-harvest (Salam) and post-harvest (Murabaha and Mursharakah). Zhou et al. (2018) grouped agricultural supply chain finance into four categories: microcredit, microloans, supply chain and industrial model, and online and offline lending.

One of the solutions through which SCF can take place is through the online platform. It could be a platform through which e-factoring or e-reverse factoring could take place, or it may occur in the form of peer-to-peer lending, or where the smaller supplier or retailer may get a necessary funding from their SC partner, which could be buyer or manufacturer (Wuttke et al. 2013a; Hofmann and Zumsteg 2015; Martin and Hofmann 2017; Tsai and Peng 2017; Gao et al. 2018). Caniato et al. (2016) also dwelled on the online form of SCF by calling them an 'advanced form of reverse factoring' and 'seller-based invoice auction'. The online platform could also be that which connects the supply chain partners, i.e., buyer, supplier, and service provider, where the documentary process involved in the transactions could be managed more quickly, visibly, and cost-effectively. Yuan (2007) did a case study on the TradeCard solution, which helps connect the supply chain partners through better managing the documentary process of international transactions. TradeCard is stated to be replacing letters of credit or open accounts in international transactions.

Suppliers may avail funding through 'inventory financing', which uses inventory as an underlying asset (Li et al. 2011; Popa 2013; Tang et al. 2018; Babich and Kouvelis 2018; Chen and Kieschnick 2018). Warehousing financing is also another popular form of financing where the concerned party may avail financing by generally pledging the warehouse receipt (Popa 2013; Luo et al. 2015; Jiang et al. 2016; Chen and Wen 2017).

Buyer direct financing is a mode through which a seller may avail funds from the buyer through advances or loans, and has also been discussed in several articles (Popa 2013; Tang et al. 2018; Babich and Kouvelis 2018; Chen and Kieschnick 2018).

Besides the above-mentioned solutions of SCF, the literature on SCF revealed several solutions such as vendor-managed inventory (Basu and Nair 2012; More and Basu 2013; Caniato et al. 2016), raw material financing (Basu and Nair 2012), third-party logistics financing (Basu and Nair 2012; More and Basu 2013), dynamic discounting (Caniato et al. 2016; Martin and Hofmann 2017), early payment discount programmes (Basu and Nair 2012; More and Basu 2013), buy-back guarantees (Chen et al. 2017; Yu and Ma 2015), credit guarantees (Yan et al. 2017), bank guarantees (Martin and Hofmann 2017), manufacturer collateral (Bi et al. 2018a), supplier's subsidy (Bi et al. 2018b); SME closed-loop supply chains (SMECLSCs) (Zhang 2016), and supply chain carbon finance (SCCF) (Yang et al. 2018). Martin (2017) also included letters of credit, bank guarantees, insurances, and credit assessment as risk mitigation aspects of SCF. Trade credit, which is a form of credit offered by the supplier to its buyer in the form of deferred payments, is discussed as 'supplier-led solutions' by Babich and Kouvelis (2018).

Although there are many solutions to SCF, it may be possible to group them based on certain characteristics, e.g., pre-shipment, in-transit, and post-shipment financing (Basu and Nair 2012; More and Basu 2013), traditional and innovative financing solutions (Caniato et al. 2016), traditional and integrated SCF practices (Babich and Kouvelis 2018, and buyer-led and supplier-led supply chain finance (Babich and Kouvelis 2018).

8. Contribution to the Existing Literature

Our study contributes to the existing literature on supply chain finance, and extends the work of Gelsomino et al. (2016b) and Xu et al. (2018) in the following ways. 1. We identified and consolidated the factors that influence SCF. Further, we also grouped these factors into five categories based on certain common characteristics. This grouping can help simplify the understanding of the factors. 2. The current study also identified various outcomes that could emerge out of the use of SCF. We did not limit ourselves only to the expected benefits resulting out of the SCF. 3. We also addressed the question: what constitutes the supply chain finance solutions? We identified several SCF solutions that have been discussed in the extant literature. In addition, we also showed which solutions are most widely discussed and which are understudied.

9. Managerial Implications

We believe our study offers managerial implications in the following ways. 1. The parties involved in the supply chain finance, whether the supplier, buyer, financial service provider, or technology service provider, can understand the important factors that influence the use of SCF. This study can help them concentrate on these factors to improve the adoption and effectiveness of SCF. 2. The parties can understand the expected outcome when SCF is implemented. Understanding this is crucial, as it can improve and enhance the adoption of SCF. For example, SMEs that are generally unaware and reluctant to explore different instruments may be encouraged to participate in SCF. Larger buyers can be encouraged to opt for viewing working capital from the SCF perspective, as it can offer a win–win situation rather than trying to think about its own gain. These buyers may also be able to bring on board their smaller suppliers under SCF by making them aware about the benefits that can be expected out of SCF. FSPs can also know that there are benefits in offering SCF solutions. FSPs and technology service providers can promote their solutions and services better to their potential clients. 3. We have identified and covered many of the SCF solutions that have been discussed in the literature. This can help create awareness for the suppliers and buyers alike, and increase an interest to explore more of these SCF solutions. Technology service providers may also benefit from knowing the various SCF solutions, and can make better decisions and steps to offer technology-fitting solutions.

10. Conclusions, Future Directions, and Limitations

Supply chain finance as a concept has seen a rise in the early 21st century. It received more attention and got a thrust after the financial crisis of September 2008, as the loans from the banks and financial institutions declined considerably. This article reviewed the articles based on three themes: SCF factors, outcomes, and solutions. We used a string of keywords, i.e., "Supply Chain Finance" OR "Supply Chain Financing" OR "Financial Supply Chain" OR "Financial Value Chain" and searched the Scopus and Web of Science databases. After removing the duplications, conference proceedings, and the articles that did not meet the themes of the paper, finally, we reviewed 70 research articles.

We found that analytical and case studies are the most widely used methodologies. There has been a growing interest in the SCF in academics whereby the highest number of publications have come in the last three years. The sources of publications have been quite diverse. Most of the publications have come from the countries such as China, Germany, the USA, and Switzerland. There is a lack of contributions from the regions such as Africa and South America.

The most widely discussed factors in the literature are collaboration, the automation of trade process/level of digitalisation, trust, reputation, image or track record, bargaining power, coordination, financing cost, information sharing, and cooperation, among others. For the simpler understanding of the factors influencing SCF, the authors also classified these factors into five categories, i.e., operational, financial, relationship, technological, and informational factors.

Outcome-wise, a lower cost of financing, reduction in cost, improvement in accessibility to financing, reduction in information asymmetry, improvement in financial performance, and enhancement of profitability were the most recurring areas in the research. Overall, the benefits of SCF can be grouped into financial benefits and non-financial benefits. The Cash-to-Cash cycle (C2C) is a metric that has been widely discussed in the literature to demonstrate the financial benefits of SCF (Randall and Farris 2009; Hofmann and Kotzab 2010; Popa 2013; Silvestro and Lustrato 2014; Hofmann and Zumsteg 2015). C2C is a time-based measure comprised of Days Sales Outstanding (DSO), Days Inventory Outstanding (DIO), and Days Payables Outstanding (DPO).

$$\mathrm{C2C} = \mathrm{DSO} + \mathrm{DIO} - \mathrm{DPO}$$

The shorter the C2C, the higher the net present value of cash generated by the assets and the overall increase in the value of the firm will be (Soenen 1993). The C2C metric is a component for enhancing the value of shareholders. C2C optimisation can be approached from a single entity perspective; however, in such cases, the focal firm may end up optimising at the expense of the supply chain partners, and can be counterproductive for the supply chain and the focal firm in the long run. As such, it is vital to view C2C from a supply chain collaborative perspective. The literature has discussed some of the instances of how SCF can manage C2C optimally at the supply chain level, e.g., shifting the inventory upstream to the suppliers, as the cost of the product is lower upstream in the chain, and the ability to shift inventory further up, even for a few days, will create savings for the entire chain. Some SC partners have strong credit and a lower weighed average cost of capital (WACC), and can reduce the cost of capital of the whole supply chain. Being able to shift the financial needs and burdens of the SC transactions to the partner with lowest WACC will result in an optimal C2C for the SC. Thus, SCF can offer a win–win situation for the SC partners (Randall and Farris 2009; Hofmann and Kotzab 2010). Not only a win–win situation in the case of a dyadic buyer–supplier relationship, but SCF can also create a 'triple win situation' (TWS) when the financial service provider (FSP) is also involved in the SCF, although there are caveats (see Hofmann and Zumsteg 2015).

The literature also revealed that the consequences of SCF might even be negative, and these may be due to risk, uncertainty, and vulnerability.

Amongst the solutions, the most widely covered solutions were reverse factoring, accounts receivables financing, purchase order financing, and agricultural supply chain finance. Although there are lots of SCF solutions, and more are expected to emerge with more innovation and need to improve the financial flow, it is possible to group them based on certain characteristics, e.g., pre-shipment, in-transit, and post-shipment financing; traditional and innovative financing solutions; traditional and integrated SCF practices; or buyer-led and supplier-led supply chain finance.

A lot of work in the literature has been analytical, case study, and simulation-based. We identified several factors from the extant literature; however, more empirical studies will be needed for validation. Although a few articles such as those of Martin (2017) and Wuttke et al. (2013b) have attempted to explain SCF with existing organisational theories, the SCF literature needs more theoretical underpinning, and surveys of the existing theoretical frameworks would be especially beneficial. Innovation diffusion theory (IDT), social exchange theory, and transaction cost theories, among others, may be especially worth considering, in order to give a framework for survey research on SCF. Out of the identified factors, some factors may be more critical than others. It will be worth exploring the relationship between these factors. For this, total interpretive structural modelling (TISM)—and with a larger survey dataset, structural equation modelling (SEM)—can be used in the future research. The same can be applied in the case of identified outcomes of SCF. Even the analytical modellings have mostly concentrated on a single period or buyer–supplier or manufacturer–retailer dyads. Future studies may look into a more complicated multi-time period or multi-level in the supply chain. Some of the solutions for SCF such as dynamic discounting, manufacturer collateral, and supplier's subsidy, among others, are very understudied. Most of the studies on SCF have viewed SCF by focussing on single solutions, and it may be possible, especially in empirical studies, to consider more than a single solution. Future research may focus on studying more than a single SCF solution. It may be difficult to take up all of the solutions of SCF, but concentrating on the particular category of SCF solutions, such as buyer-led or supplier-led; pre-shipment or post-shipment, etc. may be more manageable for empirical research. Currently, most of the contributions have come from China, followed by Germany, USA, and Switzerland. However, we found a lack of contributions from regions such as Africa and South America. More research contributions from such regions and countries with lesser contributions will be beneficial for the overall research in supply chain finance. Tsai and Peng (2017) discussed the Fintech revolution and the regulation involved therein by using it as a case study. They viewed Fintech in terms of a larger focal company offering online supply chain financing to their supplier or distributor without the intermediation of banks or financial institutions. However, Fintech companies may not necessarily offer direct financing, but may help in facilitating the SCF by linking the parties in the SCF. More study on the role of Fintechs on SCF and their regulations will be beneficial. All of the studies based on secondary data have been from USA and United Kingdom (UK), and it will be worth exploring the various aspects of SCF such as the expected benefits, risk, and cost, among others, using secondary data from other countries, especially from emerging countries. Another exciting area would be to link SCF with other emerging technologies such as blockchain, the Internet of Things (IoT) and big data.

The limitations of the paper are as follows. 1. The findings of this article are based on a review of 70 papers. We used a search string- "Supply Chain Finance" OR "Supply Chain Financing" OR "Financial Supply Chain" OR "Financial Value Chain"—to identify articles, and this may have caused the exclusion of some of the relevant papers. 2. While performing a qualitative analysis of the documents on the focussed themes, personal biases might have occurred. 3. We also did not include 'grey papers', and this may provide material for further insights into SCF.

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Review

On the Rising Complexity of Bank Regulatory Capital Requirements: From Global Guidelines to their United States (US) Implementation

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Abstract: After the Latin American Debt Crisis of 1982, the official response worldwide turned to minimum capital standards to promote stable banking systems. Despite their existence, however, such standards have still not prevented periodic disruptions in the banking sectors of various countries. After the 2007–2009 crisis, bank capital requirements have, in some cases, increased and overall have become even more complex. This paper reviews (1) how Basel-style capital adequacy guidelines have evolved, becoming higher in some cases and overall more complex, (2) how the United States (US) implementation of these guidelines has contributed to regulatory complexity, even when omitting other bank capital regulations that are specific to the US, and (3) how the US regulatory measures still do not provide equally valuable information about whether a bank is adequately capitalized.

Keywords: bank regulation; capital adequacy standards; regulatory complexity; US banking crises

JEL Classification: G01; G28; K20; L51; N22; N42

1. Introduction[1]

Banks are vital in facilitating the exchange of goods and services by providing a payment system and channeling savings to productive investment projects that foster economic activity. However, banking crises have historically contributed to declines in overall economic activity. Furthermore, the ensuing policy response to crises often calls for implementing a variety of banking reforms that may be ineffective or even undermine existing policies (e.g., White (2013); Herring (2016, 2018)).

Capital requirements can be an important tool that bank regulators use to promote a well-functioning banking system, presuming that sufficient levels of owner-contributed equity capital improve a bank's ability to withstand large shocks to asset values. These requirements have grown increasingly complexity in recent decades (see Haldane (2011); and, Herring (2016, 2018)). Fully understanding their nuances presents a challenge, even for those who have spent substantial time studying them. Further adding to the challenge is the existence of multiple capital requirements that are satisfied by different items.

This review of bank capital regulation discusses the growing complexity of Basel capital adequacy guidelines, which, when implemented by a country's regulators, pose a challenge for bank regulatory compliance, oversight, and academic and policy analysis. As evidence of that growing complexity we

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show that regulatory capital requirements can generate up to 25 percent of all regulatory restrictions and on average thousands of additional words embodied in the parts of the United States (US) Code of Federal Regulations (CFR) that concern banks.

We also show that despite the increased complexity of the regulatory capital ratios, they do not provide equally valuable information about whether a bank is adequately capitalized. The data presented clearly indicate that whether banks have too little capital or excess capital depends on the specific capital ratio on which one focuses and whether the capital ratio is based on the riskiness of a bank's business model. Some ratios may indicate that a bank has sufficient capital while other ratios indicate the opposite. A higher regulatory capital ratio that is imposed on banks may or may not affect bank behavior. The specific ratio that regulators choose to increase is crucial. In the aggregate, the market knows that not all ratios are equally revealing about a bank's actual capital adequacy, and thus some ratios receive more attention than others. Given this situation, emphasis could be placed on a straightforward and easily understood capital ratio that market participants have always paid attention to when they assess whether a bank is adequately capitalized. Indeed, some recent studies show that the benefits outweigh the costs (e.g., Karmakar (2016); Begenau and Landvoigt (2017); Egan et al. (2017); Barth and Miller (2018)).

The remainder of the paper proceeds, as follows. The next section summarizes the Basel Capital Accords and their US implementation. Section 3 discusses additional regulatory measures that US regulators apply, including Prompt and Corrective Action (PCA), comprehensive capital analyses, and supervisory stress testing to which regulators now subject the larger banks. PCA describes the actions that banking regulators are legally required to take as a bank's capital declines below specified minimum levels. This is important because, based on publicly available information, researchers are able to determine whether the regulatory authorities actually take the actions that are required when banks encounter financial difficulties. Section 4 explains that the new capital requirements have generated considerable controversy because they require banks to hire more employees with quantitative skills, which results in an increase in costs without a corresponding increase in revenues. It is not clear, moreover, whether the more extensive analyses and testing contribute to a safer and sounder banking system. Section 5 concludes with a suggestion for greater emphasis on a minimum required capital ratio that eliminates most of the confusion over determining whether a bank is adequately capitalized—one that market participants themselves relied on during the most recent banking crisis of 2007–2009.

2. Capital Adequacy Standards: Basel Guidelines and Their US Implementation

2.1. Basel Capital Adequacy Guidelines

The central bank governors of the G10 countries established a Committee on Banking Regulations and Supervisory Practices at the end of 1974 following disruptions in the international financial markets after the breakdown of the Bretton Woods system of managed exchange rates (Kapstein 1991, 1994). The committee was later renamed the Basel Committee on Banking Supervision (BCBS). The aim of that committee was and is to promote financial stability by improving banking supervision worldwide. The BCBS seeks to accomplish its aims by establishing minimum standard guidelines for the regulation and supervision of large, internationally active banks. Since its first meeting in February 1975 (see Kapstein 1991, 1994), the BCBS has been meeting regularly three or four times a year. Membership was expanded beyond the G10 in 2009 and again in 2014, so that 28 jurisdictions—27 countries and the European Union—are now included in the BCBS.[2] BCBS decisions are recommendations, and are

[2] See "Basel Committee Membership" page, Bank for International Settlements, last updated 30 December 2016, http://www.bis.org/bcbs/membership.htm.

thus not legally binding on the member jurisdictions, but the BCBS "expects full implementation of its standards by its member jurisdictions and their internationally active banks".[3]

The Latin American debt crisis of the early 1980s generated concerns about the adequacy of the capital of the large international banks (Kapstein 1991, 1994). In response, Congress passed the International Lending Supervision Act of 1983, in part to get US regulators to find a way to raise capital requirements in a multilateral way since differences existed in national capital requirements and concerns existed that these differences would adversely affect banks in the US (Kapstein 1991, 1994).[4] Through the BCBS, these efforts culminated in the first Basel Capital Accord (Basel I) in July 1988. Basel I called for a minimum capital ratio, which was based on capital relative to risk-weighted assets (RWAs).

Table 1 offers a summary of the various capital requirements across Basel regimes, which under Basel I, included two tiers of capital, Tier 1 and Tier 2, which combined to form total capital, and these capital measures based on accounting or book values. We list the composition of the different capital concepts are listed in Table 2. Tier 1 capital was initially set at 3.625 percent of RWAs and then increased to 4 percent by the end of 1992, while total capital was increased from 7.25 percent to 8 percent of RWAs over the same period. The BCBS did not recommend a leverage ratio, or non-risk-based capital ratio, at the time.

However, the BCBS intended these capital ratios to evolve over time as events unfolded and new information became available. In January 1996, for example, the BCBS issued guidelines within Basel I to incorporate market risks in capital requirements, since initially only credit risks were addressed (Basel Committee on Banking Supervision BCBS). This new capital requirement took into account the risk of losses in on-balance-sheet and off-balance-sheet positions arising from movements in market prices. At the same time, a third kind of regulatory capital, Tier 3, became part of total capital (Basel Committee on Banking Supervision BCBS). These changes were to take effect at the end of 1997 and allowed banks, for the first time, to use internal models (value-at-risk models) as a basis for calculating their market-risk capital requirements.

In June 2004, the BCBS replaced the Basel Capital Accord (Basel I) with the Revised Capital Framework (Basel II) (Basel Committee on Banking Supervision BCBS). Basel II was made up of three pillars: Pillar I, which was designed to develop and expand the minimum capital requirements in Basel I; Pillar II, which provided for supervisory review of a bank's capital adequacy and internal assessment process; and, Pillar III, which called for the effective use of disclosure as a lever to strengthen market discipline and encourage sound banking practices. The minimum required risk-based capital ratios for Tier 1 and total capital were left unchanged at 4 percent and 8 percent, respectively, as shown in Table 1. The BCBS member countries and several non-member countries agreed to adopt the new guidelines, but on varying national timescales.[5]

The BCBS agreed to Basel II.5 in July 2009 as a revision of Basel II, which BCBS members believed had failed to properly address market risk that banks took on their trading books. Basel II.5 introduced an incremental risk charge (IRC) to estimate and capture default and credit migration risk (i.e., the risk when customers move their loans from one bank to another bank). Basel II.5 also introduced an additional charge to compensate for an increase in one risk that leads to an increase in another risk (i.e., correlated risk). In addition, BCBS introduced stressed value-at-risk to require banks to calculate capital requirements under stress conditions. Lastly, standardized charges were introduced for securitization and re-securitization positions.

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3 See "Policy Development and Implementation Review", Bank for International Settlements, as of the 30 December 2016 update, https://www.bis.org/bcbs/review_process.htm.

4 For the International Lending and Supervision Act of 1983, see Title IX of Public Law No. 98–181, 97 Stat. 1278.

5 By 2014, all 27 BCBS member countries had implemented or were in the process on implementing Basel II (meaning at least one subsection had been implemented), while another 94 non-BCBS jurisdictions had done the same (see Basel Committee on Banking Supervision BCBS).

Table 1. A Timeline of Basel Capital Accords.

Regulatory Capital Standards	Basel I [a] (%)	Basel II [b] (%)	Basel II.5 [c] (%)	Basel III [d] (%)						
	1993–2010	2011	2012	2013	2014	2015	2016	2017	2018	as of 1 January 2019
Minimum Tier 1 capital (CET1 plus additional Tier 1)	4.0	4.0	4.0	4.5	5.5	6.0	6.0	6.0	6.0	6.0
Minimum total capital (Tier 1 plus Tier 2 capital)	8.0	8.0	8.0	8.0	8.0	8.0	8.0	8.0	8.0	8.0
Common equity leverage ratio [e] (viewed as a backstop to risk-based ratios)	n/a	supervisory monitoring	test period and disclosure starts 1 January 2015						3.0	3.0
Minimum CET1 capital ratio	n/a	2.0	2.0	3.5	4.0	4.5	4.5	4.5	4.5	4.5
Phase-in of deductions from CET1 (including amounts exceeding the limit for deferred tax assets, mortgage servicing rights, and financials)	n/a	n/a	n/a	n/a	20	40	60	80	100	100
Capital conservation buffer	n/a	n/a	n/a	n/a	n/a	n/a	0.625	1.25	1.875	2.50
Countercyclical capital buffer (discretionary, 0.0% to 2.5%), to be filled with Tier 1 capital	n/a	n/a	n/a	n/a	n/a	n/a	0.625	1.25	1.875	2.50
Capital surcharge for global systemically important banks	n/a	n/a	n/a	n/a	n/a	n/a	0.25 to 3.5	0.5 to 3.5	0.75 to 3.5	1 to 3.5
Capital instruments that no longer qualify as noncommon equity Tier 1 capital or Tier 2 capital	n/a	n/a	n/a	10% per year phase out over 10-year horizon beginning 1 January 2013 [f]						

Note: CET1 = common equity Tier 1, n/a = not applicable. [a] Basel I was finalized in July 1988 and implemented over the period 1988–1992. The figures in the column for Basel I show the final capital standards after implementation. [b] Basel II was finalized in June 2004 and implemented over the period 2007–2010. The figures in the column for Basel II show the final capital standards after implementation. [c] Basel II.5 was finalized in July 2009 and meant to be implemented no later than 31 December 2011. Basel II.5 enhanced the measurements of risks related to securitization and trading book exposures. [d] Basel III was finalized in December 2010 and meant to be implemented over the period 2013–2018. [e] The leverage ratio is calculated as the ratio of Tier 1 capital to balance-sheet exposures plus certain off-balance-sheet exposures. [f] The phasing works by capping the amount that can be included in capital from 90 percent on 1 January 2013, and reducing this cap by 10 percent in each subsequent year. Sources: Documents by the Basel Committee on Banking Supervision at the Bank for International Settlements in Basel, Switzerland: "International Convergence of Capital Measurement and Capital Standards", July 1988 (Basel Committee on Banking Supervision BCBS); "Amendment to the Capital Accord to Incorporate Market Risks", January 1996; "Amendment to the Capital Accord to Incorporate Market Risks", June 2004; "Revisions to the Basel II Market Risk Framework—Final Version", July 2009 (Basel Committee on Banking Supervision BCBS); "Basel III: A Global Regulatory Framework for More Resilient Banks and Banking Systems—Revised Version June 2011", June 2011; "The G-SIB Assessment Methodology—Score Calculation", November 2014a (Basel Committee on Banking Supervision BCBS); "Implementation of Basel Standards: A Report to G20 Leaders on Implementation of the Basel III Regulatory Reforms", November 2014b (Basel Committee on Banking Supervision BCBS); also Barth et al. 2012.

Table 2. Components of Total Capital.

Tier 1 capital	At least 50 percent of a bank's capital base to consist of a core element comprised of equity capital and published reserves from post-tax retained earnings minus goodwill
Tier 2 capital	Undisclosed reserves, asset revaluation reserves, general provisions/general loan-loss reserves, hybrid (debt/equity) capital instruments and subordinated debt, and limited to a maximum of 100 percent of the total of Tier 1 elements

Note: Tier 1 capital did not include goodwill, which is the present value of conjectural future profits arising from an acquisition when the amount paid is in excess of the target firm's value, because its ability to absorb losses is unclear. Goodwill shows up on the balance sheet, but is recognized as not being easily converted into cash. Sources: Documents by the Basel Committee on Banking Supervision at the Bank for International Settlements in Basel, Switzerland: "International Convergence of Capital Measurement and Capital Standards", July 1988; "Amendment to the Capital Accord to Incorporate Market Risks", January 1996.

The BCBS issued Basel III in December 2010 and revised it in June 2011, after the global banking crisis.[6] BCBS made the revisions to enhance the Basel framework and strengthen the three pillars that were established by Basel II (Basel Committee on Banking Supervision BCBS). The new framework (Basel III) also introduced several regulatory capital innovations. Basel III established new minimum common equity and Tier 1 requirements and added an additional layer of common equity (the capital conservation buffer), a countercyclical buffer, a leverage ratio (based on both a bank's on-balance-sheet assets and off-balance-sheet exposures regardless of risk weighting), and supplementary capital requirements for systemically important banks. Also introduced were a liquidity coverage ratio (intended to provide enough cash to cover funding needs over a 30-day period of stress) to be phased in from 1 January 2015, to 1 January 2019, and a longer-term net stable funding ratio (intended to address maturity mismatches over the entire balance sheet) to take effect as a minimum standard by 1 January 2018.

The final capital standards introduced by Basel III were to be phased in over time, as shown in Table 1. The recommended leverage standard will be 3 percent in 2019. The recommended Tier 1 risk-based capital standard will be 6 percent and the total risk-based capital standard will be 8 percent. If one adds the capital conservation and countercyclical capital buffers to the total capital standard, the capital ratio can be as high as 13 percent for some banks, and even as high as 16.5 percent if one adds a capital surcharge of 3.5 percent for global systemically important banks (GSIBs).[7]

The Financial Stability Board (FSB), which makes policy recommendations to G20 members, has proposed further increasing requirements on GSIBs through a total loss-absorbing capacity (TLAC) requirement. On top of the required minimum common equity Tier 1 (CET1) ratio of 4.5 percent, GSIBs would have to fund with an additional 11.5 percent of "loss absorbency" in the form of Tier 1 and Tier 2 capital relative to risk-weighted assets. This requirement would rise to 13.5 percent by 2022. The FSB expects GSIBs to meet this requirement in part through long-term, unsecured debt, which can be converted into equity when a bank fails. The emphasis on convertible debt is meant to put an end to "too big to fail" by forcing bondholders rather than taxpayers to inject capital into a large bank that fails.[8]

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6 On 7 December 2017, the BCBS released "Basel III: Finalising post-crisis reforms", available from https://www.bis.org/bcbs/publ/d424.htm (Basel Committee on Banking Supervision BCBS), which the industry has already begun referring to as "Basel IV". While the 2011 Basel III guidelines focused on perceived problems with the numerator in regulatory capital ratios, the 2017 "Basel IV" guildelines focus on perceived problems with the denominator in regulatory capital ratios by proposing new risk-weights. However, US regulators have not finalized regulations based on these guidelines so we omit them from the discussion here.

7 Under the supervisory review process, the second pillar of the Basel Capital Accord, supervisors may determine capital adequacy should be even higher based upon a bank's operating environment.

8 For a discussion of TLAC, including its implications for US banks, see Killian (2016).

2.2. US Bank Capital Requirements

While the US has for the most part adopted Basel guidelines, important differences exist, and Table 3 shows how the US implementation has varied according to Basel I, Basel II, Basel II.5, and Basel III.[9] One important difference between the Basel guidelines and the US implementation has been that, unlike the former, the latter has included a leverage capital requirement in addition to the risk-based capital requirements. In addition, the US implementation applies to every bank, although some differences exist based on the bank's asset size. The risk-based capital requirements provide an incentive for banks to focus more on assets with lower risk weights, which can lead banks to change their business models (e.g., see Merton (1995); Jones (2000); Brealey (2006); and, Miller (2018)).

Like Table 1, Table 3 reveals the growing complexity of regulatory capital requirements since Basel I, especially after US banking regulators issued the final rule regarding the Basel III implementation in July 2013.[10] Basel III regulation intends to strengthen the definition of regulatory capital, increase the minimum risk-based capital requirements for all banks, and modify the requirements for how banks calculate risk-weighted assets. It also retains the generally applicable leverage ratio requirement that banking regulators believe to be a simple and transparent measure of capital adequacy that is credible to market participants and ensures that a meaningful amount of capital is available to absorb losses. It includes both "advanced approaches" for determining the risk weight of assets for the largest internationally active banking organizations and a standardized approach that will apply to all banking organizations, except small bank holding companies (BHCs) with less than $500 million in assets. Basel III regulation became effective for advanced-approaches banks on 1 January 2014, and on 1 January 2015 for non-advanced-approaches banks. Also, advanced-approaches banks have to calculate standardized-approach RWAs in addition to advanced-approaches RWAs for purposes of applying the "Collins Floor", which establishes a bank's minimum capital ratios as the lower of its standardized-approach and advanced-approaches ratios.[11]

Under Basel III, there are several new and more stringent capital requirements, as well as different capital requirements for banks of different sizes and systemic importance. In particular, there is a new CET1 capital ratio set at 4.5 percent of risk-based assets. The Tier 1 capital ratio is set at 6 percent (an increase from 4 percent), while the total capital ratio remains at 8 percent. The capital requirements are more stringent for the advanced-approaches banks and a subset of those banks identified as GSIBs. Indeed, for GSIBs the sum of the minimum total capital, the capital conservation buffer, the countercyclical capital buffer, and the GSIB surcharge can be as high as 17.5 percent of risk-based assets. The Federal Reserve Board (FRB) in July 2015 established the methods that US GSIBs will use to calculate a risk-based capital surcharge, which is calibrated to each firm's overall systemic risk.[12] In particular, the GSIBs are required to calculate their surcharges under two methods and use the higher of the two. The first method is based on the framework that was agreed to by BCBS and considers a GSIB's size, interconnectedness, cross-jurisdictional activity, substitutability, and complexity. The second method uses similar inputs, but it is calibrated to result in significantly higher surcharges and replaces substitutability with a measure of the bank's reliance on short-term wholesale funding. The surcharges are being phased in—implementation began on 1 January 2016, and it will become fully effective on 1 January 2019.

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[9] The table also reflects the effect of the implementation of the Dodd-Frank Act on capital requirements.

[10] See Comptroller of the Currency, Federal Register 2013. To see how the new regulations increase complexity, Herring (2018) estimates that capital requirement have five distinct numerators and denominators, which generate 39 distinct capital requirements for US GSIBs; that estimate assumes all capital ratios were implemented in full, and the number would increase if the phase-in periods were used instead.

[11] See Section 171 of the "Dodd-Frank Wall Street Reform and Consumer Protection Act," Public Law No. 111–203, 124 Stat. 1376.

[12] The FSB and BCBS provide the list of GSIBs, using the assessment methodology published by BCBS. See Financial Stability Board, "2015 update of list of global systemically important banks (GSIBs)", 3 November 2015. See also Board of Governors of the Federal Reserve System, Federal Register 2015.

Table 3. A Timeline of United States (US) Capital Requirements.

Regulatory Capital Requirements	US minimum Capital Standards Based on Basel I [a] (%)		Basel II [b] (%)	Basel II.5 [c] (%)	Basel III [d] (%)						
	1991–1992	**1993–2010**	**2011**	**2012**	**2013**	**2014**	**2015**	**2016**	**2017**	**2018**	**as of 1 January 2019**
Minimum Tier 1 capital (CET1 + additional Tier 1)	3.625	4.0	4.0	4.0	4.5	5.5	6.0	6.0	6.0	6.0	6.0
Minimum total capital (Tier 1 + Tier 2 capital)	7.25	8.0	8.0	8.0	8.0	8.0	8.0	8.0	8.0	8.0	8.0
Tier 1 leverage ratio and supplementary leverage ratio [e] (viewed as a complement to risk-based ratios) [f]	4 (3 for banks that are CAMELS 1-rated)						4	4	4	3 (AA) 5 (GSIBs and 6 for their IDIs) 4 (NAA)	3 (AA) 5 (GSIBs and 6 for their IDIs) 4 (NAA)
Minimum CET1 capital ratio (introduced in 2009 in the United States)	n/a	n/a	n/a	n/a	3.5	4.0	4.5	4.5	4.5	4.5	4.5
Phase-in of deductions from CET1 (including amounts exceeding the limit for deferred tax assets, mortgage servicing rights, and financials)	n/a	n/a	n/a	n/a	n/a	20.0	40.0	60.0	80.0	100.0	100.0
Capital conservation buffer [g]	n/a	n/a	n/a	n/a	n/a	n/a	n/a	0.625	1.25	1.875	2.5
Countercyclical capital buffer for AA banks (discretionary, 0.0% to 2.5%)	n/a	n/a	n/a	n/a	n/a	n/a	n/a	0.625	1.25	1.875	2.5
Capital surcharge for GSIBs [h]	n/a	n/a	n/a	n/a	n/a	n/a	n/a	0.25 to 4.5	0.50 to 4.5	0.75 to 4.5	1 to 4.5
Capital instruments that no longer qualify as CET1 or Tier 1 capital [i]	n/a	n/a	n/a	n/a	n/a	80	60	40	20	0	0

Note: AA = advanced approaches, CET1 = common equity Tier 1, GSIB = global systemically important bank, IDI = insured depository institution, n/a = not applicable, NAA = non-advanced approaches. [a] Basel I was finalized in July 1988 and phased in over the period 1988–1992; it became fully effective in 1992 for all US banks. For the 1988–2010 period, see Federal Register 1989. [b] US banking regulators published a final Basel II rule in December 2007 with a phase-in and it did not become effective until 1 April 2008. See Federal Register 2007. US federal banking agencies chose not to apply Basel II to all US banks, but only to the very largest, internationally active "core" US banks. [c] US banking regulators published the final rule in June 2012 that became effective 1 January 2013, with revisions to certain capital requirements for trading positions and securitizations. See Federal Register 2012d. [d] US banking regulators issued a final rule in July 2013 implementing Basel III; the rule became effective for AA banks, those with more than $250 billion in assets or more than $10 billion of on-balance-sheet foreign exposures, on 1 January 2014, and for NAA banks on 1 January 2015. See Federal Register 2013. The Collins Floor, required by the Dodd-Frank Act, established a firm's minimum capital ratio as the lower of its standardized-approach and advanced-approaches ratios, which include both minimum capital standards and the capital conservation buffer. [e] The Tier 1 leverage ratio is the ratio of Tier 1 capital to on-balance-sheet assets less items deducted from Tier 1 capital. The leverage ratio applies to all banks, and must be at least 4 percent for an institution to be adequately capitalized and 5 percent to be well capitalized. The supplementary leverage ratio only applies to AA banks and is the ratio of Tier 1 capital to both on-balance-sheet and selected off-balance-sheet assets, or leverage exposure. [f] Leverage ratio for AA bank holding companies is based on both on-balance-sheet and off-balance-sheet items, while only on-balance-sheet items are included for NAA bank holding companies. [g] A bank's capital conservation buffer of 2.5 percent (on top of each risk-based ratio) will equal the lowest of the following three amounts: (1) a bank's CET1 ratio minus 4.5 percent; (2) a bank's Tier 1 risk-based capital ratio minus 6 percent; (3) a bank's total risk-based capital ratio minus 8 percent. Failure to meet these requirements results in restrictions on payouts of capital distributions and discretionary bonus payments to executives. [h] GSIBs calculate their surcharges using two methods and use the higher of the two surcharges. The first method is based on the framework agreed to by the Basel Committee on Banking Supervision and considers a GSIB's size, interconnectedness, cross-jurisdictional activity, substitutability, and complexity. The second method uses similar inputs, but is calibrated to result in significantly higher surcharges and replaces substitutability with a measure of the firm's reliance on short-term wholesale funding. [i] Basel III revised the regulatory capital treatment for Trust Securities, requiring them to be partially transitioned from Tier 1 capital into Tier 2 capital in 2014 and 2015, until fully excluded from Tier 1 capital in 2016, and partially transitioned and excluded from Tier 2 capital beginning in 2016. The exclusion from Tier 2 capital starts at 40 percent on January 1, 2016, increasing 10 percent each year until the full amount is excluded from Tier 2 capital beginning on 1 January 2022. Additional sources: Barth et al. 2012; Bank for International Settlements, Basel III: A Global Regulatory Framework for More Resilient Banks and Banking Systems (December 2010, rev. June 2011); European Parliament, US Implementation of Basel II: Final Rules Issued, but No Supervisory Approvals to Date (October 2011).

Table 4 provides information on the various components of regulatory capital that are associated with the different required capital ratios under the US implementation of the Basel Capital Adequacy Standards. Different countries were free to implement the Basel Capital Adequacy Standards as they saw fit, given that Basel III provided guidelines rather than strict rules for the bank regulatory authorities in those countries implementing it. In the US, Basel III implementation brought major changes in the components of capital. In particular, banking regulators now consider the new capital measure, CET1 capital, to be the most loss-absorbing form of capital. The new emphasis on CET1 no doubt reflects the fact that, as the banking crisis emerged, market participants chose to focus more on capital measures that reflected loss-absorbing capital than on the official regulatory measures. CET1 includes qualifying common stock, retained earnings, certain accumulated other comprehensive income (AOCI) elements (if the bank does not make an AOCI opt-out election) plus or minus regulatory deductions or adjustments as appropriate, and qualifying CET1 minority interests. The banking regulators expect the majority of CET1 capital to be in the form of common voting shares. Non-advanced-approaches banks were allowed on their 31 March 2015 Call Report to make a permanent, onetime opt-out election, enabling them to calculate regulatory capital without AOCI. Such an election neutralizes the impact of unrealized gains or losses on available-for-sale bond portfolios in the context of regulatory capital levels. For banks that did not opt out, the AOCI adjustment to CET1 capital could have a significant impact on regulatory capital ratios if significant bond portfolio appreciation or depreciation occurs.

Unfortunately, this is not the end of the story. Fully describing what counts as regulatory capital demonstrates the complexity that is associated with calculating capital that complies with the regulatory requirements. Highlighting this complexity also reveals the difficulties that researchers must confront when they assess how changes in capital requirements affect bank behavior. For example, banks may respond differently to capital requirements depending on differences in both the level of existing capital and the composition of the existing components of that capital.

Banks must fully deduct several items from CET1 capital, such as goodwill, deferred tax assets that arise from a net operating loss and tax credit carry-forwards, other intangible assets (except for mortgage servicing assets), gains on sale of securitization exposures, and certain investments in another financial institution's capital instruments. Banks also must consider threshold deductions for three specific types of assets: mortgage servicing assets, deferred tax assets that are related to temporary timing differences, and significant investments in another unconsolidated financial institution's common stock. Generally, banks must deduct, by category, the amount of exposure to these types of assets that exceeds 10 percent of a base CET1 capital calculation. In addition, there is a 15 percent aggregate limit on these three threshold deduction items in CET1.

Additional non-CET1 capital includes qualifying noncumulative perpetual preferred stock, bank-issued Small Business Lending Fund and Troubled Asset Relief Program instruments that previously qualified for Tier 1 capital, and qualifying Tier 1 minority interests, less certain investments in other unconsolidated financial institutions' instruments that would otherwise qualify as additional Tier 1 capital. Tier 2 capital includes the allowance for loan and lease losses up to 1.25 percent of risk-weighted assets, qualifying preferred stock, subordinated debt, and qualifying Tier 2 minority interests, less any deductions in the Tier 2 instruments of an unconsolidated financial institution. Previous limits on term subordinated debt, limited-life preferred stock, and the amount of Tier 2 capital that can be included in total capital no longer apply. Non-qualifying capital instruments issued before 9 May 2010, by banks with less than $15 billion in assets (as of 31 December 2009) are grandfathered, with the exception that grandfathered capital instruments cannot exceed 25 percent of Tier 1 capital.

Table 4. A Timeline of US Regulatory Capital Components.

Regulatory Capital Components	Basel I [a]		Basel II [b]	Basel II.5 [c]	Basel III [d]
	1991–1992	1993–2010	2011	2012	2013 to as of 1 January 2019
Tier 1 capital (old)	Common equity + preferred stock + qualifying hybrids + minority interests − (goodwill + other intangibles, except for MSRs, PCCR, and DTAs)				n/a
Tier 2 capital (old)	Undisclosed reserves + assets revaluation reserves + general provisions/general loan loss reserves + preferred stock + qualifying hybrids + subordinated debt				n/a
Tier 3 capital (old)	n/a	n/a	Short-term subordinated debt, solely to support the market risks in the trading book [e]		n/a
CET1, going-concern capital (new)	n/a	n/a	n/a	n/a	Common stock and retained earnings ± limited accumulated other comprehensive income items for opt-out banks (or accumulated other comprehensive income for non-opt-out and advanced-approaches banks) ± deductions and adjustments + qualifying CET1 minority interest − (goodwill + deferred tax assets + other intangibles)
Additional Tier 1 capital (AT1), going-concern capital (new)	n/a	n/a	n/a	n/a	Noncumulative perpetual preferred stock, including surplus + SBLF & TARP (bank issued) + qualifying Tier 1 minority interest − certain investments in financial institutions
Tier 2 capital, gone-concern capital (new)	n/a	n/a	n/a	n/a	Limited allowance for loan and lease losses + preferred stock and subordinated debt + qualifying Tier 2 minority interest − Tier 2 investments in financial institutions
Total capital (CET1 capital + AT1, or Tier 1 capital, + Tier 2 capital)	n/a	n/a	n/a	n/a	All of the above items with limits eliminated on subordinated debt and limited-life preferred stock in Tier 2 capital and no limit on Tier 2 capital
Capital conservation buffer (CCB) (new)	n/a	n/a	n/a	n/a	CET1 (CCB ratio must be in excess of CET1, Tier 1 and total capital ratios by at least 2.5% to avoid limits on capital distributions and certain discretionary bonus payments)
Countercyclical capital buffer (new)	n/a	n/a	n/a	n/a	CET1
Capital surcharge for global systemically important banks (new)	n/a	n/a	n/a	n/a	CET1
Leverage capital	Tier 1 (old)	Tier 1 (old)	Tier 1 (old)	Tier 1 (old)	CET1 + AT1 (new Tier 1)

Note: CET1 = common equity Tier 1, DTA = deferred tax assets, MSR = mortgage servicing rights, n/a = not applicable, PCCR = purchased credit card receivables, SBLF = small business lending fund, TARP = troubled asset relief program. [a] See Federal Register 1989. [b] See Federal Register 2007. [c] See Federal Register 2012d. [d] See Federal Register 2013. [e] For the rule introducing Tier 3 capital, see Federal Register 1996.

In assessing the financial condition of a bank, the denominator in the risk-based capital ratio is as important as the numerator, if not more so. As noted earlier, Basel I was the first capital standard based on RWAs. Then, in response to the growing importance of trading activities of large banks, Basel I was amended in 1996 to expand capital requirements to include capital charges for market risk. Then again, Basel II.5 added capital charges for certain types of trading activities by changing the calculation of risk weights for the trading book. More generally, as compared to Basel I, Basel II and II.5 provided for more detailed calculations of the risk-sensitivity of banks. Indeed, according to Andrew Haldane, "[For] a large, representative bank using an advanced internal set of models to calibrate capital. . . [its] number of risk buckets has increased from around seven under Basel I to, on a conservative estimate, over 200,000 under Basel II".[13]

In Basel III, there are two general approaches to RWAs. The standardized approach is generally designed for community banks, while the advanced approach is used by larger, more complex banks. The standardized approach applies to BHCs with $500 million or more in consolidated assets. Risk-weighted assets consist of credit-risk RWAs plus market-risk RWAs (if applicable). Credit-risk RWAs include risk-weighted assets for general credit risk, cleared transactions, default fund contributions, unsettled transactions, securitization exposures, and equity exposures. General credit risk involves the consideration of general risk weights, off-balance-sheet exposures, over-the-counter derivative contracts, cleared transactions, guarantees, credit derivatives, and collateralized transactions. Since the introduction of the risk-weighting system in the United States in the early 1990s, the general process of risk weighting assets has not changed. However, the movement from Basel I to Basel III has brought several specific changes in risk weights.

Table 5 shows that the standardized approach for Basel III involves risk weights other than the 0, 20, 50, and 100 percent categories that were initially implemented for Basel I. The Basel III risk-weighting categories allow for more detailed risk weights, and the weights now range from a low of 0 to a high of 150 percent. The risk weight for exposures to, and portions of exposures that are directly and unconditionally guaranteed by, the US government, its agencies, and the Federal Reserve is zero percent. The risk weight for high-volatility commercial real estate loans is 150 percent, up from 100 percent under Basel I. Section 939 of the Dodd-Frank Act directs the banking regulators to remove regulatory references to external credit ratings from regulations.[14] This provision was a legislative response to the failure of the ratings to adequately indicate the riskiness of various securities. That failure affected the ability to assess the riskiness of banks and other entities leading up to the 2007–2009 financial crisis.

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13 See Haldane (2011), p. 2.

14 By contrast, the Federal Reserve, Federal Deposit Insurance Corporation, and Office of the Comptroller of the Currency finalized a joint rulemaking known as the "Recourse Rule" on 29 November 2001. See Office of the Comptroller of the Currency, Board of Governors of the Federal Reserve System, Federal Deposit Insurance Corporation, and Office of Thrift Supervision, Federal Register 2001. The Recourse Rule set capital requirements for private label asset- and mortgage-backed securities and other positions in securitization transactions (except for credit-enhancing interest-only strips) according to their relative risk using credit ratings from rating agencies to measure the level of risk. As Erel et al. (2014, p. 411) note, after this change "a bank that made subprime loans was better off holding them on its books as securities backed by these loans than holding the loans directly". As they point out, the regulatory capital charge became a function of the securities' credit ratings rather than their asset class. Miller (2018) shows that the largest banking organizations with subsidiaries that commented on the regulation during the notice and comment period began increasing their holdings of the highly-rated, private label securitization tranches once the rule went into effect, and that those that held more after 2008 on average experienced greater subsequent rises in default risk and stock price volatility.

Table 5. Basel I and Basel III: US Risk Weights for On-Balance-Sheet and Off-Balance-Sheet Items for the Standardized Approach.

Selected Items	**Existing Basel I–Based Risk Weights** [a]	**US Basel III Final Rule Standardized Risk Weights** [b]		
Cash	0%	0%		
Exposures to, and portions of exposures that are directly and unconditionally guaranteed by, the US government, its agencies, and the Federal Reserve	0%	0%		
Exposures to foreign governments and their central banks	0% for direct and unconditional claims on Organisation for Economic Co-operation and Development (OECD) governments 20% for conditional claims on OECD governments 100% for claims on non-OECD governments that entail some degree of transfer risk	Risk weight depends on the sovereign's OECD country risk classification (CRC)		
				Risk weight
		Sovereign CRC	0–1	0%
			2	20%
			3	50%
			4–6	100%
			7	150%
		OECD member with no CRC		0%
		Non-OECD member with no CRC		100%
		Sovereign default		150%
Exposures to US government-sponsored enterprises	20%	20%		
Exposures to US public-sector entities, including US states and municipalities	20% for general obligations	20% for general obligations		
	50% for revenue obligations	50% for revenue obligations		
Exposures to foreign public-sector entities	20% for general obligations of states and political subdivisions of OECD countries 50% for revenue obligations of states and political subdivisions of OECD countries 100% for all obligations of states and political subdivisions of non-OECD countries	Risk weight depends on the home country's CRC		
				Risk weight for general obligations
		Sovereign CRC	0–1	20%
			2	50%
			3	100%
			4–7	150%
		OECD member with no CRC		20%
		Non-OECD member with no CRC		100%
		Sovereign default		150%
				Risk weight for revenue obligations
		Sovereign CRC	0–1	50%
			2–3	100%
			4–7	150%
		OECD member with no CRC		50%
		Non-OECD member with no CRC		100%
		Sovereign default		150%
Exposures to US depository institutions and credit unions	20%	20%		

Table 5. *Cont.*

Selected Items	Existing Basel I–Based Risk Weights [a]	US Basel III Final Rule Standardized Risk Weights [b]
Exposures to foreign banks	20% for all claims on banks in OECD countries 20% for short-term claims on banks in non-OECD countries 100% for long-term claims on banks in non-OECD countries	Risk weight depends on the home country's CRC Risk weight Sovereign CRC: 0–1 20%; 2 50%; 3 100%; 4–7 150% OECD member with no CRC 20% Non-OECD member with no CRC 100% Sovereign default 150%
Exposures to nonbank corporations	100%	100%
Exposures to residential mortgages	50% for a first-lien residential mortgage exposure that is: secured by a property that is either owner-occupied or rented; made in accordance with prudent underwriting standards; not 90 days or more past due or carried in nonaccrual status; and not restructured or modified (unless restructured or modified solely pursuant to the US Treasury's Home Affordable Mortgage Program)	Retains existing capital treatment:
	100% for all other residential mortgage exposures	50% for a first-lien residential mortgage exposure that is: secured by a property that is either owner-occupied or rented; made in accordance with prudent underwriting standards; not 90 days or more past due or carried in nonaccrual status; and not restructured or modified (unless restructured or modified solely pursuant to the US Treasury's Home Affordable Modification Program) 100% for all other residential mortgage exposures
Exposures to high-volatility commercial real estate loans	100%	150% (the definition of high-volatility commercial real estate only captures a specific subset of acquisition, development, and construction loans; not all commercial real estate loans)
Exposures to over-the-counter derivatives	Risk weight depends on counterparty category (e.g., bank, securities firm, or general corporation), subject to a 50% risk-weight ceiling	Removes the 50% risk-weight ceiling for over-the-counter derivatives
Exposures to securitizations	Ratings-based approach: risk weight depends on the external credit rating assigned to the securitization exposure	General 20% risk-weight floor for securitization exposures
Default risk weight for items not specifically assigned to a risk-weight category	100%	100%
Conversion factors that are used to measure the risk of off-balance-sheet items	0–100%	0–100%

[a] See Federal Register 1989. [b] See Federal Register 2013. Additional source: Davis Polk, U.S. Basel III Final Rule: Standardized Risk Weights Tool, accessed 27 January 2017, http://www.usbasel3.com/tool/.

The advanced approach under Basel III applies to BHCs with consolidated assets that are greater than $250 billion or balance-sheet foreign exposures greater than $10 billion. These banks are required to determine compliance with minimum capital requirements based on the lower of the capital ratios that were calculated under the standardized and advanced approaches. Using the advanced approach, risk-weighted assets are the sum of credit-risk RWAs, market-risk RWAs (if applicable), and operational RWAs. Credit-risk RWAs include risk-weighted assets for general credit risk, securitization exposures, and equity exposures. General credit risk refers to wholesale and retail RWAs, as well as the counterparty credit risk of repo-style transactions, eligible margin loans, over-the-counter derivative contracts, cleared transactions, unsettled transactions, guarantees, and credit derivatives.[15] Market-risk RWAs—which apply only to BHCs that have aggregate trading assets and liabilities equal to either 10 percent or more of total assets or at least $1 billion—are based on the following risk categories: interest rate, credit spread, equity price, foreign exchange, and commodity price. Operational-risk RWAs have the same basic RWA formula as that of market risk.

2.3. How US Bank Capital Regulation Has Grown Increasingly Complex Since 1970

Herring (2016, 2018) argues that 75 percent of the various capital requirements for US GSIBs could be eliminated without weakening capital regulation, and offers that as evidence of the growing complexity of US capital requirements. An alternative way to view the growing complexity embodied in US capital adequacy standards comes from RegData 3.1 (see McLaughlin and Sherouse (2018)). The database provides counts of the number of regulatory restrictions in the CFR, which include words, such as "may not", "must", "required", "shall", and "prohibited". More restrictions that are embodied in the CFR in principle means that banking organizations must spend more resources on compliance. In the CFR, Title 12 concerns banks and banking. Parts 1–199 concern the Office of the Comptroller of the Currency (OCC), parts 200–299 concern the Federal Reserve System (FRS) and parts 300–399 concern the Federal Deposit Insurance Corporation (FDIC).[16] The parts of the CFR that concern commercial bank capital requirements in Title 12 include "Part 3—Capital Adequacy Standards", "Part 217—Capital Adequacy of BHCs, S&L Holding Companies, and State Member Banks" for the FRS and "Part 324—Capital Adequacy of FDIC-Supervised Institutions" and "Part 325—Capital Maintenance" for the FDIC. We can present measures of the rising complexity of bank capital requirements by dividing the total number of regulatory restrictions that concern bank capital by the total number of regulatory restrictions, for each agency.

Figure 1 depicts the fraction of regulatory restrictions for the FDIC, OCC and Federal Reserve that concern capital requirements since 1970. The figure shows that the fraction of restrictions that concern bank capital for the FDIC and OCC has increased greatly relative to what existed under Basel I, and now equals nearly 25 percent. For the Federal Reserve, almost all of the regulatory restrictions have come since Basel III, and by 2017, exceeded 10 percent.[17]

As a suggestive exercise, we estimate how capital requirements contribute to overall regulatory complexity by agency by applying Mora and Reggio (2017) fully flexible approach to estimating average treatment effects. The idea is to estimate how many additional restrictions or word counts are on average generated by regulatory capital requirements.

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15 Under US generally accepted accounting principles (GAAP), banks are allowed to report their derivatives on a net basis. Under international financial reporting standards (IFRS), European banks are generally required to report their derivatives on a gross basis. This leads to a substantial decrease in the size of the balance sheet for large US banks as compared to large European banks.

16 The OCC regulates banks with a national charter. The Federal Reserve regulates bank and financial holding companies, as well as banks with state charters that are Federal Reserve member banks. The FDIC regulates banks with state charters that are not Federal Reserve member banks.

17 We exclude "Part 226—Truth In Lending" from the measure for FRS regulatory restrictions, given that that part generates by far the largest fraction of regulatory restrictions for the FRS, but does not concern the other regulators. If we include that part, the fraction falls to about 8 percent by the end of the sample.

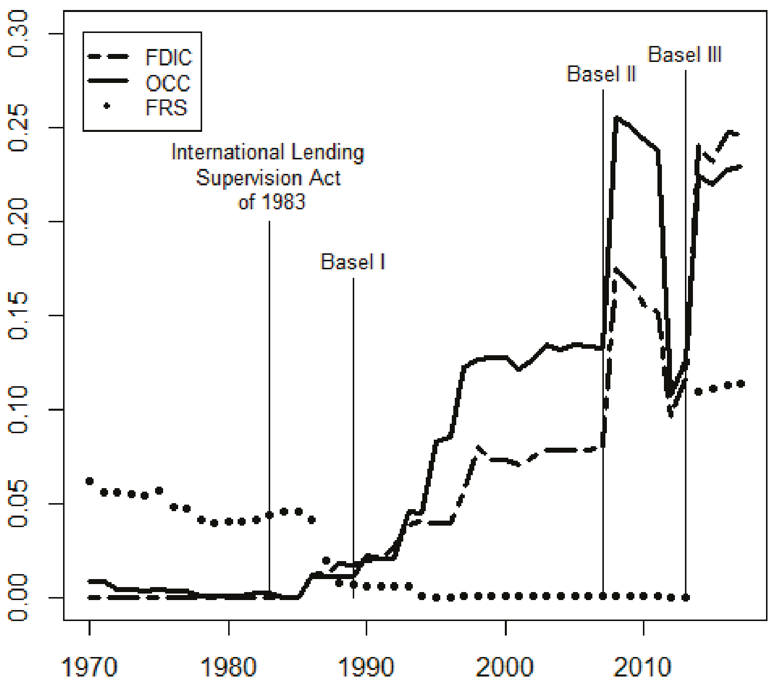

Figure 1. The Fraction of Regulatory Restrictions Arising from Bank Capital Requirements, 1970–2017.

Mora and Reggio (2017) show that, if the trends for the treatment and control groups are the same, the appropriate estimator for the average treatment effect for the difference-in-differences estimator under the parallel paths assumption yields the same treatment effects as the difference in double-differences estimator under the parallel growths assumption. This no longer holds if the pre-treatment dynamics for the treatment and control groups differ. They also propose a test for equal pre-treatment dynamics.

The outcome variable here is either the total number of regulatory restrictions or total word counts in the CFR, by year, for the OCC and FDIC; we exclude the Federal Reserve given that there were many years when Part 217 generated no regulatory restrictions. As a treatment variable, we use a dummy variable that equals one if the CFR part equals 3 for the OCC, or 324 or 325 for the FDIC, and equals zero otherwise.[18] The assumption is that restrictions (or word counts) in the parts of the CFR that concern capital contribute to the total number of restrictions (or word counts), and not vice versa. As a post-treatment period, we use the period starting in 1989, when Basel I was finalized by US regulators. As an alternative, we estimate similar average treatment effects after replacing total regulatory restrictions with total word counts. Given that we do not reject the null hypothesis of

[18] The specification used to estimate the average treatment effects is, $y_{pt} = \beta_0 + \sum_{\tau=2}^{T} \delta_\tau d_{\tau,t} + \beta_1 Treat_{pt} + \sum_{\tau=2}^{T} \beta_\tau d_{\tau,t} Treat_{pt} + \varepsilon_{it}$, where β_τ is the coefficient estimate of interest. We estimate the model with standard errors clustered by CFR part. The sample used to estimate the models for the OCC have 1285 observations and 91 parts, and the R-Squared for the model applied to restrictions (word counts) equals 0.29 (0.45). The sample used to estimate the models for the FDIC have 1513 observations and 59 parts, and the R-Squared for the model applied to restrictions (word counts) equals 0.12 (0.21). While Mora and Reggio's method does not include fixed effects, the trends in the time dummy-treatment variable interaction terms whether or not we include fixed effects are often visually indistinguishable. In addition, the median difference between pooled OLS and fixed effects estimates as a fraction of the fixed effects interaction term estimates for OCC restrictions or word counts equals 0.01 and for FDIC restrictions or word counts equals 0.10 and 0.03, respectively.

equal pre-treatment dynamics, we report results for the post-treatment effects assuming parallel paths, together with the 95 percent confidence interval, from 1989–2017 in Figure 2.[19]

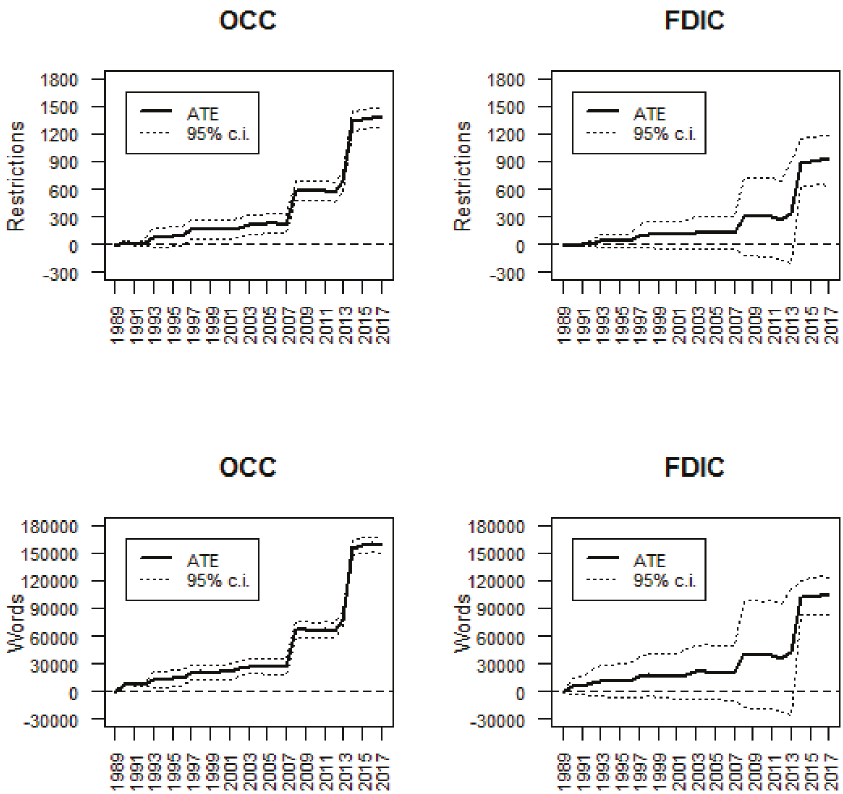

Figure 2. Average Treatment Effects of Bank Capital Requirements on Regulatory Restrictions and Word Counts Since Basel I, 1989–2017.

The figure shows that the CFR parts that concern capital requirements on average generate a substantial number of restrictions relative to all other parts. For instance, Part 3, on average, generated roughly 600 (1300) more regulatory restrictions and 70,000 (150,000) extra words than other parts under Basel II after 2007 (Basel III after 2013). For comparison, the other parts of the CFR for the OCC on average generated 55 restrictions (7000 words) after 2007 and over 65 restrictions (7000 words) after 2013. Basel II and Similarly, Parts 324 and 325 for the FDIC on average generated about 300 (900) more regulatory restrictions and 40,000 (100,000) extra words than other parts under Basel II after 2007 (Basel III after 2013). For comparison, the other parts of the CFR for the FDIC on average generated about 60 restrictions (6000–7000 words) after 2007 and over 100 restrictions (11,000 words) after 2013.

Beyond the added compliance costs, regulatory complexity also can have unintended consequences including opportunities for regulatory arbitrage, which have been observed by academics long before the 2007–2009 crisis (e.g., Merton (1995); Jones (2000); and, Brealey (2006)). Although the risk weights

[19] For OCC restrictions (word counts) the *p*-value for tests of the hypothesis of common pre-treatment dynamics equals 0.62 (0.21). For FDIC restrictions (word counts) the *p*-value for tests of the hypothesis of common pre-treatment dynamics equals 0.17 (0.47). Therefore, we report the parallel paths rather than parallel growth results.

have become much more complex since the introduction of Basel I, the basic framework—setting minimum capital requirements as a fraction of RWAs with risk weights assigned to asset categories—has remained the same. At the same time, Acharya et al. (2014, p. 38) argue that "risk weights are flawed measures of bank risks cross-sectionally as banks game their risk-weighted assets (cherry-pick on risky but low risk-weight assets) to meet regulatory capital requirements, which does not necessarily reduce economic leverage". Other studies find that non-risk-based measures of capital better predict bank stock returns or bank risk than risk-based measures (see Demirguc-Kunt et al. (2013); Hogan (2015); and, Hogan and Meredith (2016)). Moreover, Flannery (2014) observes that banks satisfied regulatory capital requirements, which rely on book values, while market valuations of capital plunged well below book values during the crisis; we examine such problems in more detail next.

3. Beyond US Basel Capital Regulations

3.1. US Prompt Corrective Action Requirements

In addition to the implementation of the Basel Capital Accords, US banks are subject to PCA requirements. The PCA regulatory regime was established pursuant to the Federal Deposit Insurance Corporation Improvement Act of December 1991 (FDICIA) and it became effective in December 1992.[20] The FDICIA requires insured depository institutions (IDIs) and federal banking regulators to take "prompt corrective action" to resolve capital deficiencies at IDIs.

Table 6 shows the old and new capital ratios that are associated with the different categories calling for the various regulatory actions to resolve capital deficiencies. The major change is that a stricter measure of capital (CET1) than the previous Tier 1 capital ratio was introduced by eliminating some components that had previously counted as capital. In addition, the associated ratios for the new measure as compared to the previous measure have been increased, at least for Tier 1 capital. The new PCA ratios became effective on 1 January 2015, for all banks. As Table 6 indicates, banks are placed into one of five categories depending on their leverage and risk-based capital (RBC) ratios. Well-capitalized banks are those banks that meet all five thresholds and are not subject to formal action to maintain a specific capital level. Banks that are less than well-capitalized are subject to increasingly stringent provisions to resolve capital deficiencies as their capital ratios decline. The regulatory authorities of banks that become critically undercapitalized must within 90 days appoint a receiver or take other such actions that would better serve the purposes of PCA (and review such actions every 90 days). Lastly, the standards for determining whether a BHC is well-capitalized are not established.

What has not changed is the "critically undercapitalized" category. This may continue to pose challenges to the effectiveness of PCA. Balla et al. (2017) show that the FDIC has been adhering to the PCA in the sense that the average amount of tangible capital relative to assets for failed banks increased from –2 percent in the 1986–1992 period to 1.4 percent in the 2007–2013 period. However, they also show that the costs of closure were higher during the latter period. Cole and White (2017) report that the FDIC estimated that the cost of closure during the most recent crisis equaled 23.8 percent of total assets and estimated that about 37 percent of the $49.8 billion costs of closure was due to delaying closure of weak banks. Cole and White (2017) suggest this may reflect problems in generally accepted accounting principles (GAAP) and also that a more effective PCA reform might focus on increasing provisions, so that banks do not overstate the book value of their capital or including non-performing assets in capital ratios.

[20] For the Federal Deposit Insurance Corporation Improvement Act (FDICIA) of 1991, see Public Law 102–242, 105 Stat. 2236. See also Balla et al. (2017) and Cole and White (2017) for a discussion.

Table 6. US Prompt Corrective Action (PCA), Old and New.

PCA Threshold	Old PCA Categories (IDIs) [a]			New PCA Categories (IDIs) [b]				
	Tier 1 Leverage (%)	Tier 1 RBC (%)	Total RBC (%)	Tier 1 Leverage (%)	Tier 1 Capital (%)	Common Equity Tier 1 RBC (%)	Total RBC (%)	Supplementary Leverage Ratio (AA/IDIs only)
Well capitalized	≥5.0	≥6.0	≥10.0	≥5.0	≥8	≥6.5	≥10.0	n/a
Adequately capitalized	≥4.0	≥4.0	≥8.0	≥4.0	≥6	≥4.5	≥8.0	≥3
Undercapitalized	<4.0	<4.0	<8.0	<4.0	<6	<4.5	<8.0	<3
Significantly undercapitalized	<3.0	<3.0	<6.0	<3.0	<4	<3.0	<6.0	n/a
Critically undercapitalized	tangible equity/total assets ≤ 2%							n/a

Note: AA = advanced approaches, IDI = insured depository institution, n/a = not applicable, RBC = risk-based capital. Tangible equity is Tier 1 capital plus non-Tier 1 perpetual preferred stock. Also, the supplementary leverage ratio becomes effective 1 January 2018. [a] See Federal Register 1992. [b] See Federal Register 2013. Additional source: Federal Deposit Insurance Corporation 2014, Regulatory Capital Interim Final Rule, https://fdic.gov/regulations/resources/director/RegCapIntFinalRule.pdf.

3.2. US Capital Planning and Stress Tests

Supervisory stress testing by banking regulators gained prominence during the banking crisis of 2007–2009. In particular, in 2009, banking supervisors conducted the Supervisory Capital Assessment Program (SCAP) to assess the largest bank holding companies' capital positions. SCAP presented two hypothetical macroeconomic scenarios, including one that was more adverse than what was expected for the US economy, for BHCs to use in estimating the impact on capital. The Federal Reserve publicly reported that 10 of the 19 BHCs that were included in SCAP did not meet the capital adequacy requirements under the adverse macroeconomic scenario. As a result, these BHCs were collectively required to add $185 billion in capital by the end of 2010 (Office of the Inspector General 2015).

Section 165(i) of the Dodd-Frank Act mandated an annual assessment by the Federal Reserve of BHCs with $50 billion or more in total consolidated assets, as well as smaller BHCs and nonbank financial institutions that are regulated by the Federal Reserve. This annual assessment includes two related programs: the Comprehensive Capital Analysis and Review (CCAR) and supervisory stress testing (DFAST).[21] These annual stress tests look at whether the BHCs have effective capital adequacy processes and sufficient capital to absorb losses during stressful conditions, while meeting obligations to creditors and counterparties and continuing to serve as credit intermediaries.

In late 2010, the Federal Reserve—acting in part in response to the statute—initiated the CCAR exercise. As part of the exercise, the Federal Reserve evaluates institutions' capital adequacy, their internal capital adequacy assessment processes, and their individual plans to make capital distributions, such as dividend payments or stock repurchases. More specifically, CCAR specifies four mandatory elements of a capital plan: (1) an assessment of the expected uses and sources of capital over the planning horizon that reflects the BHC's size, complexity, risk profile, and scope of operations, assuming both expected and stressful conditions; (2) a detailed description of the BHC's process for assessing capital adequacy; (3) the BHC's capital policy; and, (4) a discussion of any baseline changes to the BHC's business plan that are likely to have a material impact on the BHC's capital adequacy or liquidity.[22]

The Federal Reserve has conducted CCAR annually since its inception in 2010 for the largest BHCs. For the CCAR 2015 exercise, the Federal Reserve issued instructions on 17 October 2014, and received capital plans from 31 BHCs on 5 January 2015. Table 7 shows the banks participating in CCAR in 2015 as well as the required capital ratios. The 31 BHCs that are part of this CCAR held more than 80 percent of the total assets of all US BHCs, or $14 trillion as of the fourth quarter of 2014. The Federal Reserve reported that, in 2015, for the first time, no participating bank fell below the quantitative benchmarks that must be met in CCAR after some BHCs made onetime downward adjustments to their planned capital distributions or redemptions. However, the Federal Reserve did object to Santander's CCAR 2015 capital plan on qualitative grounds because of widespread and critical deficiencies across the BHC's capital planning processes. The Federal Reserve also objected on qualitative grounds to the capital plan of Deutsche Bank Trust Corporation because of numerous and significant deficiencies across its risk-identification, measurement, and aggregation processes; approaches to loss and revenue projection; and, internal controls (Board of Governors of the Federal Reserve System 2015).

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[21] For the final rule for supervisory guidance on banking organizations with greater than $10 billion in total consolidated assets, see Federal Register 2012f. For the OCC's annual stress test final rule, see Federal Register 2012c. For the FDIC's annual stress test final rule, see Federal Register 2012b. For the Fed's final rule for supervisory and company-run stress tests, see Federal Register 2012e. For the Fed's final rule for company-run stress tests for banking organizations with greater than $10 billion in total consolidated assets, see Federal Register 2012a.

[22] See Board of Governors of the Federal Reserve System (2012).

Table 7. Comprehensive Capital Analysis and Review (CCAR) 2015 Bank Holding Companies (BHCs) and Applicable Minimum Capital Ratios.

Advanced-Approaches BHCs in CCAR 2015			
American Express Company (NYC, NY, USA)	Bank of America Corporation (CHARLOTTE, NC, USA)	Bank of New York Mellon Corporation (NYC, NY, USA)	Capital One Financial Corporation (NYC, NY, USA)
Citigroup Inc. (NYC, NY, USA)	Goldman Sachs Group Inc. (NYC, NY, USA)	HSBC North America Holdings Inc. (NYC, NY, USA)	JPMorgan Chase & Co. (NYC, NY, USA)
Morgan Stanley (NYC, NY, USA)	Northern Trust Corporation (CHICAGO, IL, USA)	PNC Financial Services Group Inc. (PITTSBURGH, PA USA)	State Street Corporation (BOSTON, MA, USA)
U.S. Bancorp (PORTLAND, OR, USA)	Wells Fargo & Co. (SAN FRANCISCO, CA, USA)		
Other BHCs for CCAR 2015			
Ally Financial Inc. (DETROIT, MI, USA)	BB&T Corporation (WINSTON SALEM, NC, USA)	BBVA Compass Bancshares Inc. (BIRMINGHAM, AL, USA)	BMO Financial Corp. (WILMINGTON, DE, USA)
Citizens Financial Group Inc. (NEWHAVEN, MO, USA)	Comerica Incorporated (DALLAS, TX, USA)	Deutsche Bank Trust Corporation (NYC, NY, USA)	Discover Financial Services (RIVERWOODS, IL, USA)
Fifth Third Bancorp (CINCINNATI, OH, USA)	Huntington Bancshares Incorporated (COLUMBUS, OH, USA)	KeyCorp (ALBANY, NY, USA)	M&T Bank Corporation (BUFFALO, NY, USA)
MUFG Americas Holdings Corporation (NYC, NY, USA)	Regions Financial Corporation (BIRMINGHAM, AL, USA)	Santander Holdings USA Inc. (BOSTON, MA, USA)	SunTrust Banks Inc. (ATLANTA, GA, USA)
Zions Bancorporation (SALT LAKE CITY, UT, USA)			
Minimum capital ratios in CCAR 2015 (%)			
	2014:Q4 advanced-approaches BHCs	2014:Q4 other BHCs	2015–2016 all BHCs
Tier 1 common ratio	5	5	5
Common equity Tier 1 ratio	4	not applicable	4.5
Tier 1 risk-based capital ratio	5.5	4	6
Total risk-based capital ratio	8	8	8
Tier 1 leverage ratio	4	3 or 4	4

Source: Board of Governors of the Federal Reserve System, "Comprehensive Capital Analysis and Review 2015: Assessment Framework and Results", March 2015, available from https://www.federalreserve.gov/newsevents/press/bcreg/bcreg20150311a1.pdf.

DFAST—a complementary exercise to CCAR—is a forward-looking quantitative evaluation of the effect of stressful economic and financial market conditions on a bank's capital. In 2012, the Federal Reserve finalized the rules that implement the stress test requirements under the Dodd-Frank Act.[23] All BHCs and IDIs with $10 billion or more in total consolidated assets are required to conduct an annual company-run stress test.[24] BHCs with assets greater than $50 billion must conduct semiannual company-run stress tests and they also are subject to stress tests conducted by the Federal Reserve.

[23] See Federal Reserve System, Federal Register 2012e.
[24] As of June 30, 2016, there were 112 IDIs (1.9 percent of all IDIs) with $10 billion or more in assets and they accounted for $13,540 billion in assets (81.9 percent of the assets of all IDIs) (see FDIC Quarterly Banking Profile, Second Quarter 2016).

The company-run tests must include three scenarios, and the institutions must publish a summary of the results. The estimated losses resulting from these tests are then subtracted from a bank's capital to determine the financial buffer that a bank has to insulate itself from shocks and losses. A bank effectively fails the tests if its capital falls below a required minimum level after the theoretical losses.

While DFAST is complementary to CCAR, both efforts are distinct testing exercises that rely on similar processes, data, supervisory exercises, and requirements. However, there are important differences between the two exercises. For CCAR, the Federal Reserve uses BHCs' planned capital actions and assesses whether a BHC would be capable of meeting supervisory expectations for minimum capital levels, even if stressful conditions emerged and the BHC did not reduce planned capital distributions. By contrast, for DFAST, the Federal Reserve uses a standardized set of assumptions that are specified in the Dodd-Frank Act stress test rules. DFAST is therefore far less detailed and less tailored to a specific BHC.

The requirements, expectations, and activities relating to DFAST and CCAR do not apply to any banking organizations with assets of $10 billion or less. In particular, community banks are not required or expected to conduct the enterprise-wide stress tests that are required of larger organizations under the capital plan rule, the rules implementing the Dodd-Frank Act stress testing requirements, or the procedures described in the stress testing guidance for organizations with more than $10 billion in total consolidated assets. As noted, BHCs with $10 to $50 billion in assets are only subject to firm-run stress tests for DFAST.

Stress testing requirements are a risk-assessment supervisory tool. The goal of stress tests conducted under the Dodd-Frank Act is to provide forward-looking information to supervisors to assist in their overall assessments of a bank's capital adequacy and to aid in identifying downside risks and the potential impact of adverse outcomes on the covered bank. Further, these stress tests support ongoing improvement in a bank's internal assessments of capital adequacy and overall capital planning. Yet, according to the Office of Inspector General of the Federal Reserve, "the Federal Reverse's Model Validation Unit does not currently conduct a formal assessment of the expertise required to validate each model or maintain an inventory to track the skills and expertise of reviewers".[25] Furthermore, as evidence of additional problems at the Federal Reserve, "[T]he governance review findings include…a shortcoming in policies and procedures, insufficient model testing, insufficient planning and procedures to address the risks posed by potential key-personnel departures, and incomplete structures and information flows to ensure proper oversight of model risk management". These and other types of problems, such as a lack of transparency and forced homogeneity, call the usefulness of DFAST into question.[26]

On the positive side, CCAR and DFAST may induce banks to have more capital than they would if they were subject only to the traditional capital requirements. As a result of the stress tests and other post-crisis measures, banks may have become less susceptible to financial distress, but at the same time, to the extent that such measures have associated compliance costs, they may have affected lending decisions, especially to smaller firms (see Chen et al. (2017)).

4. Not All Capital Ratios Are Equally Informative: Actual Capital Ratios Compared to Required Minimum Capital Ratios

A number of recent academic studies suggest that a simple equity to asset leverage ratio equal to roughly 15 percent would have benefits that are associated with reducing the effects of financial stability that equal or exceed costs associated with implementing the regulation (see Karmakar (2016); Begenau and Landvoigt (2017); Egan et al. (2017); Barth and Miller (2018)). On the other hand,

At the same time, there were 97 BHCs (2.3 percent of all BHCs) with $10 billion or more in assets and they accounted for $15,386 billion in assets (93 percent of the assets of all BHCs).

25 See Office of the Inspector General 2015, pp. 9, 11.

26 Herring (2016, 2018) observes that eliminating DFAST alone would simplify capital requirements for US GSIBs.

nearly all the capital adequacy guidelines set by BCBS are based on a bank's risk-weighted assets. In this section, we provide evidence that the various capital ratios imposed on banks are not equally informative about whether a bank is adequately capitalized.

The analysis proceeds by comparing the actual capital ratios to the required minimum capital ratios for some of the largest banks in the United States for every year over the period 2000–2017Q3. There are four such capital ratio comparisons: (1) the actual risk-based Tier 1 capital ratio is compared to the required minimum ratio of 4 percent from 2000 to 2012, 4.5 percent in 2013, 5.5 percent in 2014, and 6 percent in 2015 to 2017; (2) the actual risk-based total capital ratio is compared to the required minimum ratio of 8 percent; (3) the actual non-risk-based leverage ratio is compared to the minimum required ratio of 4 percent; and, (4) the actual non-risk-based tangible common equity ratio is compared to a (hypothetical) required minimum tangible common equity ratio of 4 percent. We also provide two other ratios that furnish an additional perspective on the four ratios just mentioned. These are the ratio of RWAs to total assets and the ratio of market capitalization to tangible common equity. The lower the former ratio, the less risk-based capital required, and in the latter case, a ratio greater than 1 indicates the market values a bank more than the book values indicate. Information is also provided about the averages and standard deviations for the different variables included in each of the tables as well as information about the number of banks with capital deficiencies or market-to-book values less than 1.

The calculations are made for six of the eight GSIBs and twelve other large banks with total assets greater than $50 billion, with the banks in every Appendix table ranked by asset size. Table A1 in the Appendix A shows the percentage by which the actual risk-weighted Tier 1 capital ratio exceeds the required minimum Tier 1 capital ratios for the eighteen banks from 2000 to the third quarter of 2017. All of the percentages are positive, which means that all the banks had capital buffers, or actual capital ratios, that exceeded the required minimum ratios. It is noteworthy that every bank's minimum capital buffer occurs in 2007 or earlier, while the maximum ratio occurs in 2009 or later. For nine of the eighteen banks, the minimum capital buffer occurs in 2007, which was in the midst of the banking crisis and the year before the bailout of the largest banks. Small banks were also bailed out, mainly in 2009. On the eve of the bailout, these banks more than satisfied their required minimum capital ratios. By 2015, moreover, all of the banks had more than met the new and higher capital requirement of 8.5 percent—6 percent plus the capital conservation buffer of 2.5 percent—applicable beginning in 2019.

The situation is quite similar for the risk-weighted total capital ratio, as shown in Table 2 in the Appendix A. For every bank, the actual ratio exceeds the required minimum ratio, and by more than a trivial percentage, in each year. Importantly, just as in the case of Tier 1 capital, every bank had a positive capital buffer during 2007–2008, even though the United States was suffering the worst financial crisis since the Great Depression and it was in the midst of a severe recession. By 2015, moreover, all of the banks had sufficient capital to satisfy the minimum total capital ratio plus the capital conservation buffer of 10.5 percent.

To better understand how these banks' capital positions were changing over time, it is useful to look at the ratio of RWAs to total assets. Table 3 in the Appendix A presents this ratio in percentage terms for the eighteen banks for the years 2000–2017. Risk weighting makes it easier to exceed minimum capital ratios by lowering the total assets against which capital requirements are applied. The vast majority of the percentages in Table 3 are less than 100 percent because of the type of assets the banks have chosen to hold. After the risk-weighting formula is applied, almost all the banks' asset totals are less than the actual amount of assets. For example, for Citigroup, the ratio was 72 percent in 2000, and then trended downwards to a low of 51 percent in both 2008 and 2010. In the following two years, the ratio barely increased to 52 percent before increasing thereafter. In the two years when the ratio of risk-weighted assets to total assets was 51 percent, Citigroup did not need to have capital to back 49 percent of its assets. The decline in RWAs relative to total assets enabled the Tier 1 and total capital ratios to be higher with the same amount of capital then otherwise.

Table 4 in the Appendix A shows the actual non-risk-based leverage ratio minus the required minimum leverage ratio. All the capital buffers are positive. However, in contrast to Tables 2 and A1, the percentages for most of the banks' capital buffers are smaller. In particular, the three largest banks had the smallest capital buffers in any year over the entire period, with the exception of BNY Mellon, State Street, and BB&T. In 2007, the figures were 2.00 percent for JPMorgan Chase, 1.04 percent for Bank of America, and 0.03 percent for Citigroup.

Another non-risk-based capital ratio is the tangible common equity ratio. Table 5 in the Appendix A shows the actual tangible common equity ratio minus a (hypothetical) required minimum tangible common equity ratio of 4 percent. This particular ratio, in which the numerator is based on the actual owner-contributed common equity less the actual intangible assets of a bank, is tangible common equity divided by tangible assets. The benefits of this measure lie in the fact that (1) it is less susceptible to guesswork or questionable manipulation, (2) market participants paid more attention to it than to other measures during the recent banking crisis, and (3) it is highly correlated to a market-value measure of capital. Regarding the latter point, based on the data for the banks in the Appendix tables, the correlation coefficient between tangible common equity capital and the market value of capital is 0.84 and it is highly statistically significant. Unlike Tables 2–4 and A1, Table 5 contains quite a few negative percentages, as denoted by the cells with numerical values in parentheses. Moreover, in 2008, if tangible common equity had been the required capital measure for the minimum leverage ratio, nine banks would not have had enough capital to meet this minimum ratio.[27] In 2007, one year before the bank bailout, neither Bank of America nor Citigroup would have met such a ratio. All of these banks received capital injections from the federal government. Importantly, according to Demirguc-Kunt et al. (2013), it is found that "the relationship between stock returns and capital is stronger when capital is measured by the leverage ratio rather than the risk-adjusted capital ratio ... [and] higher quality forms of capital, such as ... tangible common equity, [was] more relevant". In addition, Haldane (2012) points out that in terms of "pre-crisis predictive power ... [m]easures of risk-weighted capital are statistically insignificant, while the leverage ratio is significant at the 1% level". He adds that "[u]sing different methods and samples, other studies support the predictive superiority, or at least equivalence, of leverage over capital ratios (International Monetary Fund (2009); Demirguc-Kunt et al. (2013); Estrella et al. (2000))".

Table 6 in the Appendix A presents the market capitalization to actual tangible common equity ratios for the eighteen banks.[28] A ratio greater than 1 means the market value of a bank is greater than indicated by its book value. The table shows that every bank had a ratio greater than 1 in every year from 2000 to 2006. In 2008 and 2009, during the midst of the banking crisis, nine banks had ratios less than 1. The three largest banks had ratios less than 1 in 2008, while two of these banks also have ratios less than 1 in 2009. In the latter year, JPMorgan had a ratio of 1.04. During the period 2009 to 2017, only six banks had ratios that were greater than 1 every year, and those same banks also had ratios greater than 1 throughout the entire period from 2000 to 2017. Moreover, three of the banks—Bank of America, Citigroup, and Regions—had ratios less than 1 every year from 2008 to 2015.

As noted earlier, the data regarding capital ratios clearly indicate that whether banks have too little or excess capital depends on the specific capital ratio on which one focuses and whether the capital ratio is risk-based or not. Some of the ratios may indicate that a bank has sufficient capital to

[27] It should be noted that BNY Mellon would not have had enough capital to meet this minimum ratio from 2007 to 2017Q3. However, BNY Mellon is a large custodial bank that provides investment management, investment services and wealth management that help institutions and individuals succeed in markets all over the world. Given its business model that is quite unique, this lack of capital posed no significant risk. Indeed, in February 2009, it was one of only three of the nation's 19 largest banks that when stress-tested would be profitable in 2010 (see http://archive.fortune.com/2009/07/23/news/companies/tarp_banks_new_york_mellon.fortune/index.htm). In 2013, stress tests indicated it was the bank least affected by hypothetical extreme economic scenarios among banks tested (see https://www.americanbanker.com/news/fed-unveils-dodd-frank-stress-test-results).

[28] A referee points out that the advantage of market based indicators is that they may incorporate risk increase faster and on a continuous basis respect to accounting based measures that can only be updated quarterly and with a significant time lapse. It is added, however, that market based ratios tend to also reflect all the noise and irrational recurrent market dynamics (plus they are available only for listed banks with a liquid market).

satisfy regulatory requirements, whereas other ratios may indicate that there is a deficiency in capital. This means that a higher regulatory capital ratio being imposed on banks may or may not affect bank behavior. To determine the outcome, one must know the specific ratio that regulators choose to increase. Importantly, in the aggregate, the market reveals that all ratios are not equally revealing about a bank's actual capital adequacy, as market participants pay more attention to some ratios than others when assessing whether a bank is adequately capitalized. Indeed, according to Graeme Wearden of The Guardian, the tangible common equity ratio ... takes a more conservative view than other measures, such as Tier 1 capital ratios, and has become an increasingly important way of assessing the banking sector as the financial crisis ... [in 2007–2008] deepened.[29] Elliott (2010)[30], moreover, states that "[c]ommon stock investors, who have the lowest repayment priority, have focused intensely at times during the recent financial crisis on the most conservative measure, tangible common equity". He adds that " ... investors recognize that they [intangible assets] are particularly difficult to turn into cash in a crisis and that they can lose value if a bank's overall franchise deteriorates. For this reason, many investors prefer to treat them as worthless when evaluating capital adequacy. Such investors focus on tangible common equity".[31]

5. Concluding Comments

Bank regulatory standards have been a work in progress in countries around the world. They have changed several times in recent decades, and most significantly in response to the last banking crisis. They have become ever more stringent and complex for banks of all sizes, but especially for the largest banks. This is certainly the case in the United States. In addition to the legally mandated actions that banking regulators are required to take as a bank's capital declines below specified minimum levels, regulators now subject the larger banks to new comprehensive capital analyses and supervisory stress. Yet, it is not clear whether regulators took appropriate actions in a timely manner to lessen the severity of the most recent banking crisis, nor whether the more extensive analyses and testing contribute to a safer and sounder banking system.

What is clear is that understanding what counts as capital and how capital requirements vary for banks of different asset sizes and business models has become mind-boggling, to say the least. Most importantly, our comparison of various actual capital ratios to the required minimum ratios for a select and important group of banks is quite revealing. The differences found demonstrate the lack of any clear message about whether a bank is or is not adequately capitalized.[32]

Whether banks have too little capital or excess capital depends on the specific required capital ratio on which one focuses and whether the required capital ratio is risk-based or non-risk-based. Some ratios indicate a bank has sufficient capital; other ratios indicate the opposite. Of course, bank supervisors may prefer a regulatory regime with several binding capital ratios, including risk-weighted and unweighted ratios, based on their view that there is no unique ratio that can always help guard against effective risk.

Nonetheless, this situation contributes to confusion, and simply adding more capital requirements is not the way to promote a safer and sounder banking system. Indeed, in 2000, only three different regulatory capital requirements were imposed on banks, two of which were risk-based. However, today there are seven such requirements, six of which are risk-based. These include Tier 1 capital ratio, total capital ratio, leverage ratio (non risk-based), CET1 capital ratio, capital conservation buffer, countercyclical capital buffer, and capital surcharge for GSIBs. While beyond the scope of this review,

[29] See https://www.theguardian.com/business/2009/feb/24/businessglossary-banking.

[30] In 2016 Douglas Elliott was the lead author of a 150-page study analyzing the impacts of the Basel reforms, building on a similar paper from several years earlier for the IMF.

[31] Also, Haldane (2012) states that "[m]ore than half of all investors do not understand or trust banks' risk weights ... ". He adds that "Their multiplicity and complexity have undermined transparency and, with it, market discipline".

[32] As a referee pointed out, the lack of any clear message may be better appreciated by comparing the evolution of a bank's capital ratio with its ratings. Given the current length of this paper, this exercise is left for another time.

instead of the existing complexity in the regulatory capital requirements, it may be better to focus to a far greater degree on a simpler, tangible equity leverage ratio as an appropriate capital requirement.[33] This ratio is fairly straightforward and easily understood by market participants. In contrast, too much of a focus on the currently constructed risk-based capital ratios has all too often been misleading with respect to whether banks were adequately capitalized. More generally, financial stability depends on not just an appropriate capital ratio, but other regulatory and supervisory factors that are well beyond the scope of this review.

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33 For a discussion of the appropriate level of the regulatory capital ratio that takes into account the risk of a systemic banking crisis, see for example Karmakar (2016), Begenau and Landvoigt (2017), Egan et al. (2017), Barth and Miller (2018) and references therein. It should also be noted that a referee indicated that in the supervisory risk assessment process a bank's specific risk factors could and should be taken into account so that the capital requirement could be set and measured in terms of a simple indicator such as the leverage ratio.

Appendix A. Data Tables

Table A1. Actual Tier 1 Capital Ratio Minus Required Minimum Tier 1 Capital Ratios.

	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017Q3
Minimum requirement	4.00	4.00	4.00	4.00	4.00	4.00	4.00	4.00	4.00	4.00	4.00	4.00	4.00	4.50	5.50	6.00	6.00	6.00
JPMorgan	4.50	4.29	4.24	4.50	4.70	4.50	4.70	4.40	6.90	7.10	8.10	8.30	8.60	7.40	6.10	7.70	8.20	8.30
Bank of America	3.50	4.30	4.22	3.85	4.20	4.25	4.64	2.87	5.15	6.40	7.24	8.40	8.89	7.94	7.60	6.90	7.60	8.00
Citigroup	4.38	4.42	4.47	4.91	4.74	4.79	4.59	3.12	7.92	7.67	8.91	9.55	10.06	9.20	7.60	9.49	9.84	9.30
Wells Fargo	3.29	2.99	3.60	4.42	4.41	4.26	4.95	3.59	3.84	5.25	7.16	7.33	7.75	7.83	6.95	7.03	6.82	7.95
U.S. Bancorp	3.20	3.70	4.00	5.20	4.60	4.20	4.80	4.30	6.60	5.60	6.50	6.80	6.80	6.70	5.80	5.10	5.00	5.10
BNY Mellon	4.60	4.11	3.58	3.44	4.31	4.38	4.19	5.32	9.30	8.10	9.40	11.00	11.10	11.70	6.70	6.30	6.60	8.60
PNC	4.60	3.80	4.80	5.50	5.00	4.30	6.40	2.80	5.70	7.40	8.10	8.60	7.60	7.90	7.10	6.00	6.00	5.60
State Street	10.50	9.60	13.10	10.00	9.30	7.70	9.70	7.20	16.30	13.70	16.50	14.80	15.10	12.80	9.20	9.90	8.70	8.50
BB&T	5.70	5.80	5.20	5.33	5.20	5.30	5.00	5.10	8.30	7.50	7.80	8.50	6.50	7.30	6.90	5.80	6.00	5.80
SunTrust	3.09	4.02	3.47	3.85	3.16	3.01	3.72	2.93	6.87	8.96	9.67	6.90	7.13	6.31	5.30	4.80	4.28	4.74
Fifth Third	9.02	8.36	7.70	6.94	6.31	4.38	4.39	4.50	6.59	9.31	9.94	7.91	6.65	5.86	5.33	4.93	5.50	5.72
Regions	5.14	5.66	4.98	5.72	5.04	4.60	4.00	3.29	6.38	7.54	8.40	9.28	8.00	7.10	7.04	5.70	5.90	6.10
Northern Trust	5.79	6.88	7.13	7.10	7.00	5.70	5.80	5.70	9.10	9.40	9.60	8.50	8.80	8.90	7.70	6.50	7.70	8.60
M&T	3.49	3.37	4.02	3.30	3.31	3.56	3.74	2.84	4.83	4.59	5.47	5.67	6.22	7.50	6.97	6.68	5.92	6.25
KeyCorp	3.72	3.43	3.74	4.35	3.22	3.59	4.24	3.44	6.92	8.75	11.16	8.99	8.15	7.46	6.40	5.36	4.89	5.11
Comerica	3.52	3.98	4.08	4.72	4.77	4.46	4.02	3.51	6.66	8.46	6.13	6.37	6.14	6.14	5.00	4.54	3.89	5.51
Huntington	3.19	3.24	4.69	4.53	5.08	5.13	4.93	3.51	6.72	8.03	7.55	8.11	8.01	7.78	6.00	4.53	4.90	5.30
Zions	4.53	4.25	5.26	5.42	5.35	3.52	3.98	3.57	6.22	6.53	10.78	12.13	9.38	8.27	8.97	8.08	7.49	7.33
Average ratio	4.76	4.79	5.13	5.17	4.98	4.54	4.88	4.00	7.24	7.79	8.80	8.73	8.38	8.01	6.81	6.41	6.40	6.77
Standard deviation	2.02	1.82	2.30	1.59	1.45	1.03	1.39	1.19	2.65	2.01	2.48	2.17	2.15	1.78	1.16	1.58	1.61	1.52
Number of banks with capital shortfall	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Number of banks reporting excess capital	18	18	18	18	18	18	18	18	18	18	18	18	18	18	18	18	18	18

Note: The required minimum Tier 1 capital ratio was 4 percent from 2000 to 2012, 4.5 percent in 2013, 5.5 percent in 2014, and 6 percent in 2015, 2016 and 2017.

Table 2. Actual Total Capital Ratio Minus Required Minimum Total Capital Ratio of 8 Percent.

	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017Q3
Minimum requirement	8.00	8.00	8.00	8.00	8.00	8.00	8.00	8.00	8.00	8.00	8.00	8.00	8.00	8.00	8.00	8.00	8.00	8.00
JPMorgan	4.00	3.88	3.95	3.80	4.20	4.00	4.30	4.60	6.80	6.80	7.50	7.40	7.30	6.30	5.10	8.00	8.40	8.40
Bank of America	3.04	4.67	4.43	3.87	3.73	3.08	3.88	3.02	5.00	6.66	7.77	8.75	8.31	7.44	6.60	7.70	8.30	8.50
Citigroup	3.23	2.92	3.25	4.04	3.85	4.02	3.65	2.70	7.70	7.25	8.59	8.99	9.26	8.68	6.53	10.54	11.08	10.54
Wells Fargo	2.43	2.45	3.31	4.21	4.07	3.64	4.50	2.68	3.83	5.26	7.01	6.76	6.63	7.43	7.53	7.45	8.08	9.28
U.S. Bancorp	2.60	3.70	4.40	5.60	5.10	4.50	4.60	4.20	6.30	4.90	5.30	5.30	5.10	5.20	5.60	5.10	5.20	5.20
BNY Mellon	4.92	3.57	3.96	3.49	4.21	4.48	4.49	5.25	9.10	8.00	8.30	9.00	8.40	9.00	4.50	4.50	5.00	7.60
PNC	4.57	3.80	4.50	5.80	5.00	4.10	5.50	2.30	5.20	7.00	7.60	7.80	6.70	7.80	7.90	6.70	6.30	5.70
State Street	7.60	6.50	10.00	7.80	6.70	6.00	7.90	4.70	13.60	11.10	14.00	12.50	12.60	11.70	8.60	9.40	8.00	7.60
BB&T	4.20	5.30	5.40	4.43	6.50	6.40	6.30	6.20	9.40	7.80	7.50	7.70	5.40	6.30	6.90	6.30	6.10	5.90
SunTrust	2.85	4.18	3.62	3.75	2.36	2.57	3.11	2.30	6.04	8.43	8.54	5.67	5.48	4.81	4.51	4.54	4.26	4.69
Fifth Third	6.76	6.42	5.51	5.38	4.31	2.45	3.07	2.16	6.78	9.48	10.14	8.09	6.42	6.08	6.33	6.13	7.02	7.16
Regions	3.40	5.23	5.84	6.46	5.51	4.76	3.54	3.25	6.64	7.78	8.35	8.99	7.38	6.70	7.26	5.90	6.10	6.20
Northern Trust	4.85	6.25	6.13	6.00	5.30	4.30	3.90	3.90	7.40	7.80	7.60	6.20	6.30	7.80	7.00	6.20	7.10	8.40
M&T	3.19	2.72	3.20	3.20	2.91	2.85	3.78	3.18	4.83	4.30	5.08	5.26	5.39	7.07	7.21	6.92	6.09	6.87
KeyCorp	3.48	3.41	4.11	4.57	3.47	3.47	4.43	3.38	6.82	8.95	11.12	8.51	7.13	6.33	5.89	4.97	4.85	5.09
Comerica	3.58	3.70	3.76	4.71	4.75	3.75	3.63	3.20	6.72	8.93	6.54	6.25	2.10	5.05	4.54	4.69	5.27	5.65
Huntington	2.46	2.29	3.60	3.95	4.48	4.42	4.79	2.85	5.91	6.41	6.46	6.77	6.51	6.57	5.56	4.64	5.05	5.39
Zions	2.83	4.20	4.94	5.52	6.05	4.23	4.29	3.68	6.32	5.28	9.15	10.06	2.96	6.67	8.27	8.12	7.24	6.99
Average ratio	3.89	4.18	4.66	4.81	4.58	4.06	4.43	3.53	6.91	7.34	8.14	7.78	6.63	7.05	6.44	6.54	6.64	6.95
Standard deviation	1.43	1.31	1.61	1.21	1.16	1.03	1.18	1.10	2.16	1.74	2.09	1.84	2.31	1.63	1.28	1.74	1.70	1.62
Number of banks with capital shortfall	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Number of banks reporting excess capital	18	18	18	18	18	18	18	18	18	18	18	18	18	18	18	18	18	18

Table 3. Risk-Weighted Assets as a Percentage of Total Assets.

	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017Q3
JPMorgan	62	66	60	66	68	71	69	67	57	59	55	54	54	58	63	62	59	58
Bank of America	84	81	79	78	71	70	72	71	73	69	64	60	55	62	60	65	54	62
Citigroup	72	66	63	59	57	59	56	57	51	59	51	52	52	58	70	66	63	61
Wells Fargo	81	85	81	79	81	80	85	84	84	82	78	77	76	75	74	72	69	66
U.S. Bancorp	97	95	90	84	87	88	89	89	87	84	80	80	81	82	79	81	80	79
BNY Mellon	–	36	34	30	78	78	75	61	49	50	41	31	31	30	44	41	44	43
PNC	89	85	87	84	81	83	84	83	86	86	82	85	85	85	82	82	82	82
State Street	36	40	32	39	42	48	44	45	40	43	37	33	32	33	39	41	41	46
BB&T	71	72	72	73	73	74	75	75	72	71	75	69	74	75	77	79	80	80
SunTrust	93	96	92	91	86	88	89	92	86	80	77	75	78	85	85	86	86	85
Fifth Third	80	84	81	82	88	93	102	104	94	89	90	90	90	89	85	86	84	83
Regions	75	74	75	76	77	81	81	82	79	73	72	72	76	83	83	84	82	82
Northern Trust	70	65	69	67	67	64	65	66	62	59	61	57	60	57	57	63	55	–
M&T	84	85	84	88	86	86	87	86	56	61	57	92	92	86	80	77	82	–
KeyCorp	96	103	101	100	106	109	110	111	102	92	85	87	89	90	91	95	89	86
Comerica	85	116	113	113	117	121	122	120	108	104	111	104	102	99	99	97	93	94
Huntington	94	98	99	92	91	90	88	84	86	84	81	84	85	84	82	82	78	77
Zions	73	79	80	84	87	88	92	90	94	100	84	81	79	81	80	78	79	78
Average ratio	78.94	79.22	77.33	76.94	80.17	81.72	82.50	81.50	75.89	74.72	71.17	71.28	71.72	72.89	73.89	74.28	72.22	72.63
Standard deviation	15.02	20.24	20.86	19.94	16.86	17.01	18.52	18.92	19.51	17.11	18.45	19.94	20.13	19.29	15.75	15.67	15.72	14.85
Number of banks with risk-weigthed assests more than total assets	0	2	2	1	2	2	3	3	2	1	1	1	1	0	0	0	0	0
Number of banks with risk-weigthed assests less than total assets	17	16	16	16	16	16	15	15	16	16	17	17	17	18	18	18	18	16

Note: The ratios for Fifth Third, KeyCorp, and Comerica exceed 100 percent because of off-balance-sheet items.

Table 4. Actual Leverage Ratio Minus Required Minimum Leverage Ratio of 4 Percent.

	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017Q3
Minimum requirement	4.00	4.00	4.00	4.00	4.00	4.00	4.00	4.00	4.00	4.00	4.00	4.00	4.00	4.00	4.00	4.00	4.00	4.00
JPMorgan	1.40	1.17	1.06	1.60	2.20	2.30	2.20	2.00	2.90	2.90	3.00	2.80	3.10	3.10	3.60	4.50	4.40	4.40
Bank of America	2.12	2.56	2.29	1.73	1.89	1.91	2.36	1.04	2.44	2.91	3.21	3.53	3.37	3.86	5.60	4.60	4.90	5.00
Citigroup	1.97	1.64	1.49	1.56	1.20	1.35	1.16	0.03	2.08	2.89	2.60	3.19	3.48	4.20	5.03	6.18	6.09	5.64
Wells Fargo	2.49	2.25	2.58	2.93	3.08	2.99	3.89	2.83	10.52	3.87	5.19	5.03	5.47	5.60	5.45	5.37	4.95	5.27
U.S. Bancorp	3.70	3.70	3.70	4.00	3.90	3.60	4.20	3.90	5.80	4.50	5.10	5.10	5.20	5.60	5.30	5.30	5.00	5.10
BNY Mellon	3.49	2.70	2.48	1.82	2.41	2.60	2.67	2.53	2.90	2.50	1.80	1.20	1.30	1.40	1.60	2.00	2.60	2.80
PNC	4.03	2.80	4.10	4.20	3.60	3.20	5.30	2.20	13.50	6.10	6.20	7.10	6.40	7.10	6.80	6.10	5.80	5.90
State Street	1.40	1.40	1.60	1.60	1.50	1.60	1.80	1.30	3.80	4.50	4.20	3.30	3.10	2.90	2.40	2.90	2.50	3.40
BB&T	3.30	3.20	2.90	3.15	3.10	3.20	3.20	3.20	5.90	4.50	5.10	5.00	4.20	5.30	5.90	5.80	6.00	5.90
SunTrust	2.98	3.94	3.30	3.37	2.64	2.65	3.23	2.90	6.45	6.90	6.94	4.75	4.91	5.58	5.64	5.67	5.22	5.50
Fifth Third	6.77	6.53	5.73	5.11	4.89	4.08	4.44	3.72	6.27	8.43	8.79	7.10	6.05	5.64	5.66	5.54	5.90	5.97
Regions	2.90	3.41	2.92	3.49	3.47	3.42	4.30	2.66	4.47	4.90	5.30	5.91	5.65	6.10	6.86	6.40	6.10	6.20
Northern Trust	2.91	3.93	3.76	3.60	3.60	3.10	2.70	2.80	4.50	4.80	4.80	3.30	4.20	3.90	3.80	3.50	4.00	4.00
M&T	2.66	2.55	3.05	2.98	2.73	2.94	3.20	2.59	4.35	4.43	5.33	5.28	6.07	6.78	6.17	6.89	5.99	6.35
KeyCorp	3.71	3.65	4.16	4.55	3.96	4.53	4.98	4.39	7.05	7.72	9.02	7.79	7.41	7.11	7.26	6.71	5.90	5.83
Comerica	4.90	5.36	5.30	6.13	6.37	5.99	5.76	5.26	7.77	9.25	7.26	6.92	6.52	6.82	6.44	6.22	6.18	6.87
Huntington	2.93	3.41	4.89	3.98	4.42	4.34	4.00	2.77	5.82	6.09	5.41	6.28	6.47	6.67	5.74	4.79	4.70	4.96
Zions	2.38	2.56	3.56	4.06	4.31	4.16	3.86	3.37	5.99	6.38	8.56	9.40	6.96	6.48	7.82	7.26	7.09	6.58
Average ratio	3.11	3.15	3.27	3.33	3.29	3.22	3.51	2.75	5.70	5.20	5.43	5.17	4.99	5.23	5.39	5.32	5.18	5.32
Standard deviation	1.28	1.32	1.28	1.31	1.28	1.14	1.24	1.22	2.86	1.98	2.09	2.06	1.65	1.65	1.63	1.40	1.22	1.09
Number of banks with capital shortfall	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Number of banks reporting excess capital	18	18	18	18	18	18	18	18	18	18	18	18	18	18	18	18	18	18

Table 5. Actual Tangible Common Equity Ratio Minus Assumed Required Minimum Tangible Common Equity Ratio of 4 Percent.

	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017Q3
Minimum requirement	4.00	4.00	4.00	4.00	4.00	4.00	4.00	4.00	4.00	4.00	4.00	4.00	4.00	4.00	4.00	4.00	4.00	4.00
JPMorgan	−0.43	−0.35	0.22	0.59	1.09	0.82	0.87	0.76	−0.17	1.27	1.59	1.62	2.26	2.35	2.46	3.23	3.23	3.52
Bank of America	1.47	1.96	1.83	1.03	0.79	0.24	0.14	−0.65	−1.17	0.51	1.86	2.52	2.63	3.10	3.38	3.69	3.69	3.74
Citigroup	1.52	0.98	0.70	0.53	0.51	0.68	−0.21	−1.28	−2.44	2.49	2.89	3.90	4.46	5.05	5.47	6.06	6.06	6.50
Wells Fargo	2.01	1.59	1.71	2.11	2.25	2.12	3.15	1.93	−1.67	1.44	2.72	3.40	4.04	4.13	4.08	4.21	4.21	4.08
U.S. Bancorp	2.18	1.52	1.71	2.12	2.45	2.29	1.17	0.74	−0.81	1.10	1.22	2.00	2.54	2.72	2.67	2.84	2.84	2.84
BNY Mellon	1.78	1.36	–	0.91	1.56	1.68	1.14	−0.19	−2.37	−0.25	−0.15	−0.57	−0.29	−0.19	−0.18	−0.07	−0.07	−0.24
PNC	1.75	1.13	2.59	2.30	1.68	1.05	3.34	0.61	−1.26	−0.47	3.43	4.53	4.34	4.77	4.88	5.40	5.40	5.10
State Street	0.71	0.67	0.93	0.55	0.53	0.75	1.15	−0.51	−1.03	1.36	2.30	1.17	1.54	0.89	0.38	0.70	0.70	0.38
BB&T	3.07	3.53	3.04	2.84	2.78	2.39	1.54	1.47	0.75	1.97	2.59	2.48	2.50	3.23	3.96	3.69	3.60	3.67
SunTrust	3.23	3.26	2.53	2.82	1.68	1.56	1.75	1.99	1.08	1.77	2.24	3.33	3.79	3.75	3.78	4.27	4.26	3.94
Fifth Third	5.42	–	5.42	4.44	4.34	2.86	3.78	2.03	0.31	2.64	3.30	5.04	5.10	4.69	4.71	5.60	4.65	4.70
Regions	2.91	2.77	2.64	3.08	2.86	2.64	2.53	1.88	1.23	2.03	1.86	2.42	4.62	5.09	5.61	5.07	5.07	4.86
Northern Trust	2.14	2.39	3.02	2.83	2.79	1.80	1.64	1.93	1.42	3.16	3.65	2.49	3.11	3.12	2.83	2.66	3.04	2.94
M&T	1.41	1.54	2.23	1.51	1.41	1.49	1.79	0.95	0.55	1.09	2.16	2.34	3.17	4.37	4.10	4.65	3.90	5.00
KeyCorp	2.12	2.33	2.73	2.94	2.35	2.68	3.01	2.58	1.95	3.56	4.19	5.88	6.02	5.70	5.80	5.93	5.27	4.84
Comerica	–	4.81	4.85	5.29	5.43	5.20	4.65	3.99	3.23	3.99	6.53	6.28	5.76	6.06	5.85	5.69	5.88	6.35
Huntington	–	2.12	3.62	2.80	3.18	3.19	2.87	0.81	−0.20	1.74	3.42	4.20	4.69	4.77	4.13	3.78	3.00	3.30
Zions	1.34	1.98	2.06	2.53	2.80	1.37	1.98	1.70	1.85	2.12	2.99	2.77	3.09	4.02	5.48	5.63	5.49	5.57
Average ratio	2.04	1.98	2.46	2.29	2.25	1.93	2.02	1.15	0.07	1.75	2.71	3.10	3.52	3.76	3.86	4.06	3.90	3.95
Standard deviation	1.27	1.19	1.34	1.31	1.28	1.17	1.27	1.29	1.58	1.18	1.39	1.69	1.56	1.61	1.73	1.73	1.66	1.76
Number of banks with capital shortfall	1	1	0	0	0	0	1	4	9	2	1	1	1	1	1	1	1	1
Number of banks reporting excess capital	15	16	17	18	18	18	17	14	9	16	17	17	17	17	17	17	17	17

Note: Negative values denoted by parentheses. Tangible common equity divided by tangible assets.

Table 6. Market Capitalization to Book Value Ratio.

	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017Q3
JPMorgan	2.15	1.79	1.16	1.66	1.32	1.29	1.44	1.19	0.87	1.04	0.99	0.71	0.86	1.1	1.1	1.09	1.35	1.43
Bank of America	1.56	2.03	2.08	2.46	1.9	1.82	1.8	1.29	0.51	0.67	0.64	0.28	0.57	0.75	0.84	0.75	0.92	1.06
Citigroup	3.98	3.26	2.12	2.58	2.31	2.17	2.3	1.3	0.52	0.62	0.84	0.43	0.64	0.8	0.82	0.75	0.8	0.92
Wells Fargo	3.64	2.71	2.63	2.92	2.8	2.61	2.64	2.11	1.84	1.35	1.39	1.13	1.24	1.55	1.72	1.62	1.58	1.51
U.S. Bancorp	2.92	2.48	2.21	2.98	2.98	2.7	3.16	2.74	2.39	1.76	1.88	1.65	1.74	2.03	2.08	1.79	2.09	2.07
BNY Mellon	6.77	4.71	2.6	3.05	2.8	2.49	2.46	1.9	1.29	1.17	1.16	0.72	0.85	1.11	1.26	1.2	1.41	1.47
PNC	3.34	2.73	1.74	2.28	2.18	2.12	2.01	1.51	1.24	1.11	1.08	0.94	0.87	1.08	1.18	1.07	1.36	1.51
State Street	6.16	4.4	2.65	3.03	2.66	2.91	3.09	2.78	1.56	1.49	1.31	1.04	1.06	1.6	1.67	1.44	1.65	1.84
BB&T	3.12	2.68	2.36	2.11	2.13	2.05	2.03	1.31	1.19	1.08	1.11	1.01	1.07	1.31	1.29	1.13	1.42	1.39
SunTrust	2.27	2.16	1.83	2.07	1.67	1.56	1.73	1.24	0.61	0.58	0.81	0.48	0.75	0.95	1.01	0.88	1.2	1.26
Fifth Third	5.69	4.68	3.97	3.93	2.96	2.22	2.27	1.46	0.61	0.78	1.12	0.91	1.01	1.33	1.17	1.04	1.36	1.32
Regions	1.74	1.71	1.77	1.85	1.54	1.47	1.32	0.83	0.41	0.44	0.66	0.41	0.67	0.89	0.89	0.74	1.11	1.14
Northern Trust	7.74	5.03	2.69	3.33	3.23	3.14	3.37	3.75	2.38	2.01	1.97	1.34	1.59	1.86	1.95	1.99	2.2	2.17
M&T	2.35	2.33	2.28	2.07	2.17	2.08	2.15	1.38	1.02	1.13	1.37	1.14	1.35	1.46	1.5	1.29	1.6	1.61
KeyCorp	1.54	1.79	1.68	1.56	1.75	1.94	1.76	1.97	1.18	0.57	0.61	0.93	0.76	0.78	1.19	1.05	1.3	1.38
Comerica	2.48	2.11	1.53	1.92	2.04	1.82	1.79	1.28	0.59	0.89	1.29	0.74	0.82	1.21	1.13	0.97	1.53	1.65
Huntington	1.72	1.79	1.89	2.26	2.26	2.08	1.86	0.91	0.52	0.72	1.28	0.94	1	1.41	1.44	1.42	1.56	1.57
Zions	3.06	2.13	1.5	2.17	2.19	1.88	1.85	0.99	0.57	0.46	0.96	0.65	0.8	1.01	0.91	0.84	1.26	1.31
Average ratio	3.46	2.81	2.15	2.46	2.27	2.13	2.17	1.66	1.07	0.99	1.14	0.86	0.98	1.24	1.29	1.17	1.43	1.48
Standard deviation	1.89	1.12	0.63	0.63	0.54	0.49	0.58	0.76	0.63	0.45	0.38	0.35	0.32	0.37	0.37	0.36	0.35	0.32
Number of banks market capital less than book value	0	0	0	0	0	0	0	3	9	9	7	12	10	5	4	6	2	1
Number of banks market capital more than book value	18	18	18	18	18	18	18	15	9	9	11	6	7	13	14	12	16	17

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Review

Big Data, Computational Science, Economics, Finance, Marketing, Management, and Psychology: Connections

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Abstract: The paper provides a review of the literature that connects Big Data, Computational Science, Economics, Finance, Marketing, Management, and Psychology, and discusses research issues that are related to the various disciplines. Academics could develop theoretical models and subsequent econometric and statistical models to estimate the parameters in the associated models, as well as conduct simulation to examine whether the estimators in their theories on estimation and hypothesis testing have good size and high power. Thereafter, academics and practitioners could apply theory to analyse some interesting issues in the seven disciplines and cognate areas.

Keywords: big data; computational science; economics; finance; management; theoretical models; econometric and statistical models; applications

JEL Classification: A10; G00; G31; O32

1. Introduction

There are many studies that link Big Data, Computational Science, Economics, Finance, Marketing, Management, and Psychology. The analysis of Big Data, medium-sized data and small data will be argued to be an important aspect of Computational Science.

There are many papers of a multidisciplinary nature that have been published in different areas. As such, there is substantial interesting and important research that has been undertaken in risk and financial management that is related to Big Data, Computational Science, Economics, Finance, Marketing, Management, Psychology, and cognate areas. As this paper discusses research that is closely related to the interests of the authors, it is focused primarily on the disciplines associated with Big Data, Computational Science, Economics, Finance, Marketing, Management, and Psychology.

Given the general level of confusion for academics and practitioners as to what constitutes big data, the paper provides a definition of big data, and distinguishes between important issues that are associated with big data, small data, and large data sets that are not necessarily satisfy the definition of big data.

Therefore, the paper discusses recent research in the areas of risk and financial management as they relate to Big Data, Computational Science, Economics, Finance, Marketing, Management, and Psychology, and cognate disciplines. The intention is to disseminate ideas to researchers who may consider working in the areas of risk and financial management in connection with Big Data, Computational Science, Economics, Finance, Marketing, Management, and Psychology.

As many, if not all, theorems for small data do not hold for big data, and, thus, analysis of big data becomes a separate topic, different from that of small data. In addition, Computational Science for both big and small data can be applied to many cognate areas, including Science, Engineering, Medical Science, Experimental Science, Psychology, Social Science, Economics, Finance, Management, and Business.

In this paper, we will discuss different types of utility functions, stochastic dominance (SD), mean-risk (MR) models, portfolio optimization (PO), and other financial, economic, marketing and management models as these topics are popular in Big Data, Computational Science, Economics, Finance, and Management. Academics could develop theory, and thereafter develop econometric and statistical models to estimate the associated parameters to analyze some interesting issues in Big Data, Computational Science, Economics, Finance, Marketing, Management, and Psychology.

Academics could then conduct simulations to examine whether the estimators calculated for estimation and hypothesis testing have good size and high power. Thereafter, academics and practitioners could apply their theories to analyze some interesting issues in the seven disciplines and other cognate areas.

In many situations, academics and practitioners have been applying existing theories and empirical methods to big data without initially verifying their appropriateness or suitability. We suggest that academics and practitioners should develop or seek appropriate models for big data before applying the techniques that might be available. The properties of estimators and tests should be verified for applications to big data.

In this paper, we review an extensive literature in economics, finance, marketing, management, psychology and computational science as we are familiar with these areas as part of our research programs on risk and financial management. There are strong theoretical links among these areas. For example, we provide a discussion in Section 2.1 that Li et al. (2018) is related to finance, economics, management, psychology, decision-making, marketing, big data, and computation science. We note that this paper is not the only research that is related to several different disciplines. Most of the research discussed in this paper is related to several different disciplines, as is highlighted in the title of the paper.

The plan of the remainder of the paper is as follows. In Section 2, a number of comprehensive theoretical models of risk and portfolio optimization are discussed. Alternative statistical and econometric models of risk and portfolio optimization are analyzed in Section 3. Alternative procedures for conducting simulations are examined in Section 4. A brief discussion of empirical models in several cognate disciplines is presented in Section 5. Some concluding remarks are given in Section 6.

2. Theoretical Models

It is important to commence any rigorous research in computational sciences for big data as well as small data in the areas of Economics, Finance, and Management by developing appropriate theoretical models. The authors have been developing some theories to extend those that have been discussed in a number of existing literature reviews. We discuss some of our research in the following subsections.

2.1. Portfolio Optimization

The mean–variance (MV) portfolio optimization procedure is the milestone of modern finance theory for asset allocation, investment diversification, and optimal portfolio construction (Markowitz 1952b). In the procedure, investors select portfolios that maximize profit subject to achieving a specified level of calculated risk or, equivalently, minimize variance subject to obtaining a predetermined level of expected gain. However, the estimates have been demonstrated to depart seriously from their theoretic optimal returns. Michaud (1989) and others have found the MV-optimized portfolios do more harm than good. Bai et al. (2009a) have proved that this phenomenon is natural.

We note that the estimates have been demonstrated to depart seriously from their theoretical optimal returns. The MV-optimized portfolios can do more harm than good for big data, especially as the number of parameters being estimated increases with the increasing dimension. For small data or big data, where the number of parameters to be estimated is fixed, the estimates do not depart significantly from their theoretical optimal returns.

Recently, Li et al. (2018) extended Maslow (1943) need hierarchy theory and the two-level optimization approach by developing the framework of the Malsow portfolio selection model (MPSM). The authors were able to do this by solving the two optimization problems to meet the need of individuals with low financial sustainability, who prefer to satisfy their lower-level (safety) need before seeking a higher-level (self-actualization) need to maximize the optimal returns. They also find a solution for some investors with high financial sustainability.

In this paper, we review an extensive selection of the literature in economics, finance, marketing, management, psychology computational science. For example, Li et al. (2018) analyse an investment issue, so that it is related to finance. The paper discusses decision-making for investors with low and high financial sustainability, so the paper is related to management, psychology, and decision-making. The paper is also related to marketing funds to investors with low and high financial sustainability, and hence is related to marketing. Moreover, the paper requires analysis of big data, not so big data, and small data, so it is also related to big data and computational science. In addition, investment changes under different economic conditions, so that the paper is also related to economics.

2.2. Cost of Capital

Gordon and Shapiro (1956) develop the dividend yield plus growth model for individual firms while Thompson (1985) improves the theory by combining the model with analysis of past dividends to estimate the cost of capital and its 'reliability'. Thompson and Wong (1991) estimate the cost of capital using discounted cash flow (DCF) methods that require forecasting dividends.

Thompson and Wong (1996) extend the theory by proving the existence and uniqueness of a solution for the cost of equity capital, and the cost of equity function is continuously differentiable. Wong and Chan (2004) have extended their theory by proving the existence and uniqueness of reliability.

2.3. Behavorial Models

Barberis et al. (1998) and others use Bayesian models to explain investors' behavioral biases by using the conservatism heuristics and representativeness heuristics in making decisions. Lam et al. (2010) extend the theory by developing a model of weight assignments using a pseudo-Bayesian approach that reflects investors' behavioral biases.

They use the model to explain several financial anomalies, including excess, volatility, short-run underreaction, long-run overreaction, and magnitude effects. Lam et al. (2012) extend their work by developing additional properties for the pseudo-Bayesian approach that reflects investors' behavioral biases, and explain the linkage between these market anomalies and investors' behavioral biases.

Fung et al. (2011) extend their work by incorporating the pseudo-Bayesian model with the impact of a financial crisis. They derive properties of stock returns during the financial crisis and recovery from the crisis.

Guo et al. (2017b) extend the model by assuming that the earnings shock of an asset follows a random walk model, with and without drift, to incorporate the impact of financial crises. They assume the earning shock follows an exponential family distribution to accommodate symmetric as well as asymmetric information. By using this model setting, they develop some properties on the expected earnings shock and its volatility, and establish properties of investor behavior on the stock price and its volatility during financial crises and subsequent recovery.

Thereafter, they develop properties to explain excess volatility, short-term underreaction, long-term overreaction, and their magnitude effects during financial crises and subsequent recovery. Egozcue and Wong (2010a) extend prospect theory, mental accounting, and the hedonic editing model by developing an analytical theory to explain the behavior of investors with extended value functions in segregating or integrating multiple outcomes when evaluating mental accounting.

Whether to keep products segregated (that is, unbundled) or integrate some or all of them (that is, bundle) has been a problem of profound interest in areas such as portfolio theory in finance, risk capital allocations in insurance, and marketing of consumer products. Such decisions are inherently complex and depend on factors such as the underlying product values and consumer preferences, the latter being frequently described using value functions, also known as utility functions in economics.

Egozcue et al. (2012a) develop decision rules for multiple products, which we generally call 'exposure units' to naturally cover manifold scenarios spanning well beyond 'products'. The findings show, for example, that the celebrated Thaler's principles of mental accounting hold as originally postulated when the values of all exposure units are positive (that is, all are gains) or all negative (that is, all are losses).

In the case of exposure unit mixed-sign values, decision rules are much more complex and rely on cataloging the Bell-number of cases that grow very fast, depending on the number of exposure units. Consequently, in this paper, we provide detailed rules for the integration and segregation decisions in the case up to three exposure units, and partial rules for the arbitrary number of units

We note that the theory of decision maker's behavior developed by Egozcue and Wong (2010a) and Egozcue et al. (2012a) is for marketing, and they develop a theory for consumer behavior.

2.4. Modelling Different Types of Investors

We have been developing some theories, estimation, and testing to examine different utility functions and the preferences of different types of investors. We summarize some of the results here. Readers may refer to Sriboonchita et al. (2009) and Bai et al. (2018) for further information.

2.4.1. Different Types of Utility Functions

Lien (2008) compares the exponential utility function with its second-order approximation under the normality assumption in the optimal production and hedging decision framework. Guo et al. (2016a) extend the theory by comparing the exponential utility function with a 2n-order approximation for any integer n. In addition, they propose an approach with an illustration to determine the smallest n that provides a good approximation.

2.4.2. Stochastic Dominance

We have been developing several theories in stochastic dominance, and discuss some here.

Behavior of Risk Averters and Risk Seekers

Wong and Li (1999) develop some properties for the convex stochastic dominance to compare the preferences of different combinations of several assets for both risk-averse and risk-seeking investors. In addition, they compare the preferences between a convex combinations of several continuous distributions and a single continuous distribution. In addition, Li and Wong (1999) develop some SD theorems for the location-and-scale family and linear combinations of random variables for risk seekers and risk averters.

Wong (2007) extends their work by introducing the first three orders of both ascending SD (ASD) and descending SD (DSD) to decisions in business planning and investment for risk-averse and risk-seeking decision makers so that they can compare both return and loss. The author provides tools to identify the first-order SD prospects and discern arbitrage opportunities that could increase their expected utility and expected wealth. Wong (2007) also introduces the mean–variance (MV) rule to decisions in business planning or investment on both return and loss for both risk-averse and risk-seeking decision makers, and show that the rule is equivalent to the SD rule under some conditions.

Chan et al. (2016) analyse properties of SD for both risk-averse and risk-seeking SD (RSD) for risk-seeking investors, which, in turn, enables an examination of their behavior. They first discuss the basic properties of SD and RSD that link SD and RSD to expected-utility maximization. Thereafter, they prove that a hierarchy exists in both SD and RSD relationships and that the higher orders of SD and RSD can be inferred by the lower orders of SD and RSD, but not vice-versa. Furthermore, they study the conditions in which third-order SD preferences are 'the opposite of' or 'the same as' their counterpart third-order RSD preferences.

In addition, they establish the relationship between the orders of the variances and that of the integrals for two assets, which enables us to establish certain relationships between the dominance of the variances and the second- and third-order SD and RSD for two assets under the condition of equal means. The theory developed in the paper provides a set of tools that enables investors to identify prospects for first-, second-, and third-order SD and RSD, and so enables investors to improve their investment decisions.

Another contribution in the paper is that the authors recommend checking the dominance of the means of the distributions to draw inferences for the preferences for two different assets for third-order risk averters and risk seekers. They illustrate this idea by comparing the investment behavior of both third-order risk averters and risk seekers in bonds and stocks.

Guo and Wong (2016) extend some univariate SD results to multivariate SD (MSD) for both risk averters and risk seekers, respectively, to n order for any $n > 0$ when the attributes are assumed to be independent and the utility is assumed to be additively separable. Under these assumptions, they develop some properties for MSD for both risk averters and risk seekers. For example, they prove that MSD are equivalent to the expected-utility maximization for both risk averters and risk seekers, respectively.

They show that the hierarchical relationship exists for MSD, and establish some dual relationships between the MSD for risk averters and risk seekers. They develop some properties for non-negative combinations and convex combinations random variables of MSD, and develop the theory of MSD for the preferences of both risk averters and risk seekers on diversification. At last, they discuss some MSD relationships when attributes are dependent, and discuss the importance and the use of the results developed in their paper.

Behavior of Investors with S-Shaped and Reverse S-Shaped Utility Functions

Wong and Chan (2008) extend the work on Prospect SD (PSD) and Markowitz SD (MSD) to the first three orders, and link the corresponding S-shaped and reverse S-shaped utility functions to the first three orders. They provide experiments to illustrate each case of the MSD and PSD to the first three orders, and demonstrate that the higher order MSD and PSD cannot be replaced by the lower order MSD and PSD. Furthermore, they show that a hierarchy exists in both PSD and MSD relationships, arbitrage opportunities exist in the first orders of both PSD and MSD, and for any two prospects under certain conditions, their third order MSD preference will be 'the opposite of' or 'the same as' their counterpart third order PSD preferences.

2.4.3. Almost Stochastic Dominance

Guo et al. (2013) provide further information on both the expected-utility maximization and the hierarchy property. For almost SD (ASD), Leshno and Levy (2002) propose a definition, and Tzeng et al. (2013) modify it to provide another definition. Guo et al. (2013) show that the former has the hierarchy property but not expected-utility maximization, whereas the latter has the expected-utility maximization but not the hierarchy property.

Guo et al. (2014) establish necessary conditions for ASD criteria of various orders. These conditions take the form of restrictions on algebraic combinations of moments of the probability distributions in question. The relevant set of conditions depends on the relevant order of ASD but not on the critical value for the admissible violation area. These conditions can help to reduce the information requirement and computational burden in practical applications. A numerical example and an empirical application for historical stock market data illustrate the moment conditions. The first four moment conditions, in particular, seem appealing for many applications.

Guo et al. (2016b) extend ASD theory for risk averters to include ASD for risk-seeking investors. Thereafter, they study the relationship between ASD for risk seekers and ASD for risk averters. Tsetlin et al. (2015) develop the theory of generalized ASD (GASD). Guo et al. (2016b) discuss the advantages and disadvantages of ASD and GASD.

2.5. Indifference Curves

Meyer (1987) extends MV theory to include comparisons among distributions that differ only by location and scale parameters, and include general utility functions with only convexity or concavity restrictions. Wong (2006) extends both Meyer (1987) and Tobin (1958) by showing that the indifference curve is convex upwards for risk averters, concave downwards for risk lovers, and horizontal for risk neutral investors, in order to include the general conditions stated by Meyer (1987). In addition, Wong (2006) develops some properties among the first- and second-order SD efficient sets and the mean–variance efficient set.

Wong and Ma (2008) extend the work on the location-scale (LS) family with general n random seed sources in a multivariate setting. In addition, they develop some properties for general non-expected utility functions defined over the LS family, and characterize the shapes of the indifference curves induced by the location-scale expected utility functions and non-expected utility functions. Thereafter, they develop properties for well-defined partial orders and dominance relations defined over the LS family, including the first- and second-order stochastic dominances, the mean–variance rule, and location-scale dominance.

Broll et al. (2010) discuss prospect theory and establish general results concerning certain covariances from which they can, in turn, infer properties of indifference curves and hedging decisions within prospect theory.

2.6. Diversification

Wong and Li (1999) extend the theory of convex SD (Fishburn 1974) by including any distribution function, developing the results for both risk seekers as well as risk averters, and including third-order stochastic dominance. Their results can be used to extend a theorem of Bawa et al. (1985) on comparisons between a convex combinations of several continuous distributions and a single continuous distribution.

Li and Wong (1999) develop some results for the diversification preferences of risk averters and risk seekers. Egozcue and Wong (2010b) incorporate both majorization theory and SD theory to develop a general theory and unifying framework for determining the diversification preferences of risk-averse investors, and conditions under which they would unanimously judge a particular asset to be superior. In particular, they develop a theory for comparing the preferences of different convex combinations of assets that characterize a portfolio to yield higher expected utility by second-order SD.

Egozcue et al. (2011a) analyse the rankings of completely and partially diversified portfolios and also of specialized assets when investors follow so-called Markowitz preferences. Diversification strategies for Markowitz investors are more complex than in the case of risk-averse and risk-inclined investors, whose investment strategies have been investigated extensively in the literature. In particular, they observe that, for Markowitz investors, preferences toward risk vary depending on their sensitivities toward gains and losses.

For example, it can be shown that, unlike the case of risk-averse and risk-inclined investors, Markowitz investors might prefer investing their entire wealth in just one asset. This finding helps us to better understand some financial anomalies and puzzles, such as the well-known diversification puzzle, which notes that investors may concentrate on investing in only a few assets instead of choosing the seemingly more attractive complete diversification.

Lozza et al. (2018) provide a general valuation of the diversification attitude of investors. First, they empirically examine the diversification of mean–variance optimal choices in the US stock market during the 11-year period 2003–2013. Then, they analyze the diversification problem from the perspective of risk-averse investors and risk-seeking investors.

Second, the authors prove that investors' optimal choices will be similar if their utility functions are not too distant, independent of their tolerance (or aversion) to risk. Finally, they discuss investors' attitudes towards diversification when the choices available to investors depend on several parameters.

2.7. Risk Measures

We have been developing properties for several risk measures to be used in finance, economics, and cognate disciplines, and discuss briefly the properties for some recent risk measures in this section.

2.7.1. VaR and CVaR

Ma and Wong (2010) establish some behavioral foundations for various types of Value-at-Risk (VaR) models, including VaR and conditional-VaR, as measures of downside risk. They establish some logical connections among VaRs, conditional-VaR, SD, and utility maximization. Though supported to some extent by unanimous choices by some specific groups of expected or non-expected-utility investors, VaRs as profiles of risk measures at various levels of risk tolerance are not quantifiable as they can only provide partial and incomplete risk assessments for risky prospects.

They also include in the discussion the relevant VaRs and several alternative risk measures for investors. These alternatives use somewhat weaker assumptions about risk-averse behavior by incorporating a mean-preserving-spread. For this latter group of investors, the authors provide arguments for and against the standard deviation versus VaR and conditional-VaR as objective and quantifiable measures of risk in the context of portfolio choice.

2.7.2. Omega Ratio

Both SD and the Omega ratio can be used to examine whether markets are efficient, whether there is any arbitrage opportunity in the market, and whether there is any anomaly in the market. Guo et al. (2017a) analyse the relationship between SD and the Omega ratio. They find that second-order SD and/or second-order risk-seeking SD (RSD) alone for any two prospects is not sufficient to imply Omega ratio dominance, insofar as the Omega ratio of one asset is always greater than that of the other. 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.

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, they apply their theory to examine the relationship between property size and property investment in the Hong Kong real estate market, and conclude that the Hong Kong real estate market is not efficient as there are expected arbitrage opportunities and anomalies in the Hong Kong real estate market.

2.7.3. High-Order Risk Measures

Niu et al. (2017) first show the sufficient relationship between the $(n + 1)$-order SD and the n-order Kappa ratio. They clarify the restrictions for necessarily beating the target for the higher-order SD consistency of the Kappa ratios. Thereafter, the authors show that, in general, a necessary relationship between SD/RSD and the Kappa ratio cannot be established. They find that when the variables being compared belong to the same location-scale family or the same linear combination of location-scale families, they can obtain the necessary relationship between the (n + 1)-order SD with the n-order Kappa ratio after imposing some conditions on the means.

2.8. Two-Moment Decision Model

Broll et al. (2006) analyze export production in the presence of exchange rate uncertainty under mean-variance preferences. We present the elasticity of risk aversion, since this elasticity concept permits a distinct investigation of risk and expectation effects on exports. Counterintutitive results are possible, e.g., although the home currency is revaluating (devaluating), exports by the firm increase (decrease). This fact may contribute to the explanation of disturbing empirical results. Broll et al. (2011) use the mean-variance approach to examine a banking firm investing in risky assets and hedging opportunities. They focus on how credit risk affects optimal bank investment in the loan and deposit market when derivatives are available. Furthermore, they explore the relationship among the first- and second-degree stochastic dominance efficient sets and the mean-variance efficient set. Broll et al. (2015) analyze a bank's risk taking in a two-moment decision framework. Their approach offers desirable properties like simplicity, intuitive interpretation, and empirical applicability. The bank's optimal behavior to a change in the standard deviation or the expected value of the risky asset's or portfolio's return can be described in terms of risk aversion elasticities, i.e., the sensitivity of the marginal rate of substitution between risk and return. The bank's investment in a risky asset position goes down when the return risk increases, if and only if the risk aversion elasticity exceeds.

Alghalith et al. (2017a) analyze the impacts of joint energy and output prices uncertainties on input demands in a mean–variance framework. They show that an increase in the expected output price will cause the risk-averse firm to increase input demand, while an increase in expected energy prices will surely cause the risk-averse firm to decrease the demand for energy, but increase the demand for the non-risky inputs.

Furthermore, the authors investigate two cases with only uncertain energy price and only uncertain output price. In the case with only uncertain energy price, they determine that the uncertain energy price has no impact on the demands for the non-risky inputs. They also show that the concepts of elasticity and decreasing absolute risk aversion (DARA) play an important role in the comparative statics analysis.

Alghalith et al. (2017b) analyze the impacts of joint energy and output prices uncertainties on the inputs demands in a mean–variance framework. They find that the concepts of elasticities and variance vulnerability play important roles in the comparative statics analysis. If the firms' preferences exhibit variance vulnerability, increasing the variance of energy price will necessarily cause the risk averse firm to decrease demand for the non-risky inputs.

Furthermore, the authors investigate two special cases with only uncertain energy price and only uncertain output price. In the case with only uncertain energy price, they show that the uncertain energy price has no impact on the demands for the non-risky inputs. If the firms' preferences exhibit variance vulnerability, increasing the variance of energy price will surely cause the risk averse firm to decrease demand for energy.

With multiple additive risks, the mean–variance approach and the expected utility approach of risk preferences are compatible if all attainable distributions belong to the same location–scale family. Under this proviso, Guo et al. (2018) survey existing results on the parallels of the two approaches with respect to risk attitudes, the changes thereof, and comparative statics for simple, linear choice problems under risk.

In the mean–variance approach, all effects can be couched in terms of the marginal rate of substitution between the mean and variance. They apply the theory developed in the paper to examine the behavior of banking firms, and study risk-taking behavior with background risk in the mean–variance model.

2.9. Dynamic Models with Background Risk

Alghalith et al. (2016) use a general utility function to present two dynamic models of background risk. They present a stochastic factor model with an additive background risk. Thereafter, they present a dynamic model of simultaneous (correlated) multiplicative background risk and additive background risk.

2.10. Regret-Aversion

Egozcue et al. (2015) examine the optimal output of a competitive firm for price uncertainty. Instead of assuming a risk-averse firm, the authors assume that the firm is regret-averse. They find that optimal output under uncertainty would be lower than under certainty, and prove that optimal output could increase or decrease as the regret factor varies.

Guo et al. (2015) investigate regret-averse firms' production and hedging behavior. They show that the separation theorem operates under regret aversion by proving that regret aversion is independent of the level of optimal production. On the other hand, the authors find that the full-hedging theorem does not always hold under regret aversion, as regret-averse firms take hedged positions differently from those of risk-averse firms in some situations. With more regret aversion, regret-averse firms will hold smaller optimal hedging positions in an unbiased futures market. Furthermore, contrary to the conventional expectations, they show that banning firms from forward trading affects their production level in both directions.

2.11. Covariances and Copulas

Chebyshev's integral inequality, also known as covariance inequality, is an important problem in economics, finance, marketing, management, and decision-making in a wide range of cognate disciplines. Egozcue et al. (2009) derive some covariance inequalities for monotonic and non-monotonic functions. The results can be useful in many applications in economics, finance, marketing, management, and decision-making, and related disciplines where optimal decision-making is desired.

Egozcue et al. (2010) sharpen the upper bound of a Grüss-type covariance inequality by incorporating a notion of quadrant dependence between random variables, and also using the idea of constraining the means of the random variables.

Egozcue et al. (2011b) show that Grüss-type probabilistic inequalities for covariances can be considerably sharpened when the underlying random variables are quadrant dependent in expectation (QDE). The established covariance bounds not only sharpen the classical Grüss inequality, but also improve upon Grüss-type bounds under the assumption of quadrant dependency (QD), which is stronger than QDE. The authors illustrate the general results with examples based on specially devised bivariate distributions that are QDE but not QD. Such results play important roles in decision-making under uncertainty, and particularly in areas such as economics, finance, marketing, management, insurance and cognate disciplines in which optimal decision-making is required.

A number of problems in economics, finance and insurance rely on determining the signs of the covariances of two transformations of a random variable. The classical Chebyshev's inequality offers a powerful tool for solving the problem, but assumes that the transformations are monotonic, which is not always the case in applications.

For this reason, Egozcue et al. (2011c) establish new results for determining the covariance signs and provide further insights into the area. Unlike many previous contributions, their method of analysis, which is probabilistic in nature, does not rely on the classical Hoffding's representation of the covariances or on any of the numerous extensions and generalizations.

Egozcue et al. (2012b) establish the smallest upper bound for the p'th absolute central moment over the class of all random variables with values in a compact interval. Numerical values of the bound are calculated for the first ten integer values of p, and its asymptotic behaviour derived when p tends to infinity. In addition, the authors establish an analogous bound in the case of all symmetric random variables with values in a compact interval. Such results play important roles in a number of areas, including actuarial science, economics, finance, marketing, management, operations research, and reliability.

It is well known that quadrant dependent (QD) random variables are also quadrant dependent in expectation (QDE). The recent literature has offered examples that establish rigorously the fact that there are QDE random variables that are not QD. The examples are based on convex combinations of specially chosen positive and negative QD copulas. Egozcue et al. (2013) establish general results that determine when convex combinations of arbitrary QD copulas yield negative or positive QD/QDE copulas. In addition to being an interesting mathematical exercise, the established results are helpful from a practical perspective when modelling insurance and financial portfolios.

3. Statistical and Econometric Models

Another suggestion is to develop statistical and econometric models in the areas related to management information, decision sciences, economics, finance, and cognate disciplines. After developing mathematical models, one might consider developing related statistical and econometric models. We have developed several econometrics papers related to management information, decision sciences, economics, and finance, among others.

3.1. Portfolio Optimization

We have developed some novel theoretical results on portfolio optimization. When the dimension of the data is large, the theoretical model of the classical MV portfolio optimization developed by Markowitz (1952a) has been found to have problematic issues in estimation as substituting the sample mean and covariance matrix into the MV optimization procedure will result in a serious departure of the optimal return estimate. Moreover, the corresponding portfolio allocation estimates will deviate from their theoretical counterparts when the number of assets is large. We call this return estimate the "plug-in" return, and its corresponding estimate for the asset allocation the "plug-in allocation."

Bai et al. (2009a) prove that this phenomenon is normal and call it "over-prediction". In order to circumvent over-prediction, the authors use a new method by incorporating the idea of the bootstrap into the theory of a large dimensional random matrix. They develop new bootstrap-corrected estimates for the optimal return and its asset allocation, and prove that these bootstrap-corrected estimates can analytically correct over-prediction and drastically reduce the error. The authors also show that the bootstrap-corrected estimate of return and its corresponding allocation estimate are proportionally consistent with their counterpart parameters.

Bai et al. (2009a) propose a bootstrap-corrected estimator to correct the overestimation, but there is no closed form for their estimator. Thus, it has to be obtained by using a bootstrap approach, which, as a result, is difficult for practitioners to adopt the estimation technique in practice. In order to circumvent this limitation, Leung et al. (2012) develop a new estimator for the optimal portfolio return based on an unbiased estimator of the inverse of the covariance matrix and its related terms, and derive explicit formulae for the estimator of the optimal portfolio return.

Bai et al. (2016a) improve on the estimation by using the spectral distribution of the sample covariance. They develop the limiting behavior of the quadratic form with the sample spectral corrected covariance matrix, and explain the superior performance to the sample covariance as the dimension increases to infinity with the sample size proportionally. Moreover, the authors derive the limiting behavior of the expected return and risk on the spectrally corrected MV portfolio. They also illustrate the superior properties of the spectral corrected MV portfolio in practice.

In simulations, they compare the spectrally corrected estimates with the traditional and bootstrap-corrected estimates, and show the performance of the spectrally corrected estimates are superior in terms of the portfolio return as well as for the portfolio risk. They also compare the performance of the novel proposed estimation method with different optimal portfolio estimates for real S&P 500 data.

We note that portfolio optimization can be used for big data as well finite samples that might not be classified as big data. In the theory developed by Bai et al. (2009a, 2009b), Leung et al. (2012) and Bai et al. (2016a) have already mentioned their theory holds when the observations tend to infinity. Academics and practitioners can use portfolio optimization in their analysis for big data, and for finite samples. The literature for using portfolio optimization in their theoretical and empirical analyses includes Abid et al. (2009, 2013, 2014), and Hoang et al. (2015a, 2015b) among others.

3.2. Testing Investors' Behavorial Models

Lam et al. (2010, 2012) developed a Bayesian model of excess volatility, short-term underreaction and long-term overreaction. Guo et al. (2017b) extend their model to excess volatility, short-term underreaction and long-term overreaction during financial crises. Fabozzi et al. (2013) develop three tests of the magnitude effect of short-term underreaction and long-term overreaction.

We note that the testing Investors' behavorial models developed by Lam et al. (2010, 2012), and Guo et al. (2017b) can be used for big data as well as in finite samples. Fabozzi et al. (2013) have already developed three tests and use S&P data to test for the magnitude effect of short-term underreaction and long-term overreaction. Academics and practitioners can apply the tests developed in Fabozzi et al. (2013) for broader data sets, such as for international markets and over time, leading to dynamic panel data models, so that the tests can be used for big data as well as for finite samples.

Wong et al. (2018) conduct a questionnaire survey to examine whether the theory developed by Lam et al. (2010, 2012) and Guo et al. (2017b) holds empirically by studying the conservative and representative heuristics of Hong Kong small investors who adopt momentum and/or contrarian trading strategies. It is worth noting that academics and practitioners could conduct a questionnaire survey for big data as well as finite samples associated with this topic.

3.3. Stochastic Dominance

Ng et al. (2017) develop tests for stochastic dominance by proposing and translating the inference problem of stochastic dominance into parameter restrictions in quantile regressions. They are variants of the one-sided Kolmogorov–Smirnoff statistic with a limiting distribution of the standard Brownian Bridge. The procedure to obtain the critical values of the proposed test statistics are provided. Simulation results show superior size and power compared with alternative procedures. They apply the estimation method to the NASDAQ 100 and S&P 500 indexes to investigate dominance relationship before and after major turning points. The empirical results show no arbitrage opportunities between the bear and bull markets.

Bai et al. (2015) derive the limiting process of stochastic dominance statistics for risk averters as well as for risk seekers, both for when the underlying processes are dependent or independent. They take account of the dependency of the partitions and propose a bootstrap method to determine the critical points. In addition, they illustrate the applicability of the stochastic dominance statistics for both risk averters and risk seekers to analyze the dominance relationship between the Chinese and US stock markets for the full sample period, as well as for the sub-periods before and after crises, including the internet bubble, the recent sub-prime crisis, and global financial crisis.

The empirical findings could be used to draw inferences on the preferences of risk averters and risk seekers in investing in the Chinese and US stock markets. The results also enable an examination as to whether there are arbitrage opportunities in these markets, whether these markets are efficient, and if investors are rational.

Bai et al. (2011a) develop new statistics for both PSD and MSD of the first three orders. These statistics provide tools to examine the preferences of investors with S-shaped utility functions in prospect theory and investors with RS-shaped investors. They also derive the limiting distributions of the test statistics to be stochastic processes, propose a bootstrap method to decide the critical points of the tests, and prove the consistency of the bootstrap tests. The authors also illustrate the applicability of their proposed statistics by examining the preferences of investors with the corresponding S-shaped and RS-shaped utility functions vis-a-vis returns on iShares, and vis-a-vis returns of traditional stocks and Internet stocks, before and after the internet bubble.

Academics and practitioners can apply stochastic dominance tests in many different areas for big data, and for finite samples that might not be characterized as big data. The interesting literature in applying stochastic dominance tests includes Fong et al. (2005, 2008), Gasbarro et al. (2007), Lean et al. (2007, 2010, 2012, 2015), Qiao et al. (2010, 2012, 2013), Chan et al. (2012), Qiao and Wong (2015), Hoang et al. (2015a, 2015b), among others.

3.4. Risk Measures

Leung and Wong (2008) apply the technique of the repeated measures design to develop the Multiple Sharpe ratio test statistic to test the hypothesis of the equality of the multiple Sharpe ratios. They also establish the asymptotic distribution of the statistic and its properties. In order to demonstrate the superiority of the proposed statistic relative to the traditional pairwise Sharpe ratio test, they illustrate their approach by testing the equality of the Sharpe ratios for eighteen iShares.

The pairwise Sharpe ratio test shows that the performance of all 18 iShares are indistinguishable, as they reject the equality of the Sharpe ratios in each year as well as for the entire sample. These empirical results imply that the 18 iShares perform differently in each year, as well as for the entire sample, with some tests outperforming others in the market.

Recent results in optimal stopping theory have shown that a 'bang-bang' (buy or sell immediately) style of trading strategy is, in some sense optimal, provided that the asset price dynamics follow certain familiar stochastic processes. Wong et al. (2012) construct a reward-to-variability ratio (specifically, the mixed Sharpe ratio) that is sufficient for purposes of implementing the strategy.

The use of the novel ratio for optimal portfolio selection is discussed, and evidence for it varying over time is established. The performances of the 'bang-bang' and 'buy-and-hold' trading strategies are compared, and the former is found to be significantly more profitable.

Bai et al. (2011c) develop the mean–variance-ratio statistic to test the equality of the mean–variance ratios and prove that our proposed statistic is uniformly most powerful unbiased. In addition, they illustrate the applicability of our proposed test to compare the performances of stock indices.

Thereafter, Bai et al. (2012) propose and develop mean–variance-ratio (MVR) statistics for comparing the performance of prospects after the effect of the background risk has been mitigated. They investigate the performance of the statistics in large and small samples and show that, in the non-asymptotic framework, the MVR statistic produces a uniformly most powerful unbiased (UMPU) test.

The authors discuss the applicability of the MVR test in the case of large samples, and illustrate its superiority in the case of small samples by analyzing the Korea and Singapore stock returns after the impact of the US stock returns (which is viewed as the background risk) has been deducted. They find, in particular, that when samples are small, the MVR statistic can detect differences in asset performance while the Sharpe ratio, which is the mean-standard-deviation-ratio statistic, may not be able to do so.

Academics and practitioners can apply different risk measures estimators and test statistics in many different areas in the presence of big data, and large finite samples that might not be classified as big data. The literature in applying different risk measures estimators and test statistics includes Gasbarro et al. (2007), Lean et al. (2007, 2010, 2012, 2015), Chan et al. (2012), Qiao et al. (2012, 2013), Bai et al. (2013), Qiao and Wong (2015), Hoang et al. (2015a, 2015b), among many others.

3.5. Economic and Financial Indicators

We have developed financial indicators and have applied some economic indicators to examine several important economic issues. For example, Wong et al. (2001) develop a new financial indicator to test the performance of stock market forecasts by using E/P ratios and bond yields. They also develop two test statistics to use the indicator and illustrate empirically the tests in several stock markets. They show that the forecasts generated from the indicator would enable investors to escape most of the crashes and catch most of the bull runs. The trading signals provided by the indicator can also generate profits that are significantly superior to the buy-and-hold strategy.

Exploring the characteristics associated with the formation of bubbles that occurred in the Hong Kong stock market in 1997 and 2007, and the 2000 dot-com bubble of Nasdaq, McAleer et al. (2016) establish trading rules that not only produce returns that are significantly greater than the buy-and-hold strategies, but also produce greater wealth compared with technical analysis (TA) strategies without trading rules. They conclude the bubble detection signals help investors generate greater wealth from applying appropriate long and short Moving Average strategies.

Chong et al. (2017) develop a new market sentiment index for the Hong Kong stock market, one of the largest stock markets in the world by using the turnover ratio, short-selling volume, money flow, Hong Kong Interbank Offer Rate (HIBOR), and returns of the US and Japanese markets, and the Shanghai and Shenzhen Composite indices.

Thereafter, they incorporate the threshold regression model with the sentiment index as a threshold variable to capture the state of the Hong Kong stock market. The authors find that the practical trading rule that sells (buys) the Hang Seng Index (HSI) or S&P/HKEx LargeCapIndex[1] when the sentiment index is above (below) the upper threshold value can beat the buy-and-hold strategy.

Sethi et al. (2018) examine the sectoral impact of disinflationary monetary policy by calculating the sacrifice ratios for several OECD (The Organisation for Economic Co-operation and Development) and non-OECD countries. Sacrifice ratios calculated through the episode method reveal that disinflationary monetary policy has a differential impact across three sectors in both OECD and non-OECD countries. Of the three sectors, the industry and service sectors show significant output loss due to a tight monetary policy in OECD and non-OECD countries.

The agricultural sector shows a differential impact of disinflation policy, namely a negative sacrifice ratio in OECD countries, thereby indicating that output growth is insignificantly affected by a tight monetary policy. Non-OECD countries yield positive sacrifice ratios, suggesting that the output loss is significant. Furthermore, it is observed that sacrifice ratios calculated from aggregate data are different from ratios that are calculated using sectoral data.

Financial and economic indicators can be used for big data, and for large data sets that might not be classified as big data. For example, Wong et al. (2001) use their indicator to test in markets for the USA, UK, Japan, Germany, and Singapore. This is not especially big data. Academics and practitioners could use it to test for stock markets for a large number of international markets using dynamic panel data models. The authors can use it to test not only for stock markets, but also for any financial products, and also to test for big data sets.

Similarly, Sethi et al. (2018) apply the sacrifice ratios to examine the sectoral impact of disinflationary monetary policy for several OECD and non-OECD countries. This is not especially associated with big data. However, academics and practitioners can apply the sacrifice ratios to examine the sectoral impact of disinflationary monetary policy for a large number of countries worldwide, which would be classified as a large data set.

3.6. Contagion

Wan and Wong (2001) provide a simple example of a refinancing game with incomplete information, where the lack of transparency is both necessary and sufficient for the propagation of local financial distress across disjoint financial networks. The authors note that contagion is an important topic in both economics and finance.

There are some tests for contagion, for example, the test developed by Fry et al. (2010), and Fry-McKibbin and Hsiao (2015). The tests can be used for big data, and also for large data sets that might not be characterized as big data.

[1] The S&P/HKEX LargeCap is a 25-stock index representing the large cap universe for Hong Kong.

3.7. Technical Analysis

The new financial indicator introduced by Wong et al. (2001) to test the performance of stock market forecasts can be classified as technical analysis. Substantial research have been undertaken in technical analysis. For example, Wong et al. (2003) use technical analysis in signalling the timing of stock market entry and exit.

The authors introduce test statistics to test the performance of the most established of the trend followers, namely the Moving Average, and the most frequently used counter-trend indicator, namely the Relative Strength Index. Using Singapore data, the empirical results indicate that the indicators can be used to generate significantly positive return. It is found that member firms of the Singapore Stock Exchange tend to enjoy substantial profits by applying relatively simple technical indicators.

Wong et al. (2005) examine the profitability of applying technical analysis that signals the entry and exit from the stock market in three Chinese stock markets, namely the Shanghai, Hong Kong and Taiwan Stock Exchanges. Applying the trading signals generated by the MA family to the Greater China markets, generate significantly positive returns that outperform the buy-and-hold strategy. The cumulative wealth obtained also surpasses that of the buy-and-hold strategy, regardless of transaction costs.

In addition, the authors analyse the performance of the MA family before and after the 1997 Asian Financial Crisis, and find that the MA family works well in both sub-periods, as well as in different market conditions of bull runs, bear markets and mixed markets. The empirical observation that technical analysis can forecast the directions in these markets implies that the three China stock markets are not efficient. Lam et al. (2007) examine whether a day's surge or plummet in stock price serve as a market entry or exit signal. Returns of five trading rules based on one-day and intraday momentum are estimated for several major world stock indices. It is found that the trading rules perform well in the Asian indices, but not in those of Europe and the USA.

Kung and Wong (2009a) investigate whether these measures have led to less profitability for those investors who employ technical rules for trading stocks. Their results show that the three trading rules consistently generate higher annual returns for 1988–1996 than those for 1999–2007. Furthermore, they generally perform better than the buy-and-hold (BH) strategy for 1988–1996, but perform no better than the BH strategy for 1999–2007. These findings suggest that the efficiency of the Singapore stock market has been considerably enhanced by the measures implemented after the financial crisis.

Kung and Wong (2009b) use two popular technical trading rules to assess whether the gradual liberalization of Taiwan's securities markets has improved the efficiency in its stock market. The results show that the two rules have considerable predictive power for 1983–1990, become less predictive for 1991–1997, and cannot predict the market for the period 1998–2005. These empirical results indicate that the efficiency of the Taiwan stock market has been greatly enhanced by the liberalization measures implemented in the past 20 years. The above studies examine technical analysis for reasonably big data sets. In addition, academics and practitioners can apply technical analysis to examine the performance of a larger number of stock markets, as well as other financial market for larger data sets.

3.8. Cost of Capital

Gordon and Shapiro (1956) develop the dividend yield plus growth model for individual firms, while Thompson (1985) improves the theory by combining the model with an analysis of past dividends to estimate the cost of capital and its 'reliability'. Thompson and Wong (1996) extend the theory by obtaining estimates of the cost of equity capital and its reliability.

Wong and Chan (2004) extend the theory by developing estimators of the reliability, and prove that the estimators are consistent. Estimation of the cost of equity capital and its reliability can be used for both big data, and large data sets that might not be classified as big data.

3.9. Robust Estimation

Bian and Dickey (1996) develop a robust Bayesian estimator for the vector of regression coefficients using a Cauchy-type g-prior. This estimator is an adaptive weighted average of the least squares estimator and the prior location, and is robust with respect to flat-tailed sample distributions.

Bian and Wong (1997) develop an alternative approach to estimate the regression coefficients. Wong and Bian (2000) introduce the robust Bayesian estimator developed by Bian and Dickey (1996) to the estimation of the Capital Asset Pricing Model (CAPM), in which the distribution of the error component is widely known to be flat-tailed.

In order to support their proposal, the authors apply both the robust Bayesian estimator and the least squares estimator in simulations of CAPM, and also in the analysis of CAPM for US annual and monthly stock returns. The simulation results show that the Bayesian estimator is robust and superior to the least squares estimator when the CAPM is contaminated by large normal and non-normal disturbances, especially with Cauchy disturbances.

In their empirical study, the authors find that the robust Bayesian estimate is uniformly more efficient than the least squares estimate in terms of the relative efficiency of one-step ahead forecast mean square errors, especially in small samples. They introduce the robust Bayesian estimator developed by Bian and Dickey (1996) as this robust Bayesian estimator is adaptive and robust with respect to flat-tailed sample distribution. However, few papers have used this estimator in practice.

This estimator is adaptive and robust in the sense that if the sample does not contain outliers, the estimator will rely more on the sample information. On the other hand, if there are many outliers in the sample, the robust Bayesian estimator will use more information arising from the prior. To the best of our knowledge, only the estimator in Bian and Dickey (1996) has this feature, and so this estimator is recommended. It should be noted that the robust Bayesian estimator can be used for big data, and for large data sets that might not be interpreted as such.

3.10. Unit Roots, Cointegration, Causality Tests, and Nonlinearity

We have applied several tests related to unit roots, cointegration, and causality, including for higher moments, specifically a simple test for causality in volatility (see Chang and McAleer 2017), and discuss a few of the innovations below.

Tiku and Wong (1998) develop a unit root test to accommodate data that follow an AR(1) process. We use the three moment chi-square and four moment F approximations to test for unit roots in an AR(1) model when the innovations have one of a wide family of symmetric Student's *t*-distributions. In cointegration analysis, vector error-correction models (VECMs) have become an important means of analysing long run cointegrating equilibrium relationships.

The usual full-order VECMs assume all nonzero entries in their coefficient matrices. However, applications of VECMs to economic and financial time series data have revealed that zero entries are indeed possible. If indirect causality or Granger non-causality exists among the variables, the use of a full-order VECM will incorrectly conclude only the existence of Granger causality among these variables.

In addition, the statistical and numerical accuracy of the cointegrating vectors estimated in a misspecified full-order VECM will be problematic. It has been argued that the zero–non-zero (ZNZ) patterned VECM is a more straightforward and effective means of testing for both indirect causality and Granger non-causality. Wong et al. (2004) present simulations and an application that demonstrate the usefulness of the ZNZ patterned VECM.

Lam et al. (2006) develop some properties on the autocorrelation of the k-period returns for the general mean reversion (GMR) process, in which the stationary component is not restricted to the AR(1) process but takes the form of a general autoregressive–moving-average (ARMA) process. The authors derive some properties of the GMR process and three new nonparametric tests that compare the relative variability of returns over different horizons to validate the GMR process as an alternative to a random walk. The authors examine the asymptotic properties of the novel tests, which can be used to identify random walk models from the GMR processes.

The traditional linear Granger causality test has been widely used to examine linear causality among several time series in bivariate settings, as well as in multivariate settings. Hiemstra and Jones (1994) develop a nonlinear Granger causality test in a bivariate setting to investigate the nonlinear causality between stock prices and trading volume. Bai et al. (2010) extend the work by developing a nonlinear causality test in multivariate settings.

Bai et al. (2011b) discuss linear causality tests in multivariate settings, and thereafter develop a nonlinear causality test in multivariate settings. A Monte Carlo simulation is conducted to demonstrate the superiority of the proposed multivariate test over its bivariate counterpart. In addition, the authors illustrate the applicability of the proposed test to analyze the relationships among different Chinese stock market indices.

Hui et al. (2017) propose a simple and efficient method to examine whether a time series process possesses any nonlinear features by testing dependence remaining in the residuals after fitting the data with a linear model. The advantage of the proposed nonlinearity test is that it is not required to know the exact nonlinear features and the detailed nonlinear forms of the time series process. It can also be used to test whether the hypothesized model, including linear and nonlinear components of the variable being examined, is appropriate as long as the residuals of the model being used can be estimated.

The simulation study shows that the proposed test is stable and powerful. The authors apply the proposed statistic to test whether there is any nonlinear feature in sunspot data, and whether the S&P 500 index follows a random walk. The conclusion drawn from the proposed test is consistent with results that are available from alternative tests.

An early development in testing for causality (technically, Granger non-causality) in the conditional variance (or volatility) associated with financial returns was the portmanteau statistic for non-causality in the variance of Cheung and Ng (1996). A subsequent development was the Lagrange Multiplier (LM) test of non-causality in the conditional variance by Hafner and Herwartz (2008), who provided simulation results to show that their LM test was more powerful than the portmanteau statistic for sample sizes of 1000 and 4000 observations.

Although the LM test for causality proposed by Hafner and Herwartz (2008) is an interesting and useful development, it is nonetheless arbitrary. In particular, the specification on which the LM test is based does not rely on an underlying stochastic process, so the alternative hypothesis is also arbitrary, which can affect the power of the test.

Chang and McAleer (2017) derive a simple test for causality in volatility that provides regularity conditions arising from the underlying stochastic process, namely a random coefficient AR process, and a test for which the (quasi-) maximum likelihood estimates have valid asymptotic properties under the null hypothesis of non-causality. The simple test is intuitively appealing as it is based on an underlying stochastic process, is sympathetic to Granger (1969, 1988) notion of time series predictability, is easy to implement, and has a regularity condition that is not available in the LM test.

We note that using cointegration, causality and nonlinearity tools is very useful in analyzing many important issues and explains many financial and physiological phenomena well. For example, using cointegration, causality and nonlinearity tools, Batai et al. (2017) examine the factors that maintain a long-run equilibrium, short-run impact, and causality with the exchange rate of Mongolia over China to shed light on exchange rate determination.

The authors find that, in the long run, the gross domestic product (GDP) of China and the index of world price have significantly positive effects, while Mongolia's GDP and the Shanghai stock index have significantly negative effects on the Mongolian exchange rate.

The research also reveals the existence of a short run dynamic interaction, and highly significant linear and nonlinear multivariate causality from all the explanatory variables to the Mongolian exchange rate. The authors observe that there is strong linear causality from each of the GDPs of

Mongolia and China and the index of world price to Mongolian exchange rate, but not from the index of world price. Moreover, there is strongly significant nonlinear causality from the Shanghai stock index to the Mongolian exchange rate, and weakly significant nonlinear causalities from both the GDP of China and the index of world price on the Mongolian exchange rate, but not from Mongolia's GDP. The empirical findings are useful for investors, manufacturers, and traders for their investment decision-making, and for policy makers for their decisions regarding both monetary and fiscal policies that could affect the Mongolian exchange rate.

Academics and practitioners can apply unit root, cointegration, causality, and nonlinearity tests in many different areas for big data, and large data sets, as in empirical finance that uses nano-tick data, and dynamic panel data models with both large cross section and time series components. The literature in applying unit root, cointegration, causality and nonlinearity tests includes Wong et al. (2004, 2006), Qiao et al. (2007, 2008a, 2008b, 2009, 2011), Foo et al. (2008), Chiang et al. (2009), Vieito et al. (2015), Chang and McAleer (2017), among many others.

3.11. Confidence Intervals

Homm and Pigorsch (2012) use the Aumann and Serrano index to develop a new economic performance measure (EPM), which is well known to have advantages over alternative measures. Niu et al. (2018) extend the theory by constructing a one-sample confidence interval of EPM, and construct confidence intervals for the difference of EPMs for two independent samples. The authors also derive the asymptotic distribution for EPM and for the difference of two EPMs when the samples are independent. They conduct simulations to show the proposed theory performs well for one and two independent samples.

The simulations show that the proposed approach is robust in the dependent case. The theory developed is used to construct both one-sample and two-sample confidence intervals of EPMs for the Singapore and USA stock indices. It is worth noting that estimation of the confidence intervals can be used for big data, and large finite samples that are not regarded as big data.

The theory of confidence intervals for EPM developed in Niu et al. (2018) can be used to develop the theory of confidence intervals for any risk measure or economic indicator, which, in turn, could be used to construct confidence intervals for big data, large finite data samples that are not otherwise classified as big data.

3.12. Other Econometrics Models and Tests

The literature provides numerous alternative econometric/statistic models/tests, several of which have been used in a number of cognate disciplines, including economics, finance, management, marketing and statistics. Some of these are discussed below.

Wong and Miller (1990) develop a theory and methodology for repeated time series (RTS) measurements on autoregressive integrated moving average noise (ARIMAN) process. The theory enables a relaxation of the normality assumption in the ARIMAN model, and to identify appropriate models for each component series of the relevant stochastic process. The authors discuss the properties, estimation, and forecasting of RTS ARIMAN models and illustrate with examples.

Wong et al. (2001) extend the theory and methodology of Wong and Miller (1990) by allowing the error variance, as well as the number of repetitions, to change over time. They show that the model is identified, and derive the maximum likelihood estimator using the Kalman filter technique.

Tiku et al. (2000) consider AR(q) models in time series with non-normal innovations represented by a member of a wide family of symmetric distributions (Student's t). Since the ML (maximum likelihood) estimators are intractable, we derive the MML (modified maximum likelihood) estimators of the parameters and show that they are remarkably efficient. We use these estimators for hypothesis testing, and show that the resulting tests are robust and powerful.

Tiku et al. (1999a) extend the methods by considering AR(q) models in time series with asymmetric innovations represented by two families of distributions, namely (i) gamma with support IR: $(0, \infty)$, and (ii) generalized logistic with support IR: $(-\infty,\infty)$. As the maximum likelihood estimators (MLE) are intractable, the authors derive modified maximum likelihood (MML) estimators of the parameters and show that they are very easy to compute and are also efficient. The authors investigate the efficiency properties of the classical LS (least squares) estimators. Their efficiencies relative to the proposed MML estimators are very low.

Tiku et al. (1999b) estimate coefficients in a simple regression model in the presence of autocorrelated errors. The underlying distribution is assumed to be symmetric, namely one of Student's t family for illustration. Closed form estimators are obtained and shown to be remarkably efficient and robust.

Wong and Bian (2005) extend the results to the case where the underlying distribution is a generalized logistic distribution. The generalized logistic distribution family represents very wide skewed distributions ranging from highly right skewed to highly left skewed. Analogously, the authors develop MML estimators as the ML estimators are intractable for the generalized logistic data. The authors examine the asymptotic properties of the proposed estimators and conduct simulations to establish small sample properties of small size and high power.

Bian and Dickey (1996) develop a robust Bayesian estimator for the vector of regression coefficients using a Cauchy-type g-prior. This estimator is an adaptive weighted average of the least squares estimator (LSE) and the prior location, and is robust to fat-tailed sample distributions. Wong and Bian (2000) introduce the robust Bayesian estimator to the estimation of the Capital Asset Pricing Model (CAPM) in which the distribution of the error component is well known to be fat-tailed.

In order to support their proposal, the authors apply both the robust Bayesian estimator and the least squares estimator (LSE) in simulations of CAPM, and also in analysing CAPM for US annual and monthly stock returns. The simulation results show that the Bayesian estimator is robust and superior to LSE when CAPM is contaminated by large normal and/or non-normal disturbances, especially by Cauchy disturbances.

In the empirical study, the authors find that the robust Bayesian estimate is uniformly more efficient than the LSE in terms of the relative efficiency of one-step ahead forecast mean square errors, especially in small samples. Bian et al. (2013) develop a modified maximum likelihood (MML) estimator for the multiple linear regression model with underlying Student's *t*-distribution.

The authors obtain a closed form solution of the estimators, derive the asymptotic properties, and demonstrate that the MML estimator is more appropriate for estimating the parameters of the Capital Asset Pricing Model (CAPM) by comparing its performance with LSE for monthly returns of US portfolios. The empirical results reveal that the MML estimators are more efficient than LSE in terms of the relative efficiency of one-step-ahead forecast mean square errors in small samples.

Bian et al. (2011) develop a new test, namely the trinomial test, for pairwise ordinal data samples to improve the power of the sign test by modifying its treatment of zero differences between observations, effectively increasing the use of sample information. Simulations demonstrate the power superiority of the proposed trinomial test statistic over the sign test in small samples in the presence of tied observations.

The authors also show that the proposed trinomial test has substantially higher power than the sign test in large samples and also in the presence of tied observations, as the sign test ignores information from observations resulting in ties.

It is worth noting that all of the above estimation and testing procedures can be used for big data, as well as for finite samples that might not be classified as big data.

4. Simulations

After developing statistical theories for Big Data, Computational Science, Economics, Finance, Marketing, Management, Psychology, and cognate disciplines, academics and practitioners could consider conducting simulations to examine whether the estimators and hypothesis tests that have been developed have good size and high power. We conduct simulations to examine the performance in finite samples of small dimension. For example, Tiku and Wong (1998) conduct simulations to examine whether their unit root test have good size and high power.

Tiku et al. (1999b) consider AR(q) models in time series with asymmetric innovations represented by the gamma and generalized logistic distributions. They derive MML (modified maximum likelihood) estimators of the parameters and show that they are remarkably efficient. The authors conduct simulations to examine whether their estimators have small size and high power.

Tiku et al. (1999a) develop the theory to estimate the coefficients in a simple regression model with autocorrelated errors under the Student's *t*-distribution. The authors conduct simulations to examine whether the estimators have small size and high power.

Tiku et al. (2000) consider AR(q) models in time series with non-normal innovations represented by a member of a wide family of symmetric distributions (Student's *t*). The authors derive the MML estimators of the parameters and show that they are efficient. The authors use the estimators for hypothesis testing, and conduct simulations to show that the resulting tests are robust and powerful.

Checking the theory on estimation and hypothesis testing leads to tests that have small sizes and high power, academics and practitioners could then apply the theory and estimation and testing methods to analyze some interesting and important issues for big data and in large finite samples that are deemed not to be big data.

5. Empirical Studies

After developing theoretical models, as well as econometric and statistical models to estimate the parameters, academics and practitioners could then apply the theories to analyse some interesting issues in the seven disciplines and cognate areas.

5.1. Applications in Economics and Finance

Readers may refer to Chang et al. (2016a) for applying the theoretical models, and econometric and statistical models, to behavioural, finance, health and medical economics; Chang et al. (2016b) for applying the theory, and econometric and statistical models, to informatics, data mining, econometrics and financial economics; Chang et al. (2016c) for applying the theory, and econometric and statistical models, to management science, economics and finance; and Chang et al. (2017) for applying the theory, and econometric and statistical models, to management information, decision sciences, and financial economics.

Academics and practitioners could apply their theories to other financial economic problems. For example, Raza et al. (2016) investigate the empirical influence of tourism development (TD) on environmental degradation in a high-tourist-arrival economy (that is, USA) using the wavelet transformation framework. This new methodology enables the decomposition of time series at different time frequencies.

In the paper, the authors use the maximal overlap discrete wavelet transform (MODWT), wavelet covariance, wavelet correlation, continuous wavelet power spectrum, wavelet coherence spectrum and wavelet-based Granger causality analysis, in order to analyse the relationship between TD and CO_2 emissions in the USA by using monthly data for the period 1996(1) to 2015(3). The results indicate that TD has a significant positive influence over CE in the short, medium and long run. The authors find unidirectional influences of TD on CE in the short, medium and long run in the USA.

In addition, SD can be used to examine income inequality. For example, Chow et al. (2015) apply SD tests to analyze the relative welfare levels of income distributions for the poor and rich in different groups of individuals. Bai et al. (2016b) extend the theory by applying MSD and PSD to develop SD tests for the poor (test for poorness), the rich (test for richness), and middle class (test for middle class) to achieve a more robust analysis of relative welfare levels in the analysis of income distributions. Applying the SD test, Tsang et al. (2016) find the first-order SD in the Hong Kong property market, implying that there exists arbitrage opportunity in the Hong Kong property market. Wong et al. (2008) apply SD tests to study Asian hedge funds, Wong et al. (2006) find that the winners portfolio and the losers portfolio do not dominate each other. Lean et al. (2010) examine the market efficiency of oil spot and futures prices. Gasbarro et al. (2012) use both ascending and descending stochastic dominance procedures to test for risk-averse and risk-seeking behavior and find evidence of all four utility functions: concave, convex, S-shaped and reverse S-shaped. Clark et al. (2016) show that both spot and futures markets can exist when only risk averters are present, but futures can dominate spot only if there is some risk-seeking behavior.

On the other hand, Qiao et al. (2008c) uses linear and nonlinear Granger causality tests to study the lead–lag relations among China's segmented stock markets. Liew et al. (2010) investigate the linearity and stationarity properties of government bond returns for the G7 economies.

5.2. Applications in Psychology

In this sub-section, we discuss applications in marketing, management, and psychology. We first discuss applications in psychology. Chang et al. (1997) hypothesize that, when measured as an intrinsic need rather than as an inference from actual achievement and/or achievement-related images, the motivation to achieve may be a transcultural construct.

The authors use the Work and Family Orientation Scale (WOFO) to tap this intrinsic need. They conducted a series of surveys in Singapore with four samples of students and employed workers, comprising a total sample size of 1147. Factor analyses of the results revealed three oblique factors that are similar in content to those of reported US data. Comparisons of the factor structure from subsamples in Singapore revealed good reliability.

Confirmatory factor analysis showed a high degree of correspondence. Structural equation modeling indicated that this three-dimensional model: work ethics, mastery and competition, is an appropriate model for the Singaporean data. Predictive validity of WOFO was established by differentiating two groups of students with varying achievement levels. Convergence validity was supported by correlations with the Social and Individual-Oriented Achievement Scale developed in Taiwan, especially for the Chinese.

Chang et al. (2000) conducted a survey on two hundred and seventeen male (45%) and female (55%) Singaporean Chinese secondary school students (mean age = 16), with the Work and Family Orientation Scale (WOFO) designed to measure the intrinsic motivation to achieve and the Individual-oriented and Social-oriented Achievement Motivation Scale (10AM-SOAM), a culture-specific measure of Chinese achievement tendencies. They use the causal model to explore the relationships between the different dimensions of WOFO and 10AMSOAM.

Chang et al. (2003) conducted a series of three studies to test the internal structure of the Chinese value hierarchy (CVH) in Singapore. Study 1 identified the empirically best–fit model with six factors, namely Prudence, Industry, Civic–Harmony, Moral Development, Social Power and Moderation. The relative magnitudes and interfactor correlations suggested that these factors could be further grouped into two superordinate clusters, namely (i) the Modern factor, with significantly higher magnitude, consisting of Prudence, Industry, Civic–Harmony and Moral Development; and (ii) the Tradition factor, with lower magnitude, consisting of Social Power and Moderation.

Study 2 surveyed university students with differential preference for language usage, namely English or Chinese. Both language groups were equally high on the Modern factor, but the Chinese-language-preferred group showed a significantly higher endorsement for the Tradition factor, Chinese Worldview (CWV) and Chinese Health Beliefs (CHB).

Further convergence validation for the Modern and Tradition factors was obtained by investigating their correlations with traditional Chinese beliefs and practices for the two language groups separately. Study 3 tested generational differences in CVH. University participants (Self) were compared with their parents (Parents) and friends (Friends).

There were no differences between Self and Friends on both the Modern and Tradition factors, CWV and individual differences of modernity. Parents and Self did not differ on individual differences of modernity. Parents, however, were higher on the Modern factor, the Tradition factor and CWV.

The results were discussed to support the concept of 'multiple modernity' in Asian societies, and the 'revised convergence hypothesis'.

5.3. Applications in Marketing and Management

We now discuss applications in marketing and management. Liao and Wong (2008) explore empirically the major considerations associated with Internet-enabled e-banking systems and systematically measure the determinants of customer interactions with e-banking services. The results suggest that the perceived usefulness, ease of use, security, convenience and responsiveness to service requests significantly explain variations in customer interactions. Exploratory factor analysis and reliability tests indicate that these constructs are relevant and reliable.

Confirmatory factor analysis confirms that they possess significant convergent and discriminatory validities. Both perceived usefulness and perceived ease of use were found to have significant impacts on customer interactions with Internet e-banking services. Perceived security, responsiveness and convenience also represent primary avenues that influence customer interactions. In particular, stringent security control is critical to Internet e-banking operations. Prompt responses to service requests can also encourage customers to use Internet e-banking services.

The empirical findings have managerial implications for enhancing extant Internet e-banking operations and developing viable Internet e-banking services. Liao et al. (2012) explore empirically consumer perceptions of the smartcard as e-cash for purchasing goods and services at retail outlets in Hong Kong. The authors design a multi-attribute model to test the hypotheses using the survey data collected from individual consumers.

The empirical results show that perceived ease of use, convenience, automatic add-value service, compact design, security, reliability, and merchant support have significant effects on perceived usefulness of the smartcard for micro e-payment. The findings contribute to the literature of consumer behavior with regard to the applications of information technology in retailing, and have implications for implementing emerging technology to enhance retail services in different contexts.

Liao et al. (2014) examine the sustainability of smartcard payments in retailing and consumer services. The analytical results of the survey data suggest that usefulness, ease of use, convenience, automatic add-value service, security, reliability, and participation of popular service providers have considerable effects on a continuous use of smartcard payment.

The authors identify empirically and justify the key determinants of sustainable smartcard payment from the perspective of consumers. The findings provide managerial insights for the implementation of cutting-edge technology to enhance sales and service operations and make important contributions to research and practice in technology-based service innovation and service operations management.

Moslehpour et al. (2017) examine the key factors that influence Taiwanese consumers to repurchase Korean beauty products. They use a quantitative approach to test the proposed hypotheses using structural equation modelling. A causal research design is used in the research to identify a cause-and-effect relationship among the constructs. Primary data collection is used for the empirical analysis.

This contribution provides a better understanding of the key factors that influence Taiwanese consumers' repurchase intentions (RI) of Korean cosmetics products. They find that perceived price (PP) and country of origin (COO) significantly influence word-of-mouth (WOM), while PP, COO and WOM significantly influence RI. WOM is the most influential variable toward RI, followed by COO and PP.

Very few studies have examined a general construct of RI related to beauty products. The empirical findings imply several practical directions for marketers of beauty product industries, specifically for Taiwanese consumers. The analysis helps to understand the factors that form a basic consideration for Taiwanese consumers in repurchasing Korean beauty products. Second, it underscores the role of WOM between the independent variables (PP and COO) and RI as the dependent variable.

The mediating role of customer satisfaction has been widely discussed in the existing literature. However, to the best of our knowledge, there is still a lack of studies that focus on the low-cost airline industry, especially in Vietnam. For this reason, Moslehpour et al. (2018b) investigate the factors that influence purchase intentions and the mediating role of customer satisfaction in VietJet Air in Vietnam. A quantitative research method is applied, with the data being collected through an online questionnaire from three main regions in Vietnam, namely the North, Center, and South.

The empirical results indicate that customer satisfaction mediates the relationship between the independent variables (customer expectation/perceived value) and the dependent variable (purchase intention) in the case of VietJet Air (Hanoi, Vietnam). In general, the analysis not only enriches the existing literature, but might also be an invaluable reference to VietJet Air and similar low cost Vietnamese carrier managers to consider their strategic marketing plans.

Moslehpour et al. (2018a) propose a new model that combines personality traits (PT) and Technology Acceptance Model (TAM) to examine the influences of personality characteristics (conscientiousness, openness), and perception of technology (perceived usefulness, perceives ease of use) on e-purchase intentions by using a questionnaire survey to collect a similar sample of Taiwanese online consumers.

The authors find that conscientiousness (CON) (personality attribute) significantly influences perceived usefulness (PU), perceived ease of use (PEOU) (technology perception attributes), and openness to experience (OPE). PU, PEOU, and OPE have significant impacts on online purchase intention (INT). PEOU has the strongest positive impact on (INT). In addition, PU, PEOU, and OPE combined mediate the relationship between CON and INT. Further analysis of mediation shows that PU and PEOU (separately) are both significant mediators. However, OPE alone is not a significant mediator.

6. Conclusions

In this paper, we discussed different types of utility functions, stochastic dominance, mean-risk models, portfolio optimization, and others as these topics are important in Big Data, Computational Science, Economics, Finance, Marketing, Management, and Psychology in terms of theory and econometric and statistical analysis. Authors could extend their work to link the seven cognate disciplines.

Although we have discussed the contributions in SD, MR, and PO related to Big Data, Computational Science, Economics, Finance, Marketing, Management, and Psychology, there are theoretical contributions in other areas that could also be useful in these cognate disciplines. Readers may refer to Chang et al. (2016a, 2016b, 2016c, 2017) for contributions in other cognate areas that might be useful in theory and practice.

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