

Article

Revisiting the Distress Risk Anomaly: The 52-Week High Effect and Lottery-Seeking in Distressed Stocks

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Abstract

Objective: Contrary to the traditional notion of risk–return trade-off, prior studies document that financially distressed stocks tend to earn lower future returns than their healthier peers. Extending this strand of literature, this study revisits the distress risk anomaly in UK stocks and further examines whether proximity to the 52-week high and lottery-like characteristics of stocks help explain the financial distress anomaly, if any. **Data and methods:** In this paper, we analyse the distress risk anomaly using a sample of 4514 UK stocks over the period 2000–2021. The analysis is conducted using both the portfolio-sorting method and Fama–MacBeth cross-sectional regressions. **Key findings:** The empirical findings confirm the persistence of the financial distress anomaly, showing that high-distress stocks earn lower returns than their low-distress counterparts. Consistent with a mispricing explanation, this inverse distress–return relationship is more pronounced for stocks that are difficult to arbitrage and is stronger following periods of market optimism. Furthermore, the analysis reveals that both the 52-week high effect and lottery-like trading, independently and jointly, contribute to the poor performance of financially distressed stocks. This suggests that underreaction and overreaction interact to shape the observed overvaluation of distressed stocks. These findings remain robust to a battery of robustness checks. The results have several important implications for investors, researchers, and regulators.

Keywords: financial distress risk; distress risk anomaly; behavioural finance; anchoring bias; 52-week high effect; lottery-seeking behaviour; investor sentiment; limits to arbitrage; stock returns predictability



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1. Introduction

The association between financial distress risk and anticipated stock returns is one of the most tenacious anomalies that test the premises of the modern asset pricing theory. The Capital Asset Pricing Model (CAPM) and its multi-factor extensions, such as the Fama–French three-factor model (Fama & French, 1993) and the Carhart four-factor model (Carhart, 1997), share a common fundamental assumption: rational risk-averse investors are expected to earn higher returns in cases where they have to bear higher systematic risk.

In this paradigm, equities with high risk of default, which represent a vivid expression of financial distress, should have higher-risk premiums to compensate investors against the risk of bearing a catastrophic loss. Empirical studies, however, are often in opposition to this theoretical expectation, and a negative cross-sectional relationship between default risk and future stock returns has been documented.

The classic paper of Dichev (1998) was the first to provide a systematic record of this so-called distress risk anomaly, where it was shown that the higher the risk of bankruptcy of a firm, the lower the returns accrued by the investors as compared to its financially robust counterparts. This opposite outcome was later supported by Campbell et al. (2008), who developed an all-inclusive measure of financial distress risk and validated that the underperformance of distressed stocks continued to underperform non-distressed stocks in the next year. The robustness of this anomaly is a serious threat to the efficient market hypothesis, as well as the traditional risk–reward trade-off model, which suggests that investors systematically underprice securities with a high risk of default.

The emergence of behavioural finance has provided alternative theoretical models to explain the anomalous pricing behaviours that do not conform to the rational models of traditional finance. According to the behavioural finance theory, investors may fail to fully incorporate relevant information into asset prices due to their limited cognitive capacity and the presence of systematic behavioural biases, e.g., limited attention (Hong & Stein, 1999; Hirshleifer & Teoh, 2003; Peng & Xiong, 2006). Empirical evidence supports this argument and suggests that investor underreaction plays a significant role in generating the poor performance observed among financially distressed stocks (e.g., Agarwal & Taftler, 2008; Avramov et al., 2022; Chen et al., 2023).

Drawing on the plausibility of the underreaction-based channel, anchoring bias may represent an underexplored mechanism that offers a specific explanation for the financial distress anomaly. In particular, anchoring bias provides a distinct underreaction mechanism that differs from those examined in prior studies. For instance, prior studies rely on the media and analyst coverage of firms as proxies for the underreaction channel. While these measures provide valuable insight into investor underreaction, they may be more closely related to the dissemination of information than to investors' underlying beliefs. Building on the arguments presented by George and Hwang (2004), George et al. (2015), and Huang et al. (2021), the 52-week high ratio may be viewed as a proxy for the anchoring bias, reflecting a salient reference point that influences how investors update their beliefs and process new information.

Accordingly, there is a plausible theoretical rationale for investigating whether the 52-week high plays a role in the observed misvaluation of financially distressed firms. Stocks that are traded at prices further away from their 52-week highs may appear under-valued to investors, even when substantial deterioration in fundamentals has occurred. This psychological attachment to prior price peaks can lead to the systematic mispricing of distressed stocks, as investors tend to underestimate the likelihood of further declines while overestimating potential recoveries. In this study, the 52-week high ratio, defined as the current price relative to the highest price in the past 52 weeks, is used as a proxy for the anchoring bias intensity and as a conditioning variable in explaining the financial distress anomaly.

Another potential behavioural channel explaining distressed stock mispricing arises from lottery-seeking behaviour, as revealed by Kumar (2009) and Bali et al. (2011). Barberis and Huang (2008) argue that probability distortion may cause investors to overweight low-probability, high-payoff outcomes, which can lead to the overpricing and subsequent underperformance of positively skewed securities. Empirical evidence demonstrates that distressed equities have small probabilities of large upside events that may attract investors

who prefer positively skewed returns (Campbell et al., 2008; Conrad et al., 2014). Khasawneh et al. (2024) present evidence suggesting lottery-seeking patterns in UK stocks. This gambling-inspired demand may push the prices of distressed securities above their underlying values, thus creating the subsequent underperformance.

Empirical evidence links the lottery-seeking trading intensity to the 52-week high effect. Particularly, Byun et al. (2020) document that lottery-seeking behaviour is concentrated in stocks trading further below their 52-week high, suggesting that the anchoring effect contributes to the lottery-driven demand and mispricing. This interplay between lottery-seeking behaviour and the 52-week high effect is particularly relevant for distressed stocks trading at very low levels relative to their 52-week highs, as such securities may be perceived simultaneously as ‘cheap’ by anchor-biased investors and as lottery-like by skewness-seeking investors.

From a behavioural finance perspective, lottery-seeking behaviour and the 52-week high effect arise from distinct behavioural mechanisms: the former reflects biased beliefs about return distributions, while the latter is typically associated with cognitive constraints in processing and incorporating information into prices. Their empirical and theoretical linkage raises an important question about how these forces interact in explaining financial distress anomaly, with potential implications for other asset pricing anomalies and the development of more comprehensive models.

Distressed stocks are characterised by high fundamental uncertainty, making them difficult to value and particularly susceptible to behavioural biases and mispricing (Baker & Wurgler, 2006). Anchoring on the 52-week high may cause investors to underreact to fundamental information when prices deviate substantially from this reference point, contributing to persistent mispricing. At the same time, limited attention to fundamentals may shift investor focus toward more salient signals, such as lottery-like characteristics and extreme return potential, thereby amplifying skewness-seeking demand. In this setting, anchoring and lottery preferences interact, suggesting that the distress anomaly may reflect both underreaction to fundamentals and overreaction to perceived upside potential.

While prior research documents the distress anomaly, the 52-week high effect, and lottery effects separately, less is known about their joint role in pricing distressed stocks. It remains unclear how anchoring and lottery preferences interact in explaining the abnormal returns of financially distressed firms. To the best of our knowledge, the potential joint role of these behavioural channels in explaining the financial distress anomaly has received limited attention in previous studies.

The United Kingdom is a useful setting due to its creditor friendly insolvency regime, which grants secured lenders substantial control during financial distress (Gao et al., 2018). Within the framework of Merton (1974), stronger creditor rights are expected to reduce the option-like value of equity and weaken the distress anomaly. Consistent with this prediction, Aretz et al. (2018) document a stronger relation between distress risk and returns in countries with greater creditor protection. The UK therefore provides a stringent environment for testing whether behavioural mechanisms remain relevant under strong creditor rights.

This study seeks to address the gaps identified above by adopting a conditional behavioural framework to examine the distress risk effect in the UK market. In particular, it explores whether the financial distress anomaly is more pronounced when the stock prices of distressed firms are further below their 52-week highs and whether these stocks exhibit lottery-like characteristics. First, the study employs multiple measures of financial distress. In addition to the Charitou et al. (2004) z-score, it utilises the Taffler (1983) z-score and the Bharath and Shumway (2008) distance-to-default measure. Second, it applies double-sorted portfolio analyses and the Fama–MacBeth cross-sectional regression approach to examine

whether the relationship between financial distress and stock returns may be conditional on the 52-week high ratio. The empirical analysis takes place through the following stages. Firstly, descriptive statistics and correlation are used to show the relationship between default risk, 52-week highs, lottery-style properties, and other variables. Secondly, single-sort analysis is performed to determine whether there a distress risk anomaly exists. Thirdly, double-sort analysis is applied to determine whether the effect of the distress risk anomaly differs at different levels of the 52-week highs. Finally, the Fama–MacBeth approach is conducted to examine whether distress risk, the 52-week highs, and their interaction affect future returns, taking into account other factors known to be relevant in explaining returns.

In light of the above discussion, our contributions are fourfold. First, we expand on the UK evidence on financial distress anomaly. While Agarwal and Taffler (2008) document that UK investors underreact to financial distress risk, we revisit the anomaly using more timely and objective measures of financial distress and examine the behavioural mechanisms underlying its persistence. This is particularly relevant in light of evidence that many documented anomalies attenuate following publication (McLean & Pontiff, 2016). By reassessing the anomaly in a market characterised by strong creditor protection and substantial institutional participation, we provide evidence on its robustness and behavioural foundations. Second, we introduce anchoring on the 52-week high as a behavioural mechanism underlying the distress anomaly, linking reference-point formation to mispricing of financially distressed stocks. Third, we extend the literature by using an empirically validated proxy for lottery-like characteristics to examine the hypothesised influence of lottery-seeking behaviour on the mispricing of financially distressed stocks. Fourth, we integrate anchoring with lottery-seeking preferences to show how underreaction to fundamentals and skewness-driven demand jointly shape the financial distress anomaly, highlighting a previously underexplored source of return predictability in high-uncertainty environments.

The results show that the distress anomaly persists in a market characterised by strong creditor protection and substantial institutional participation. This may imply that institutional factors by themselves are unlikely to completely resolve mispricing. We also find compelling evidence of two complementary mechanisms: first, the 52-week high appears to be associated with return patterns that are suggestive of anchoring-based underreaction behaviour. This implies that investors partially neglect or slowly incorporate fundamental news when prices are evaluated relative to salient historical highs. Second, lottery-seeking preferences are linked to the overvaluation of distressed stocks, consistent with excess demand for skewness. This suggests that speculative preferences for extreme upside potential contribute to upward price distortions.

Further, the results indicate that these forces interact in shaping the predictive power of the poor returns of distressed stocks. This implies that mispricing is not driven by a single channel but by the joint effect of underreaction to fundamentals and overreaction to perceived upside potential. More broadly, the evidence suggests that returns predictability arises from the combined influence of financial distress, reference dependency, and skewness preferences. This implies that a multidimensional behavioural framework is required to explain the anomaly. Finally, the persistence of these effects in a sophisticated institutional environment implies that behavioural biases remain economically relevant even in settings with strong market infrastructure and professional participation.

2. Theoretical Framework and Hypothesis Development

The research draws its motivation from behavioural asset pricing theory and not risk compensation theory. In the traditional model of asset pricing, securities which are riskier, especially with respect to negative outcomes such as defaults, should attract higher

expected returns (Sharpe, 1964). Contrary to what the risk–return paradigm postulates, however, the distressed firm literature shows that stocks with greater potential for financial distress experience lower returns in the future (Dichev, 1998; Campbell et al., 2008).

Therefore, the theoretical framework is based on two major behavioural channels and two boundary conditions. Two major behavioural channels include reference-point anchoring, measured by the 52-week high ratio, and lottery-type demand, measured by highly positive returns and other skewness-related factors. Meanwhile, investor sentiment and limits of arbitrage are seen as boundary conditions capable of exacerbating and amplifying the problem of mispricing rather than the main theme of this paper. Since the empirical setting mostly involves portfolio sorting and Fama–MacBeth regression analysis, all hypotheses are stated in terms of conditional return predictability. Thus, empirical results should be interpreted as supportive evidence, but not conclusive proof of investors' behaviour and motivation.

2.1. Financial Distress Risk and Subsequent Stock Returns

According to behavioural finance theory on asset pricing, the existence of the financial distress anomaly is possible due to the complexity, graduality, and costliness of processing deteriorating conditions of company fundamentals. Distress-related information is usually communicated through poor accounting performance, low profitability, poor market performance, high volatility, and balance sheet frailty. Since such information does not come at once, slow price adjustments are observed.

This is in line with past findings. First, Dichev (1998) documents that the greater the bankruptcy risk of firms, the lower their subsequent return. Second, Campbell et al. (2008) find that distressed firms generate abnormally low returns on average. Finally, Agarwal and Taftler (2008) document that the negative distress premium in UK firms is consistent with underreaction of the stock market to the risk of financial distress. In general, Chen et al. (2023) argue that underreaction anomalies depend on investor attention. Hence, if distress information becomes part of the stock price slowly, then distressed stocks earn lower returns. Thus, we hypothesise:

H1. *Financial distress risk is negatively associated with subsequent stock returns.*

2.2. Investor Sentiment and Limits to Arbitrage as Boundary Conditions

Sentiment and limits to arbitrage are viewed as boundary conditions. According to Baker and Wurgler (2006), sentiment influences stocks that are hard to value and hard to arbitrage, while Ding et al. (2019) find that sentiment-prone securities are more susceptible to noise trader demand. Given the assumptions that distressed stocks are hard to value and expensive to arbitrage, the distress–return relationship becomes even more significant in periods of positive sentiment and when higher arbitrage costs exist. Therefore, examining the effects of limits to arbitrage and market sentiment on the returns of distressed stocks provides an indirect test of the mispricing hypothesis. Therefore, the following hypotheses are proposed:

H2a. *The distress risk anomaly is stronger during periods of high investor sentiment.*

H2b. *The distress risk anomaly is stronger among stocks with greater limits to arbitrage.*

2.3. 52-Week High Anchoring and the Pricing of Distress Risk

A substantial strand of prior evidence supports the view that the financial distress anomaly is a manifestation of investors underreaction. One potential underreaction-based mechanism that may contribute to the distress risk anomaly is reference-point anchoring.

Following prior evidence, the 52-week high could act as an effective reference point for current prices. George and Hwang (2004) found that proximity to the 52-week high predicts future returns, whereas subsequent research linked the 52-week high anomaly to value-relevant information processing (Zhu et al., 2023).

Within the distress framework, the 52-week high ratio may influence investor expectations regarding fundamentals deterioration and the distribution of future returns. In particular, given its associated with bad news, it is expected that the financial distress anomaly is more pronounced for stocks traded at prices further below their 52-week highs. Although this is not direct evidence of anchoring bias, the results appear consistent with this explanation. Hence, the following hypothesis is proposed:

H3. *The negative distress–return relationship is stronger among stocks trading farther below their 52-week highs.*

2.4. Lottery Preference, Skewness-Seeking and Distressed Stocks

Skewness-seeking behaviour, which offers another distinct mechanism that may drive financial distress. Recent advances in behavioural finance suggest that investors derive utility depend not only on the mean and variance of returns, but also on the possibility of extreme positive payoffs. According to Kumar (2009), investors exhibit a preference for lottery-like stocks, while Bali et al. (2011) show that stocks experiencing extreme daily returns tend to deliver lower expected returns due to overvaluation driven by lottery-seeking demand. According to Conrad et al. (2014), firms with a high default probability may have a payoff structure akin to jackpots. If investors place high weight on positive-payoffs likelihood, lottery-like features could further amplify the effect of distress risk on future returns. Empirically, this suggests that the distress–return relationship will be more pronounced for firms with lottery-like features. Thus, the third hypothesis is:

H4. *Lottery-like characteristics strengthen the negative association between financial distress risk and subsequent stock returns.*

2.5. Joint Role of Lottery-like Characteristics and 52-Week High Anchoring

Anchoring and lottery strategies can also work together in tandem. When the price of a distressed stock is very low compared to its 52-week high price level, it may seem like there is potential for it to recover from that price level, whereas if it generates extremely high returns, then it seems to be a good bet for an investor looking for skewness. Byun et al. (2020) provides supporting evidence for this suggestion. Therefore, we argue that both effects, jointly, may help identify the financial distress anomaly. Hence, the following hypothesis is proposed:

H5. *The joint effect of financial distress risk and lottery-like characteristics is stronger among stocks trading farther below their 52-week highs.*

3. Sample, Variables, Methodology

3.1. Sample

This study employs a comprehensive sample of common stocks listed on the London Stock Exchange to investigate the proposed return predictability. To address the well-documented issue of survivorship bias in cross-sectional asset pricing research, the sample includes both delisted and active firms. This issue is particularly important in studying financially distressed firms. Delisting returns are not explicitly incorporated into the monthly return series. As a result, returns are observed only up to the final available trading month prior to delisting.¹ The primary sample consists of 4514 stocks over the

period from January 2000 to August 2021, incorporating daily and monthly stock price data along with additional firm-specific information.

Following tradition in asset pricing studies, financial firms are excluded from the sample. To address issues related to non-synchronous trading, stocks with fewer than 120 trading days in the prior year are removed. Additionally, months with missing data are excluded, along with stocks priced below £3 and firms reporting negative book values. However, stocks with very low prices and negative book values represent important distress observations. Their exclusion is a common practice in the asset pricing literature, as such stocks are often subject to significant microstructure noise, including illiquidity, price discreteness, and non-synchronous trading. These issues can distort return distributions and bias empirical results. Therefore, we exclude these stocks to ensure that the findings are not driven by mechanical pricing frictions but instead reflect the underlying economic relations of interest.² Market data are sourced from Thomson Reuters DataStream, while accounting information is obtained from the Worldscope database. All data are reported in UK pounds. Table A1 in Appendix A summarises the data construction and the selection criteria.

3.2. Variable Definitions

We measure stock returns at a monthly frequency using the total return index, which incorporates both price changes and dividends. In both time series or cross-sectional analyses, we use raw returns.

Distress risk and related aspects of mispricing are inherently difficult to quantify and lack universally accepted metrics. Consequently, prior literature employs a range of proxies, which we adopt and extend in this study.

To assess financial distress, we employ three commonly used proxies. The main analysis relies on the z-score proposed by [Charitou et al. \(2004\)](#). For robustness, we employ two additional measures of financial distress: the z-score of [Taffler \(1983\)](#) and the distance-to-default (DD) metric proposed by [Bharath and Shumway \(2008\)](#). These alternative measures enhance generalizability by capturing both market-based and accounting-based approaches to evaluating financial distress.³ These models were originally calibrated in their respective studies against observed corporate distress events, including bankruptcy, default, and failure, and are widely used as established predictors of financial distress. For the accounting-based approaches, the measures are estimated using the specifications and coefficients reported in the original studies rather than being re-estimated using this study's sample. Employing the original model specifications enhances comparability with prior research.

To ensure comparability across measures, the probability of default for each index is estimated using a logistic transformation, with higher values indicating a greater likelihood of default:

$$P(Y = 1) = \frac{1}{1 + e^{-z}}$$

where z denotes the employed distress risk measure. Using the logistic function enables transformation of the unbounded values of each accounting-based distress measure into a standardised probability bounded between 0 and 1. This transformation preserves the ordering of firms implied by the original score while enhancing interpretability and comparability across different measures. Higher values of the financial distress measure therefore correspond to higher estimated probabilities of default.

To examine the potential role of anchoring bias in the financial distress anomaly, we follow [George and Hwang \(2004\)](#) by employing the 52-week high ratio (PH52). Following the literature, PH52 is defined as the ratio of the current month's closing price to the 52-week high price. The 52-week high price includes the current closing price; therefore,

this value of PH52 is bounded above by 1. This measure reflects the tendency of investors to update their valuation gradually when the current price is either near or far from the prior 52-week high. Such a measure has been widely adopted in the literature (e.g., [George et al., 2015](#); [Huang et al., 2021](#); [Zhu et al., 2023](#); among others).

Following [Bali et al. \(2011\)](#), extreme returns are used to proxy lottery-like features. Specifically, we define the lottery-likeness as the average of the five highest daily returns for each stock in the prior month (MAX5). Given that the measure is based on the five highest daily returns, using months with very few trading observations could mechanically inflate the statistic and introduce measurement noise. Therefore, to avoid biased trading and ensure statistical reliability, months with fewer than 12 daily return observations are excluded. The 12-day threshold follows standard practice in the lottery-like return literature, where a minimum trading activity condition is used to balance data availability with reliability of the estimated tail-return measure. This proxy has been widely adopted in the literature (e.g., [Byun et al., 2020](#); [Blau et al., 2020](#); [Lu et al., 2022](#)) to capture the skewness-driven attractiveness of lottery-like stocks.

Since arbitrage difficulties are unobservable ([Sha et al., 2023](#)), we follow the widely used approach and employ idiosyncratic volatility, illiquidity, bid–ask spreads, firm size, and firm age as proxies for limits to arbitrage. Higher volatility, lower liquidity, wider bid–ask spreads, smaller market capitalisation, and younger firms are associated with more costly arbitrage. Principal component analysis (PCA) is used to aggregate these proxies into a single arbitrage-difficulty index derived from the first principal component, where higher values indicate stronger constraints on arbitrage.

Finally, to ensure that our findings are not driven by previously documented return predictors, we control for a comprehensive set of established anomalies. Prior research has identified predictable return patterns such as short-term reversals ([Jegadeesh, 1990](#)) and medium-term momentum ([Jegadeesh & Titman, 1993](#)). [Fama and French \(1993, 2015\)](#) emphasise the importance of market value, book-to-market ratio, return on assets, and asset growth in explaining stock returns. In addition, illiquidity measures ([Amihud, 2002](#)) have been shown to explain cross-sectional return variation.

All accounting variables are measured using data from the previous fiscal year and are matched to returns beginning in June of the following year. This procedure imposes a six-month lag after the fiscal year-end, ensuring that financial statement information is publicly available, thereby mitigating look-ahead bias. To mitigate the impact of outliers, all variables are winsorised at the 1% level in both tails of the distribution. The Newey–West lag length is set to two, given the monthly frequency of the data.⁴ To adjust portfolio performance for common risk factors, the pricing factors are estimated using UK data following [Fama and French \(1993\)](#). The market return is calculated from the FTSE All-Share index.

Table A2 in Appendix A provides a summary of the variable measurements.

3.3. Method

To examine the existence of financial distress anomaly and the potential role of the 52-week high effect in explaining it, this study employs both portfolio analysis and cross-sectional regressions. These complementary methods are widely used in the asset pricing literature.

In the portfolio analysis, each month, stocks are allocated into deciles based on their level of financial distress. Portfolio performance is then evaluated using the return of each decile portfolio over the subsequent month. To further examine the role that the 52-week high effect may play in shaping the financial distress anomaly, a double-sorting procedure is employed, whereby stocks are independently sorted into quantiles based on distress

risk and the 52-week high ratio. At the end of each month, stocks are independently sorted into five quintile portfolios based on the distress risk proxy and into five quintile portfolios based on the 52-week high ratio. The resulting portfolios are then intersected to form 25 portfolios representing all possible combinations of distress risk and 52-week high ratio quintiles. This independent double-sorting procedure allows the examination of the joint effects of distress risk and the 52-week high ratio on subsequent stock returns. This approach allows us to assess the performance of distress-based portfolios conditional on the level of the 52-week high ratio. The portfolio breakpoints are based on the selected sample of monthly observations. The statistical significance of these portfolio returns is evaluated using the Newey–West t-statistic. Given that autocorrelation in monthly returns is expected to be low, we use a lag length of two. However, unreported results show that using longer lag lengths yields similar and, in some cases, even stronger results.

Although portfolio analysis provides an intuitive and nonparametric method to examine patterns in returns, it becomes less effective if many variables are involved. To address this limitation, we resort to the Fama–MacBeth cross-sectional approach, which is more effective for estimating predictive relationships and isolating the marginal effect of individual variables within a multivariate framework (Fama & MacBeth, 1973). This approach enables us to assess the robustness of the empirical findings while controlling for a wider range of potential factors. The equations below present the monthly Fama–MacBeth regressions estimated at different stages of the study:

$$R_{i,t+1} = \alpha_t + \beta_{1,t} \times DR_{i,t} + \beta_{2,t} \times \text{Beta} + \beta_{3,t} \times \text{LnMV} + \beta_{4,t} \times \text{LnBM} + \beta_{5,t} \times \text{MOM12} + \beta_{6,t} \times \text{ROA} + \beta_{7,t} \times \text{AG} + \beta_{8,t} \times \text{Amih} + \beta_{9,t} \times \text{Last} + \varepsilon_{i,t} \quad (1)$$

$$R_{i,t+1} = \alpha_t + \beta_{1,t} \times DR_{i,t} + \beta_{2,t} \times \text{Beta} + \beta_{3,t} \times \text{LnMV} + \beta_{4,t} \times \text{LnBM} + \beta_{5,t} \times \text{MOM12} + \beta_{6,t} \times \text{ROA} + \beta_{7,t} \times \text{AG} + \beta_{8,t} \times \text{Amih} + \beta_{9,t} \times \text{Last} + \beta_{10,t} \times \text{PH52}_{i,t} + \beta_{11,t} \times (\text{DR}_{i,t} \times \text{PH52}_{i,t}) + \varepsilon_{i,t} \quad (2)$$

$$R_{i,t+1} = \alpha_t + \beta_{1,t} \times DR_{i,t} + \beta_{2,t} \times \text{Beta} + \beta_{3,t} \times \text{LnMV} + \beta_{4,t} \times \text{LnBM} + \beta_{5,t} \times \text{MOM12} + \beta_{6,t} \times \text{ROA} + \beta_{7,t} \times \text{AG} + \beta_{8,t} \times \text{Amih} + \beta_{9,t} \times \text{Last} + \beta_{10,t} \times \text{LOTT}_{i,t} + \beta_{11,t} \times (\text{DR}_{i,t} \times \text{LOTT}_{i,t}) + \varepsilon_{i,t} \quad (3)$$

$$R_{i,t+1} = \alpha_t + \beta_{1,t} \times DR_{i,t} + \beta_{2,t} \times \text{Beta} + \beta_{3,t} \times \text{LnMV} + \beta_{4,t} \times \text{LnBM} + \beta_{5,t} \times \text{MOM12} + \beta_{6,t} \times \text{ROA} + \beta_{7,t} \times \text{AG} + \beta_{8,t} \times \text{Amih} + \beta_{9,t} \times \text{Last} + \beta_{10,t} \times \text{LOTT}_{i,t} + \beta_{11,t} \times (\text{DR}_{i,t} \times \text{LOTT}_{i,t}) + \beta_{12,t} \times \text{LPH}_{i,t} + \beta_{13,t} \times (\text{DR}_{i,t} \times \text{LOTT}_{i,t} \times \text{LPH}) + \varepsilon_{i,t} \quad (4)$$

Equation (1) specifies the baseline model of this study, where $R_{i,t+1}$ represents the subsequent month's return for firm i in month t , and $DR_{i,t}$ denotes the financial distress proxy for firm i in month t . Beta represents the stock systematic risk, LnMV is the natural logarithm of market value, LnBM is the natural logarithm of book-to-market ratio, MOM12 is the medium-term momentum, ROA denotes the return on assets, AG represents asset growth, Amih is the Amihud (2002) illiquidity measure, and Last is the previous month's return. Collectively, these variables serve as control variables in the model. Note that, in the main analysis, the regressions include only Beta, LnMV, and LnBM as control variables. Equation (2) extends the baseline model by incorporating the PH52 _{i,t} and its interaction with the distress proxy. PH52 _{i,t} denotes the 52-week high ratio for firm i in month t , while $DR_{i,t} \times \text{PH52}_{i,t}$ represents the interaction term between the distress risk and 52-week high ratio. Equation (3) extends the baseline specification by incorporating lottery-like characteristics to examine their effect on distress risk pricing. LOTT _{i,t} and $DR_{i,t} \times \text{LOTT}_{i,t}$ represents the lottery-like proxy and its interaction term with distress risk, respectively. Lastly, Equation (4) tests whether the 52-week high moderates the interaction between lottery-like trading and financial distress risk. LPH is an indicator variable equalling 1 for stocks in the lowest quantile of PH52 distribution, and 0 otherwise. Note that the 52-week high effect is modelled as a dummy variable to capture its marginal effect. The coefficients α and β represent the estimated parameters of the corresponding variables.

4. Empirical Findings

4.1. Descriptive Statistics and Correlation Analysis

Table 1 presents the descriptive statistics (Panel A) and the correlation coefficients for the study variables (Panel B). As shown in Panel B, next-month returns are negatively correlated with all proxies of distress risk. Regarding the relationship with the 52-week high ratio (PH52), all proxies of distress risk are negatively related to PH52. This provides initial evidence that distressed stocks tend to trade further away from their 52-week highs.

Table 1. Descriptive statistics and Correlation Matrix. This table presents descriptive statistics and correlation analysis, where R_{t+1} is the next-month returns, and CHz is the probability of financial distress measured by Charitou et al. (2004)'s model. Taffz is the probability of financial distress measured by Taffler (1983)'s model. DDz is the probability financial distress measured by distance to default, following the approach proposed by Bharath and Shumway (2008). Beta is stock beta estimated using the CAPM. LnMV is the logarithm of market capitalisation. LnBM is the logarithm of book-to-market ratio. MOM12 is the cumulative return over the past 12 months. ROA is return on assets. AG is asset growth. Amih is the Amihud (2002) illiquidity measure. Past is the last-month return. sd denotes the standard deviation, and p5 and p95 are the 5th and 95th percentiles of the distribution.

Panel A: Descriptive Statistics														
Stats	R_{t+1}	CHz	Taffz	DDz	PH52	MAX5	Beta	LnMV	LnBM	MOM12	AG	ROA	Amih	Past
mean	−0.29	0.33	0.28	0.37	0.76	2.98	0.15	5.58	−1.03	3.19	0.16	−0.01	2.79	0.28
sd	14.07	0.41	0.4	0.44	0.22	2.02	0.11	1.92	1.13	56.41	0.406	0.3	17.05	14.44
p5	−23.28	0	0	0	0.31	0.81	0	2.68	−3	−98.19	−0.273	−0.45	0.0004	−22.94
p95	20.72	1	1	1	1	7.04	0.36	8.97	0.68	86.14	0.891	0.23	8.03	22.54
Panel B: Correlation														
	R_{t+1}	CHz	Taffz	DDz	PH52	MAX5	Beta	LnMV	LnBM	MOM12	ROA	AG	Amih	
CHz	−0.04													
Taffz	−0.03	0.71												
DDz	−0.04	0.08	0.08											
PH52	0.09	−0.2	−0.15	−0.53										
MAX5	−0.02	0.25	0.21	0.12	−0.36									
Beta	−0.04	0.12	0.07	0.08	−0.25	0.24								
LnMV	0.04	−0.23	−0.2	−0.12	0.37	−0.28	0.12							
LnBM	0	−0.1	−0.06	0.35	−0.31	0.06	−0.03	−0.21						
MOM12	0.06	−0.05	−0.02	−0.63	0.78	−0.16	−0.12	0.18	−0.39					
ROA	0.05	−0.55	−0.44	−0.06	0.21	−0.23	−0.09	0.25	0.03	0.08				
AG	−0.04	−0.05	−0.11	0.05	−0.14	0.07	0.1	−0.06	−0.06	−0.12	−0.19			
Amih	0	0.06	0.06	0.05	−0.07	0.1	−0.06	−0.14	0.08	−0.05	−0.05	−0.03		
Past	0.02	−0.01	0	−0.2	0.34	−0.11	−0.05	0.06	−0.12	0.31	0.02	−0.05	0.01	

Furthermore, distress risk proxies are positively related to MAX5, whereas PH52 is negatively related to MAX5, suggesting that financially distressed stocks, as well as those with prices further below their 52-week highs, are more likely to be held by skewness-seeking investors. Overall, these unconditional relationships offer preliminary support for the aim of this study.

4.2. Performance of Distressed Stocks: Portfolio Analysis

To examine the performance of distressed stocks in the UK market, we first conduct a portfolio analysis. Specifically, in this section, stocks are sorted into deciles based on the distress measure proposed by Charitou et al. (2004) and used to construct ten distress-based portfolios. We then evaluate the performance of these portfolios using their next-month returns, calculated on both an equal-weighted and value-weighted basis. Table 2 displays the results of portfolio performance.

Table 2. Portfolio analysis. This table presents the portfolio analysis based on the probability of financial distress measured by Charitou et al. (2004)'s model. The P1 (P10) portfolio includes stocks with the lowest (highest) level of financial distress. FF3F is the Fama–French three-factor model alpha.

	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	P10–P1	FF3F
Panel A: Equal-weighted												
R_{t+1}	−0.05	0.08	0.08	0.40	0.25	0.03	0.03	−0.39	−1.55	−2.57	−2.52	−2.25
t-stat	0.11	0.22	0.21	1.11	0.70	0.08	0.06	−0.91	−2.93	−4.40	−8.45	−7.76
Panel B: Value-weighted												
R_{t+1}	0.00	0.40	0.36	0.63	0.49	0.15	0.41	0.25	−0.38	−2.55	−2.55	−1.87
t-stat	0.00	1.09	1.11	2.32	1.99	0.55	1.28	0.84	−0.92	−3.70	−4.84	−3.56

As shown in Table 2, stocks with the highest distress risk (P10) underperform compared to the stocks with the lowest distress risk (P1). Specifically, Panel A shows that the equal-weighted next-month return for portfolio P10 (P1) is −2.57% (−0.05%), with a Newey–West t-statistic of −4.4 (0.11). This divergence in performance generates a statistically significant spread of 2.52%, with a Newey–West t-statistic of −8.85. Taking the risk into consideration does not change the result. Adjusting for the Fama–French three-factor model generates a significant spread in alpha (FF3) with a value of −2.25% and Newey–West t-statistic of −7.76. Panel B shows that weighting the returns of these portfolios by their constituent market values does not alter the results.

Therefore, the portfolio analysis in Table 2 reveals that the financial distress anomaly exists in the UK stock market. This is in line with the prior evidence from the U.S. market (Campbell et al., 2008; Andreou et al., 2021). Moreover, the failure of standard risk factors to explain the anomalously poor performance of highly distressed stocks leaves room for behavioural explanations, with investor underreaction representing one plausible mechanism.

4.3. Investor Sentiment, Arbitrage Difficulties, and Distress-Stock Mispricing

Under standard asset pricing theory, mispricing is expected, but it is quickly eliminated by informed arbitrageurs with frictionless and unlimited capital. However, real-world limits on arbitrage contradict this assumption (Shleifer & Vishny, 1997). Building on this, behavioural finance models argue that limited arbitrage is a necessary condition for observing mispricing in financial markets (e.g., Hong & Stein, 1999). Empirical evidence supports this link (e.g., Stambaugh et al., 2015; Khasawneh et al., 2024). Additionally, sentiment-driven trading is a key component of many behavioural finance models (see, for example, De Long et al., 1990; Barberis et al., 1998). This trading is driven by speculative reasons rather than the rational goal of utility maximisation. Trading on sentiment creates noise trading that is found to be systematic and represents risk to arbitrageurs (Barber et al., 2009). Consistent with its nature, sentiment-based trading creates overvaluation and subsequently predictable patterns in security prices (Baker & Wurgler, 2006; Stambaugh et al., 2015). Consequently, investors influenced by sentiment underreact to value-relevant news (Riedl et al., 2021). Sentiment-based mispricing is more pronounced when arbitrage is costly for stocks such as volatile, young, small, and financially distressed (see Baker & Wurgler, 2006).

Following from the discussion above, investor sentiment will be viewed as the environment in which speculative demand might intensify, while problems with arbitrage will be seen as a condition that could hinder the correction of any pricing errors. Accordingly, if poor performance of distressed securities is driven by behavioural mispricing, then its impact should be amplified in high-sentiment environments and among more difficult-to-arbitrage securities.

Arbitrage costs are largely unobservable. Prior literature relies on various proxies to represent limits to arbitrage. Following this approach, we employ idiosyncratic volatility, illiquidity, bid–ask spreads, firm size, and firm age as proxies for limits to arbitrage. Higher volatility, lower liquidity, wider bid–ask spreads, smaller market capitalisation, and younger firms are associated with more costly arbitrage. Using principal component analysis (PCA), we combine these proxies into a single arbitrage-difficulty index based on the first principal component, where higher values indicate greater limits to arbitrage.

The proportion of total variance explained by the first component, along with its factor loadings, support using it as a proxy for arbitrage difficulty. On average, the first component captures nearly 36% of the total variation among the underlying individual proxies, while the second component explains about 20% of the variation. In addition, the signs of the loadings on the first components are consistent with the theoretical interpretation of each variable. For example, IVOL, SP, and Amih all have positive loadings on the first component, suggesting that higher idiosyncratic uncertainty, trading costs and illiquidity are associated with higher values of this component. Moreover, size and age proxies have negative loadings on this component, which is consistent with expectations that smaller and younger firms tend to exhibit higher arbitrage costs. In contrast, the signs of the loadings on other components do not align with the expected roles of these variables. For instance, in the second component, IVOL, size, and age have negative loadings, while SP and Amih have positive loadings. Therefore, we argue that the first principal component provides a valid proxy for the common factor related to arbitrage difficulty.

To gauge the market sentiment, we align with studies that use survey-based measures (see, for example, [Lemmon & Portniaguina, 2006](#)). Specifically, we employ the Economic Sentiment Indicator (ESI) produced by the European Commission.⁵ This survey-based index is constructed from UK market data, capturing general expectations for the UK economy. Employing the European Commission index for the UK sample is also supported by prior studies such as [Salhin et al. \(2016\)](#) and [Ferrer et al. \(2016\)](#). By construction, these surveys reflect both rational and irrational expectations of investors. To isolate the rational expectation, we orthogonalize the raw index with respect to a set of macroeconomic variables. Practically, we regress the ESI on a recession indicator, the market return over the past three months, growth in unemployment, growth in industrial production, inflation, term premium, and dividend yield. The rolling three-month sum of the estimated residuals is used to proxy the market sentiment.

Consistent with the mispricing-based explanation, Table 3 demonstrates concentration of the financial distress mispricing phenomena in the optimism state of the market. Highly distressed stocks underperform the low distressed stocks only when the stocks are costly to arbitrage and that the market is optimistic (i.e., high sentiment). As reported in Panel B of Table, the spread between the high-distress portfolio and the low distress portfolio is significantly negative only following periods of markets optimism and when the stocks are costly to arbitrage. The spread is -2.73 , with a Newey–West t-statistic of -3.34 . Adjusting this spread to the Fama and French 5-factor model produces an alpha of -2.55 , with a Newey–West t-statistic of -3.08 . In contrast, as shown under Panel A, outside the periods of market optimism and among stocks that are easy to arbitrage, financial distress anomaly generates an insignificant spread. When arbitrage limitations are not binding or the investors are pessimistic, none of the distress-based portfolio spreads are statistically significant.

Table 3. Mispricing of distressed stocks. This table displays the combined effect of sentiment and arbitrage difficulties level on the financial distress anomaly. Probability of financial distress is measured using Charitou et al. (2004)’s model. P1 (P3) is the group of stocks in the lowest (highest) tercile of financial distress levels. P3–P1 represents the difference in returns between the P3 portfolio and the P1 portfolio. Opt (Pess) denotes months where the market is optimistic (pessimistic). Low (High) Arbitrage Difficulties is the group of stocks in the lowest (highest) quantile of the mispricing index. R_{t+1} is the next-month return. FF3F α is the alpha of Fama and French (1993) three-factor model. t-stat is a Newey–West t-statistic.

Sentiment and Arbitrage Difficulties							
	P1	Pess P3	P3–P1	P1	Opt P3	P3–P1	Opt–Pess
Panel A: Low-Arbitrage Difficulties							
R_{t+1}	1.00	1.13	0.13	0.03	−0.08	−0.11	−0.24
t-stat	1.94	2.25	0.56	0.06	−0.16	−0.45	−0.73
FF3F α	0.35	0.49	0.14	0.05	−0.01	−0.05	−0.19
t-stat	0.24	1.76	0.58	0.11	−0.01	−0.23	−0.58
Panel B: High-Arbitrage difficulties							
R_{t+1}	−0.24	0.17	0.42	−1.43	−3.73	−2.31	−2.73
t-stat	−0.28	0.18	0.75	−1.86	−4.45	−3.9	−3.34
FF3F α	−0.86	−0.54	0.32	−0.68	−3.01	−2.33	−2.64
t-stat	−1.57	−0.85	0.56	−1.01	−4.47	−3.94	−3.25

Overall, Table 3 supports the mispricing argument regarding the financial distress anomaly. The sentiment channels and arbitrage costs jointly play a crucial role in generating this mispricing. During optimism periods, investors may overestimate the positive signals regarding likelihood of financial failure, leading to the overvaluation of highly distressed stocks. This overvaluation of distressed stocks persists only when arbitrage costs are present and hinder rational arbitrageurs from moving prices toward their fundamental values. The absence of these conditions leads to more efficient pricing of distressed stocks. Thus, the financial distress anomaly is driven by mispricing behaviour. These findings are consistent with arguments in Zhu and Shen (2025).

4.4. Role of the Anchoring Effect

As an alternative to the risk-based explanation, we examine the potential role of the anchoring effect as a mechanism that may lead investors to underreact to the negative information underlying the firm’s distress status. To do so, the performance of distress-based portfolios is conditioned on the level of the 52-week high ratio, which serves as a proxy for anchoring effect. Specifically, the stocks, each month, are sorted into quantiles based on the distress risk and PH52, independently. Then, we intersect these quantiles to generate 25 portfolios with different levels of distress and PH52. Table 4 shows the next-month returns for these portfolios.

Table 4 shows that the magnitude of financial distress anomaly weakens with the higher level of PH52. The spread between the highest and lowest quantiles of distressed stocks is greatest in the lowest quantile of PH52, with a value of −1.59% and a Newey–West t-statistic of −4.43. Moving to the highest quantile of PH52, the spread is neither economically nor statically significant, with a value of −0.04% and a Newey–West t-statistic of −0.12. When value-weighting returns, the effect of proximity to the past 52-week high on the financial distress anomaly becomes more pronounced. The financial distress anomaly is only significant when the price is furthest from the 52-week high. Panel B shows, within the lowest PH52 quantile (PH1), that the spread is −2.6% with a Newey–West t-statistic of

−4.07. Adjusting the distress-based spread to the Fama–French three-factor model does not alter the results.

Table 4. Double-sort analysis: distress risk and 52-week high ratio. This table presents portfolio analysis based on distress level and PH52. Probability of financial distress is measured by Charitou et al. (2004)’s model. Stocks are allocated into quantiles based on PH52 and financial distress, independently. PH1 (PH5) includes stocks with the lowest (highest) quantile of 52-week high ratio. P1 (P5) includes stocks with the lowest (highest) quantile of financial distress.

	Panel A: Equally Weighted					Panel B: Value-Weighted				
	PH1	PH2	PH3	PH4	PH5	PH1	PH2	PH3	PH4	PH5
P1	−1.53	−0.41	0.42	0.65	0.90	−0.78	−0.15	0.37	0.48	0.51
t-stat	−2.34	−0.84	1.11	1.94	2.82	−1.13	−0.27	0.81	1.26	1.37
P2	−1.28	−0.27	0.48	0.74	0.70	−1.05	0.00	0.44	0.76	0.38
t-stat	−2.06	−0.60	1.33	2.30	2.49	−1.49	0.00	1.00	2.66	1.51
P3	−1.58	−0.11	0.32	0.75	0.81	−0.68	0.02	0.39	0.70	0.36
t-stat	−2.28	−0.23	0.88	2.29	2.81	−0.84	0.05	1.21	2.64	1.36
P4	−2.24	−0.53	0.23	0.51	0.92	−2.04	0.06	0.06	0.34	0.66
t-stat	−3.17	−1.09	0.62	1.48	3.17	−2.37	0.12	0.14	1.14	2.66
P5	−3.13	−1.72	−0.71	−0.23	0.86	−3.38	−0.75	−0.16	0.08	0.34
t-stat	−4.67	−3.28	−1.35	−0.44	1.71	−4.84	−1.39	−0.27	0.17	0.65
P5–P1	−1.59	−1.30	−1.13	−0.89	−0.04	−2.60	−0.60	−0.53	−0.40	−0.17
t-stat	−4.43	−4.39	−3.48	−2.44	−0.12	−4.07	−1.14	−0.95	−0.99	−0.35
FF3F	−1.52	−1.13	−0.86	−0.67	0.04	−2.46	−0.13	0.20	−0.03	0.00
t-stat	−3.94	−3.69	−2.55	−1.83	0.11	−3.69	−0.25	0.35	−0.08	−0.01

In Tables 2 and 4, the evidence is drawn from single and double sorting on distress portfolio and PH52 without controlling for potential return predictors across the stocks. To examine the validity of the results in a multivariate setting, we report the Fama and MacBeth regressions in Table 5. In this analysis, we regress next-month returns on the distress proxy (CHz), PH52, and the interaction term between them, while controlling for market value, beta, and book-to-market ratio. Confirming the results reported in Tables 2 and 4, the reported results reveal that the distress risk is negatively associated with the next-month returns and this predictive power decreases with proximity to past 52-week highs. As shown under C1–C4, distress risk, proxied by the Charitou et al. (2004) z-score (CHz), has a highly significant negative coefficient. For example, C4 shows that while controlling for widely used returns predictors, the coefficient of CHz is −1.21 with a Newey–West t-statistic of −8.45.

Columns C5–9 introduce the 52-week high effect along with its effect on the financial distress anomaly. As shown in column C5, introduce the PH52 reduces but does not subsume the distress risk effect completely. The PH52 has significant predictive power for the next-month return with a coefficient of 5.63 and a Newey–West t-statistic of 7.24. However, this effect on the financial distress anomaly is marginal, where the coefficient of CHz remains highly significant with a value of −0.915 and a Newey–West t-statistic of −4.88. Notably, Columns C6–C9 confirm the influence of PH52 in moderating the predictive effect of distress risk on stock returns. In line with Table 3, introducing the interaction term (PHxCHz) reveals that the inverse association between the distress risk and the next-month returns is mitigated with proximity to the 52-week high. To illustrate, C6 demonstrates that the coefficient of term PHxCHz is positive with a value of 2.55 and a Newey–West t-statistic of 4.49. Therefore, in comparison to the main distress effect (−2.78), the total effect of CHz is nearly zero ($CHz + PHxCHz = -0.23$).⁶ The inclusion of control

variables further confirms the key role of the 52-week high in driving the magnitude of the financial distress anomaly.

Table 5. Fama–MacBeth cross-sectional regressions. This table presents the Fama–MacBeth regressions with an extended set of returns predictors. CHz is the probability of financial distress measured by Charitou et al. (2004)’s model. Beta is stock beta estimated using the CAPM. LnMV is the logarithm of market capitalisation. LnBM is the logarithm of book-to-market ratio. Numbers in parentheses are the Newey–West t-statistic. ^a, ^b, and ^c denote statistical significance at 1%, 5%, and 10%, respectively.

	C1	C2	C3	C4	C5	C6	C7	C8	C9
CHz	−1.68 ^a (−6.82)	−1.45 ^a (−7.015)	−1.5 ^a (−7.72)	−1.21 ^a (−8.45)	−0.915 ^a (−4.88)	−2.78 ^a (−6.235)	−2.63 ^a (−6.037)	−2.60 ^a (−6.21)	−2.55 ^a (−6.08)
PH					5.63 ^a 7.24	4.62 ^a 5.56	4.32 ^a 5.85	4.35 ^a 6.46	4.08 ^a 6.504
PHxCHz						2.55 ^a 4.49	2.415 ^a 4.321	2.467 ^a 4.554	2.415 ^a 4.457
Beta		−2.145 ^c (−1.69)	−2.17 ^c (−1.917)	−2.843 ^b (−2.275)			−0.623 (−0.646)	−0.477 (−0.546)	−0.754 (−0.763)
LnBM			−0.191 ^c (−1.854)	−0.114 (−1.127)				0.083 1.00	0.086 0.98
LnMV				0.204 ^a 3.5					0.039 0.781
Const	0.302 0.86	0.66 ^b 2.43	0.47 1.477	−0.59 (−1.25)	−4.38 ^a (−5.33)	−3.58 ^a (−4.10)	−3.21 ^a (−4.28)	−3.18 ^a (−4.46)	−3.164 ^a (−4.22)
Obs	157,041	157,041	156,416	156,416	156,534	156,534	156,534	156,416	156,416
Adj R ²	0.01	0.028	0.038	0.048	0.041	0.043	0.052	0.057	0.064

Taken together, the evidence reported so far lends support to the behavioural mechanism, specifically underreaction biases. The findings imply that investors are less attentive to information embedded in firm’s distress when the stock prices are farther from the 52-week high. Consequently, investors are more likely to overvalue distressed stocks when their prices lie further below the 52-week high. These findings are consistent with behavioural models of Barberis et al. (1998), in which investors exhibit conservatism bias that leads them to update their beliefs slowly in response to new information. Confirming the results in George and Hwang (2004), investors are slower in updating their beliefs about bad news when the stocks prices are far from their 52-week high.

5. Robustness Test

This section offers a battery of analysis aimed at checking how sensitive the reported results are to methodological changes. Firstly, the reported results may correspond to the employed measure of financial distress and if the findings are robust against employing various proxies of distress risk. Second, we examine the ability of the results to hold against additional risk factors and return predictors. Third, we examine the stability of the findings across subperiods within the overall sample period. Fourth, pricing anomalies literature suggests that reported mispricing is only evident in small part of the stock sample (i.e., micro stocks); to rule out this concern, the main results are reported after excluding the smallest stocks. Finally, while the main analysis focuses on short-term effects of distress risk, we extend the analysis to longer time horizons.

5.1. Alternative Proxies for Default Probability and Additional Return Predictors

The financial distress anomaly reported so far is based on a single proxy, Charitou et al. (2004) z-score. To assess robustness, we re-examine the results using two alternative measures: Taffler (1983)’s z-score, which is accounting-based, and the distance-to-default

measure by [Bharath and Shumway \(2008\)](#), which combines both market and accounting information to measure financial distress.

Table 6 confirms the empirical evidence reported for the [Charitou et al. \(2004\)](#)'s measure in Table 2. Both the Taffler z-score (Taffz) and distance-to-default (DDz) are negatively associated with the next-month returns across the UK stocks. For example, the adjusted equal-weighted alphas of the zero-cost portfolios (P10–P1) constructed using the Taffz and DDz measures are -1.58% (Newey–West t-statistic = -5.43) and -1.79% (Newey–West t-statistic = -4.21), respectively. The value-weighted portfolios show a similar effect.

Table 6. Alternative distress proxies. This table presents the portfolio analysis-based alternative distress measures: Taffz is the probability of financial distress measured by [Taffler \(1983\)](#)'s model and DDz is the probability financial distress measured by distance to default, which measured following the approach proposed by [Bharath and Shumway \(2008\)](#). P1 (P10) portfolio includes the stocks with lowest (highest) distress level. FF3F is the Fama and French three-factor model alpha.

Panel A: Taffz												
	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	P10–P1	FF3
EW	−0.74	−0.22	0.18	0.17	0.14	0.14	0.17	−0.12	−0.86	−2.45	−1.71	−1.58
t-stat	−1.39	−0.51	0.50	0.44	0.38	0.36	0.42	−0.28	−1.98	−4.33	−6.11	−5.43
VW	−0.24	0.11	0.46	0.48	0.31	0.38	0.46	0.13	0.02	−1.39	−1.15	−1.03
t-stat	−0.43	0.25	1.74	1.70	0.94	1.40	1.71	0.45	0.05	−2.52	−2.41	−2.05
Panel B: DDz												
	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	P10–P1	FF3
EW	−0.02	0.44	0.21	0.21	0.13	−0.01	−0.35	−0.55	−1.06	−2.06	−2.04	−1.79
t-stat	−0.04	1.15	0.58	1.17	0.40	−0.04	−0.90	−1.18	−1.97	−3.03	−4.30	−4.21
VW	0.05	0.18	0.35	0.35	0.35	0.51	0.34	−0.37	0.17	−1.17	−1.22	−1.84
t-stat	0.12	0.49	1.11	2.82	1.84	1.82	1.08	−0.83	0.32	−1.58	−1.84	−2.09

In addition to the Fama–French three-factor model, several further return predictors have been proposed in the literature. The [Carhart \(1997\)](#) four-factor model extends the framework by adding momentum, while the [Fama and French \(2015\)](#) five-factor model incorporates profitability and investment-related factors. [Agarwal and Taffler \(2008\)](#) document a relationship between distress risk and momentum, while [Agarwal and Bauer \(2014\)](#) find that the pricing of financial distress is largely driven by accounting profitability. Prior studies suggest that returns predictability may be driven by market microstructure such short-term reversal and liquidity (see, [Jegadeesh & Titman, 1995](#)). Table 7 presents Fama–MacBeth cross-sectional regressions with various distress risk proxies and additional set of returns predictors.

As shown in Table 7, the observed financial distress anomaly is robust to various distress proxies and controlling for an additional set of predictors. For instance, Columns C3 and C8 show that the coefficients of Taffz and DDz are significantly negative, with values of -1.29 (Newey–West t-statistic = -7.48), and -1.68 (Newey–West t-statistic = -6.16), respectively. Moreover, the role that PH52 plays in shaping the financial distress anomaly is evident across various distress measures and control specifications. Columns C2, C7, and C12 demonstrate that introducing PH52 and the interaction terms (PHxCHz and PHxTaffz) reduces the magnitude of the financial distress anomaly for stocks with high PH52. Using DDz as a proxy for the distress risk, Column C12 shows that the inclusion of the main term of PH52 is sufficient to fully absorb the distress effect.⁷ These findings confirm both the existence of the financial distress anomaly and the role of the 52-week high effect in explaining it.

Table 7. Additional pricing factors. This table presents the Fama–MacBeth regressions with extended set of returns predictors. PH52 is the ratio of current price to the past 52-week high. CHz is the probability of financial distress measured by Charitou et al. (2004)’s model. Taffz is the probability of financial distress measured by Taffler (1983)’s model. DD is the probability of financial distress measured by distance to default, following the approach proposed by Bharath and Shumway (2008). Beta is stock beta estimated using the CAPM. LnMV is the logarithm of market capitalisation. LnBM is the logarithm of the book-to-market ratio. MOM12 is the cumulative stock return over the past 12 months. ROA is return on assets. AG is the asset growth. Amih is the Amihud (2002) illiquidity measure. Last is the last-month return. Numbers in parentheses are the Newey–West t-statistic. ^a, ^b, and ^c denote statistical significance at 1%, 5%, and 10%, respectively.

	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12
CHz	−0.69 ^a (−4.96)	−2.06 ^a (−4.69)										
PHxCHz		1.99 ^a 3.627										
Taffz			−1.29 ^a (−7.48)	−0.72 ^a (−4.95)	−2.02 ^a (−4.16)	−1.72 ^a (−3.75)	−1.4 ^a (−3.1)					
PHxTaffz					1.821 ^a 3.09	1.549 ^a 2.769	1.336 ^b 2.362					
DDz								−1.68 ^a (−6.16)	0.006 0.028	0.676 1.156	−0.138 (−0.25)	0.09 0.156
PHxDDz										−0.974 (−1.36)	−0.153 (−0.23)	−0.261 (−0.38)
PH52		2.278 ^a 3.215		5.832 ^a 7.361	5.201 ^a 6.14	4.617 ^a 7.119	2.508 ^a 3.456		6.102 ^a 7.182	6.599 ^a 7.608	5.283 ^a 7.677	3.356 ^a 4.615
Beta	−1.688 (−1.59)	−0.876 (−0.92)				−0.896 (−0.91)	−0.961 (−1.02)				−1.116 (−1.1)	−1.074 (−1.09)
LnMV	0.11 ^b 2.043	0.033 0.703				0.038 0.737	0.029 0.609				0.07 1.333	0.038 0.807
LnBM	0.117 1.413	0.097 1.213				0.099 1.10	0.101 1.25				0.136 1.577	0.119 1.537
AG	−0.55 ^a (−3.80)	−0.50 ^a (−3.59)					−0.55 ^a (−4.03)					−0.35 ^b (−2.50)
ROA	0.871 ^a 2.985	0.544 ^b 2.04					0.765 ^a 2.84					1.101 ^a 4.202
AMIH	−0.10 ^b (−2.29)	−0.10 ^b (−2.19)					−0.08 ^c (−1.90)					−0.09 ^b (−2.33)
MOM	0.015 ^a 7.163	0.008 ^a 3.311					0.008 ^a 3.497					0.008 ^a 3.33
Last	0.008 ^c 1.689	0.002 0.388					0.002 0.357					0.002 0.345
cons	−0.135 (−0.29)	−1.67 ^b (−1.99)	0.127 0.342	−4.62 ^a (−5.47)	−4.12 ^a (−4.62)	−3.62 ^a (−4.67)	−1.87 ^b (−2.16)	0.331 0.964	−5.01 ^a (−5.41)	−5.40 ^a (−5.73)	−4.33 ^a (−5.36)	−2.67 ^a (−3.18)
Obs	154,046	154,046	155,039	154,580	154,580	154,466	152,141	147,533	147,533	147,533	147,420	145,122
Adj R ²	0.069	0.075	0.006	0.04	0.042	0.064	0.076	0.015	0.041	0.044	0.066	0.078

5.2. Alternative Anchor Bias Proxy

In this section, we re-estimate the Fama–MacBeth regressions using an alternative proxy for the price reference point. Instead of the 52-week high ratio, we use the ratio of the current stock price to its highest level over the preceding five years. Table 8 presents the results. Consistent with the evidence based on the 52-week high ratio and the anchoring-based explanation, the 5-year high ratio exhibits significant positive predictive power for subsequent one-month returns in the UK stock market.

Furthermore, the results in Table 8 reinforce the evidence presented in Table 7 in support of the anchoring-based explanation of the financial distress anomaly. Across most specifications, the interaction terms between the 5-year high ratio and the various distress risk proxies are statistically significant at conventional levels or, at a minimum, marginally significant. For example, considering Charitou et al. (2004)’s distress measure, Column C2 shows that the coefficient of interaction term PH5YxCH is 1.205 with a Newey–West t-statistic of 2.68.

Table 8. Alternative proxy of price anchoring. This table presents the Fama–MacBeth regressions with an extended list of returns predictors. PH5Y is the ratio of current price to the past 5-year high level. CHz is the probability of financial distress measured by Charitou et al. (2004)’s model. Taffz is the probability of financial distress measured by Taffler (1983)’s model. DD is the probability of financial distress measured by distance to default, which is measured following the approach proposed by Bharath and Shumway (2008). Beta is stock beta estimated by CAPM. LnMV is the logarithm of Market capitalisation. LnBM is the logarithm of book-to-market ratio. MOM12 is the cumulative stock return over the past 12 months. ROA is return on assets. AG is the asset growth. Amih is the Amihud (2002) illiquidity measure. Last is the last-month return. Numbers in parentheses are the Newey–West t-statistic. ^a, ^b, and ^c denote statistical significance at 1%, 5%, and 10%, respectively.

	C1	C2	C3	C4	C5	C6
CHz	−1.452 ^a (−4.44)	−1.213 ^a (−4.409)				
PH5Y	2.712 ^a 4.394	0.897 ^b 2.252	3.039 ^a 4.886	1.181 ^a 2.962	2.839 ^a 5.757	1.554 ^a 4.374
PH5YxCH	1.131 ^b 2.55	1.205 ^a 2.68				
Taffz			−1.041 ^a (−3.214)	−0.944 ^a (−3.302)		
PH5YxTaffz			0.819 ^c 1.87	0.84 ^b 1.97		
DDz					−1.137 ^a (−2.927)	−0.217 (−0.652)
PH5YxDDz					1.042 ^c 1.753	0.317 0.619
Beta		−0.919 (−0.912)		−0.952 (−0.948)		−1.143 (−1.12)
LnMV		0.067 1.278		0.058 1.08		0.064 1.204
LnBM		0.178 ^b 2.164		0.185 ^b 2.238		0.21 ^a −2.617
AG		−0.644 ^a (−4.359)		−0.7 ^a (−4.933)		−0.517 ^a (−3.512)
ROA		0.301 1.36		0.389 ^c 1.709		0.576 ^a 2.647
Amih		−0.074 (−0.864)		−0.052 (−0.582)		−0.085 (−1.005)
MOM12		0.015 ^a 7.123		0.015 ^a 7.138		0.015 ^a 6.653
Last		−0.019 ^a (−4.383)		−0.019 ^a (−4.505)		−0.018 ^a (−4.424)
cons	−1.752 ^a (−2.603)	−0.534 (−0.862)	−2.038 ^a (−2.981)	−0.682 (−1.087)	−1.817 ^a (−2.972)	−1.006 ^c (−1.722)
Obs	154,810	152,322	152,914	150,475	145,885	143,474
R-squared	0.04	0.095	0.039	0.095	0.043	0.098
Adj R ²	0.035	0.076	0.034	0.076	0.037	0.078

5.3. Subsample Analysis

In this section, we assess the temporal stability of the reported financial distress anomaly. Specifically, we analyse the distress-based decile portfolio performance across two subperiods, 2000–2008 (pre-2009) and 2009–2021 (post-2009). Additionally, we examine the sensitivity of the financial distress anomaly to the size of stocks included in the portfolio. Previous studies suggest that anomalous pricing is primarily driven by small firms, and distressed stocks are more likely to be small-cap stocks.

As shown in Table 9, the underperformance of distressed stocks remains consistent across different periods. The spread between the lowest and highest decile of distressed stocks is economically and statistically significant in both subperiods. For instance, using DDz as the distress measure, the spreads for the pre-2009 and post-2009 periods are -1.75% and -2.30% , with a Newey–West t-statistic of -2.08 and -4.54 , respectively. Controlling for the Fama–French three-factor model does not alter the results.

Table 9. Subperiods analysis. This table presents the portfolio analysis based on alternative distress measures: CHz is the probability of financial distress measured by Charitou et al. (2004)’s model. Taffz is the probability of financial distress measured by Taffler (1983)’s model and DDz is the probability of financial distress measured by distance to default, following the approach proposed by Bharath and Shumway (2008). P1(P10) portfolio includes stocks with lowest (highest) distress level. FF3F is the Fama–French three-factor model alpha. The returns are equally weighted.

	CHz		Taffz		DDz	
	Pre-2009	Post-2009	Pre-2009	Post-2009	Pre-2009	Post-2009
P1	−0.42	0.28	−1.34	−0.22	−0.60	0.50
t-stat	−0.55	0.72	−1.31	−0.49	−0.78	1.21
P2	−0.44	0.54	−0.69	0.19	0.06	0.76
t-stat	−0.67	1.33	−0.89	0.46	0.10	1.87
P9	−1.79	−1.35	−0.94	−0.79	−1.58	−0.61
t-stat	−1.93	−2.32	−1.26	−1.60	−1.63	−1.12
P10	−3.15	−2.06	−2.92	−2.05	−2.35	−1.81
t-stat	−2.98	−3.56	−2.94	−3.37	−1.95	−2.51
P10–P1	−2.72	−2.34	−1.58	−1.82	−1.75	−2.30
t-stat	−5.65	−6.34	−3.53	−5.17	−2.08	−4.54
FF3F	−1.80	−2.24	−1.19	−1.78	−1.23	−1.84
t-stat	−3.63	−6.16	−2.64	−4.89	−1.82	−4.15

Table 10 reports the performance of distress-based portfolios across different levels of market value. Specifically, each month, the stocks are independently sorted based on the Charitou et al. (2004) z-score and market capitalisation. The two independent sorts are then intersected to construct 25 portfolios varying in both distress and size. As shown, the financial distress anomaly is weaker for the stocks in the largest market-value group, but it remains economically and statistically significant.

5.4. Including Stocks with Low Prices and Negative Book Values

Stocks with low prices and negative book values are more likely to be financially distressed. Accordingly, these screening rules may be overly restrictive, potentially omitting a considerable number of distressed stocks. Consequently, this exclusion may introduce sample-selection bias and undermine the validity of the empirical results. Therefore, to mitigate this potential bias, we re-examine the documented relationship in this study using a sample that includes stocks with prices below £3 and negative book values. Table 11 reports the results of the portfolio performance analysis.

The findings confirm those reported in Table 3. Specifically, stocks with high distress risk underperform relative to low-distress stocks, and the return spread between the two groups remains economically and statistically significant across alternative measures of distress risk. This result persists after controlling for common asset-pricing factors, providing further support for the existence of the financial distress anomaly in the UK stock market.

Table 10. Size effect. This table presents the effect of firm size on the distress-based portfolio performance. Distress proxy is based on the measure developed by Charitou et al. (2004). P1 (P5) denotes the portfolio of stocks in the lowest (highest) distress quintile. MV1 (MV5) denotes the portfolio of stocks in the smallest (largest) size quintile. WE (VW) refers to equal-weighted (value-weighted) returns. FF3F denotes the alpha estimated from the Fama–French three-factor model.

	EW			VW		
	MV1	MV3	MV5	MV1	MV3	MV5
P1	−0.86	0.212	0.39	−0.48	0.2451	0.259
t-stat	−1.76	0.54	0.95	−1.03	0.63	0.68
P2	−0.345	0.392	0.531	0.382	0.348	0.558
t-stat	−0.79	0.98	1.93	−0.88	0.86	2.2
P3	−0.383	0.368	0.43	−0.294	0.348	0.45
t-stat	−0.79	0.84	1.49	−0.61	0.79	1.97
P4	−0.982	0.187	0.14	−0.75	0.181	0.295
t-stat	−1.94	0.39	0.43	−1.47	0.37	1.09
P5	−2.10	−1.28	−0.623	−1.95	−1.27	−0.51
t-stat	−3.59	−2.21	−1.33	−3.35	−2.23	−1.23
P5–P1	−1.232	−1.496	−0.998	−1.47	−1.52	−0.759
t-stat	−3.73	−4.02	−2.59	−4.4	−4.00	−1.79
FF3F	−1.180	−1.41	−0.751	−1.423	−1.470	−0.372
t-stat	−3.39	−3.84	−1.87	−4.21	−3.9	−0.85

Table 11. Including stocks with low prices and negative book value. This table presents the effect of including stocks with prices lower than £3 and firms with negative book value on distress-based portfolio performance. CHz is the probability of financial distress measured by Charitou et al. (2004)’s model. Taffz is the probability of financial distress measured by Taffler (1983)’s model and DDz is the probability of financial distress measured by distance to default, following the approach proposed by Bharath and Shumway (2008). P1 (P10) portfolio includes the stocks with lowest (highest) distress level. FF3F is the Fama–French three-factor model alpha. The returns are equally weighted.

	CHz	Taffz	DDz
P1	−0.10	−0.82	−0.18
t-stat	−0.25	−1.54	−0.42
P2	−0.01	0.11	0.22
t-stat	−0.03	−0.28	0.59
P9	−2.11	−1.75	−1.27
t-stat	−4.13	−3.82	−2.38
P10	−2.75	−2.89	−2.74
t-stat	−4.59	−4.94	−4.11
P10–P1	−2.65	−2.07	−2.56
t-stat	−8.16	−7.24	−5.63
FF3F	−2.39	−1.92	−2.28
t-stat	−7.38	−6.48	−5.62

5.5. Skip the First Month

Microstructure noise is an inherent characteristic of financial markets that would exert an effect on the observed pricing movements. This bias would generate a reversal over the short-term period (e.g., next month) (see, for example, Jegadeesh & Titman, 1995; Andrade et al., 2008). To examine this issue, we re-estimate Fama and MacBeth cross-sectional analysis, excluding the first next month and including longer horizon return. If the reported negative association between the next-month return and the financial distress

risk is a manifestation of the reversal caused by microstructure frictions, it would disappear after skipping a month in the analysis.

The results reported in Table 12 do not support this argument. The financial distress anomaly is robust even when the first month is excluded and persists over a medium-term horizon (i.e., 12 months). To illustrate, Columns C1–C3 report an inverse association between the financial distress and subsequent 12-month returns. Across various measures of financial distress, the distress–return coefficient ranges from -1.697 to -1.076 , all of which are highly statistically significant at the 1% level. Thus, the reported underperformance of the highly distressed stocks is distinguished from the short-term reversal caused by the market microstructure frictions.

Table 12. Long horizon performance of distressed-based portfolios. This table presents the Fama–MacBeth cross-sectional analysis with a one-month skip-ahead period. Specifically, average returns over the subsequent 2–12 months are regressed on the financial distress proxy and a set of control variables. CHz is the probability of financial distress measured by Charitou et al. (2004)’s model. Taffz is the probability of financial distress measured by Taffler (1983)’s model. DD is the probability of financial distress measured by distance to default, following the approach proposed by Bharath and Shumway (2008). Beta is stock beta estimated using the CAPM. LnMV is the logarithm of market capitalisation. LnBM is the logarithm of book-to-market ratio. MOM12 is the cumulative stock return over the past 12 months. ROA is return on assets. AG is the asset growth. Amih is the Amihud (2002) illiquidity measure based on price impact. Past is the last-month return. Numbers in parentheses are the Newey–West t-statistic. ^a, ^b, and ^c denote statistical significance at 1%, 5%, and 10%, respectively.

	C1	C2	C3	C4	C5	C6
CHz	-1.697^a (-12.446)			-0.902^a (-12.176)		
Taffz		-1.293^a (-14.484)			-0.666^a (-9.837)	
DDz			-1.076^a (-6.493)			-0.427^a (-5.989)
Beta				-1.56^a (-2.916)	-1.706^a (-3.173)	-1.866^a (-3.416)
LnMV				0.157^a 5.47	0.167^a 5.8	0.168^a 5.874
LnBM				0.123^a 2.679	0.13^a 2.688	0.151^a 3.541
MOM12				0.008^a 9.091	0.009^a 9.423	0.007^a 7.323
ROA				0.506^a 3.135	0.686^a 4.125	0.992^a 7.017
AG				-0.667^a (-8.803)	-0.645^a (-8.149)	-0.556^a (-7.801)
Amih				0.026 1.438	0.034^c 1.806	0.027 1.409
Last				0.01^a 6.385	0.011^a 6.469	0.01^a 5.984
cons	0.295 1.561	0.105 0.524	0.119 0.617	-0.362 (-1.539)	-0.494^b (-2.049)	-0.494^b (-2.108)
Obs	157,040	155,038	147,533	154,046	152,141	145,122
Adj R ²	0.034	0.019	0.029	0.128	0.126	0.122

In sum, all robustness tests presented above confirm the stability of the main results and indicate that the findings are not sensitive to alternative specifications, variable definitions, sample selections, or holding horizons.

6. Further Analysis

Gambling Attitude (Lottery-like Stocks)

One of the key arguments of behavioural asset pricing theory is the failure of the neoclassical rational paradigm to incorporate the various dimensions of investor utility. The dominant two-moment paradigm of asset allocation states that investors maximise their wealth by focusing on the expected value and volatility of asset payoffs, as illustrated in the seminal work of Markowitz (1952). Behavioural models subsequently extended this analysis by suggesting that investors may pursue non-standard objectives in addition to wealth maximisation. One such objective is a preference for positively skewed returns and lottery-like characteristics in asset payoffs (see Mitton & Vorkink, 2007; Barberis & Huang, 2008). Maximising the skewness and likelihood of positive gains induces risk-seeking behaviour. Recent empirical evidence supports the existence of this non-standard preference among investors (see Kumar, 2009; Bali et al., 2011; Han & Kumar, 2013; Lin & Lin, 2021; Khasawneh et al., 2024). Empirical tests have linked the financial distress anomaly to the lottery-like preference (see Conrad et al., 2014; Coelho et al., 2014; Kausar et al., 2024).⁸ Moreover, the extant empirical results demonstrate that the investors' overreaction toward the lottery-like stocks holds true only for stocks far from their 52-week high (see Byun et al., 2020). As discussed above, the distance from the 52-week high may serve as a proxy for underreaction in this study.

From a behavioural finance perspective, skewness-seeking behaviour and the 52-week high effect appear to originate from distinct behavioural mechanisms. The former is commonly attributed to biased beliefs regarding the return distributions, whereas the latter is often linked to cognitive constraints in processing and incorporating information into prices. The empirical and theoretical association between these seemingly distinct behavioural forces raises an important question: how do they interact in explaining financial distress anomaly? Addressing this question would provide deeper insight into the behavioural foundations of the financial distress anomaly, with implications that may extend to other market anomalies. Furthermore, such an investigation could contribute to the development of more comprehensive and explanatory asset pricing models.

Distressed stocks are associated with considerable uncertainty about firms' underlying fundamentals, making them particularly difficult to value and more susceptible to behavioural biases and mispricing (Baker & Wurgler, 2006). The anchoring effect suggests that distance from the 52-week high price would induce investors to process this information with delay, which manifested in underreaction behaviour and persistent poor performance observed for the distressed stocks. Paying little attention to fundamentals, fundamental uncertainty and anchoring effect would cause investors to pay more attention to more salient information such as recent extreme price movements (e.g., lottery-like features). Thus, the 52-week high effect would exacerbate the investors' biased beliefs about the extreme gain potential of the distressed stocks. Consequently, both the 52-week high effect and skewness-seeking behaviour interact to explain the distress anomaly. In other words, the anomaly reflects both the investor underreaction to fundamentals and overreaction to the perceived probability of extreme gains.

Following Bali et al. (2011) the lottery demand is proxied by the daily extreme returns over the past month (MAX5). By their nature, the extreme returns are a salient feature and attractive to overconfident investors. These returns become particularly salient in the context of the poor performance of distressed stocks. Kumar (2009) suggests that idiosyncratic volatility and skewness serve as proxies for lottery likeness. To mitigate the noisiness of any single measure, we also employ an alternative proxy that captures multiple dimensions of lottery likeness. Following Kumar (2009), we construct a composite

lottery index based on three proxies: extreme daily returns, idiosyncratic volatility, and idiosyncratic skewness.

Table 13 reports the estimation results for Equations (5) and (6). Equation (5) is specified as follows:

$$R_{i,t+1} = \alpha_t + \beta_{1,t} \times DR_{i,t} + \beta_{2,t} \times \text{Beta} + \beta_{3,t} \times \text{LnMV} + \beta_{4,t} \times \text{LnBM} + \beta_{5,t} \times \text{MOM12} + \beta_{6,t} \times \text{ROA} + \beta_{7,t} \times \text{AG} + \beta_{8,t} \times \text{Amih} + \beta_{9,t} \times \text{Last} + \beta_{10,t} \times \text{LOTT}_{i,t} + \beta_{11,t} \times (\text{DR}_{i,t} \times \text{LOTT}_{i,t}) + \varepsilon_{i,t} \quad (5)$$

Table 13. Joint effect of anchoring bias and lottery-seeking behaviour. This table presents the joint effect of lottery-like trading and the 52-week high effect on financial distress. LOTT is a quantile-based index derived from MAX5 or the composite lottery index, where MAX5 is the average of the highest 5 daily returns over the past month. LPH is a dummy variable that equals 1 if the stocks are in the lowest quantile of PH52. CHz is the probability of financial distress measured by Charitou et al. (2004)'s model. Beta is stock beta estimated by CAPM. LnMV is the logarithm of market capitalisation. LnBM is the logarithm of book-to-market ratio. MOM12 is the cumulative return over the past 12 months. ROA is return on assets. AG is asset growth. Amih is the Amihud (2002) illiquidity measure. Last is the last-month return. Numbers in parentheses are the Newey–West t-statistics. ^a, ^b, and ^c denote statistical significance at 1%, 5%, and 10%, respectively.

	C1	C2	C3	C4	C5	C6	C7	C8
CHz	−0.173 (−0.661)	0.045 −0.175	−0.28 (−1.08)	−0.043 (−0.168)	−0.384 (−1.493)	−0.114 (−0.441)	−0.376 (−1.133)	−0.158 (−0.478)
LOTT	−1.739 ^a (−3.687)	−1.138 ^a (−4.29)	−1.037 ^a (−2.92)	−1.143 ^a (−4.493)	−1.022 ^a (−2.908)	−1.116 ^a (−4.474)	−0.559 (−0.972)	−0.777 ^b (−2.019)
LOTTxCHz	−1.388 ^a (−3.592)	−1.034 ^a (−2.796)	−0.615 (−1.568)	−0.581 (−1.484)	−0.499 (−1.246)	−0.525 (−1.305)	−0.766 (−1.432)	−0.641 (−1.245)
LPH			−1.527 ^a (−4.529)	−0.176 (−0.766)	−1.565 ^a (−4.644)	−0.241 (−1.066)	−1.79a (−4.914)	−0.382 ^c (−1.698)
LPHxCHz			−0.859 ^a (−3.08)	−0.671 ^b (−2.355)				
LOTTxLPHxCHz					−0.941 ^a (−2.98)	−0.656 ^b (−2.058)	−0.829 ^b (−2.282)	−0.581 ^b (−2.13)
Beta		−0.898 (−0.956)		−0.744 (−0.813)		−0.752 (−0.821)		−0.91 (−1.006)
LnMV		−0.006 (−0.129)		−0.022 (−0.482)		−0.021 (−0.465)		0.011 0.237
LnBM		0.129 1.563		0.122 1.516		0.122 1.514		0.108 1.358
MOM12		0.015 ^a 7.404		0.013 ^a 6.256		0.013 ^a 6.213		0.014 ^a 6.392
ROA		0.41 ^c 1.778		0.391 ^c 1.691		0.399 ^c 1.72		0.396 ^c 1.75
AG		−0.552 ^a (−3.833)		−0.539 ^a (−3.785)		−0.531 ^a (−3.75)		−0.522 ^a (−3.753)
Amih		−0.088 ^b (−1.989)		−0.09 ^b (−2.05)		−0.089 ^b (−2.032)		−0.091 ^b (−2.036)
Last		0.006 1.433		0.005 1.042		0.004 1.026		0.003 0.84
cons	1.154 ^a 4.485	1.05 ^b 2.556	0.982 ^a 3.739	1.174 ^a 2.805	0.98 ^a 3.709	1.163 ^a 2.769	0.793 ^b 2.395	0.849 ^c 1.881
Obs	157,041	154,046	157,041	154,046	157,041	154,046	157,041	154,046
Adj R ²	0.027	0.072	0.041	0.077	0.041	0.077	0.044	0.0783

Equation (6) expands on Equation (5) by incorporating the 52-week high effect:

$$R_{i,t+1} = \alpha_t + \beta_{1,t} \times DR_{i,t} + \beta_{2,t} \times \text{Beta} + \beta_{3,t} \times \text{LnMV} + \beta_{4,t} \times \text{LnBM} + \beta_{5,t} \times \text{MOM12} + \beta_{6,t} \times \text{ROA} + \beta_{7,t} \times \text{AG} + \beta_{8,t} \times \text{Amih} + \beta_{9,t} \times \text{Last} + \beta_{10,t} \times \text{LOTT}_{i,t} + \beta_{11,t} \times (\text{DR}_{i,t} \times \text{LOTT}_{i,t}) + \beta_{12,t} \times \text{LPH}_{i,t} + \beta_{13,t} \times (\text{DR}_{i,t} \times \text{LOTT}_{i,t} \times \text{LPH}) + \varepsilon_{i,t} \quad (6)$$

These specifications are designed to test the role of lottery-like trading in the financial distress risk anomaly and to assess the extent to which the 52-week high effect moderates this role. LOTT denotes the lottery-like proxy. For ease of interpretation and comparability, the raw lottery-like proxies are converted into quantiles and then scaled to range from 0.2 to 1. PH52 is defined as an indicator variable that equals 1 if the stock belongs to the lowest quantile of the PH52 distribution. This transformation maps the unbounded values of these two effects into a variable bounded above at 1. This transformation is particularly useful in interaction settings, where it facilitates a clearer interpretation of conditional marginal effects and enhances comparability across observations.

Similarly to the 52-week high effect, the results indicate that lottery-like trading plays an important role in explaining financial distress anomaly. As shown in Table 13, the lottery-like proxy moderates the negative relationship between distress risk and the next-month return. The empirical analysis in Column C1 demonstrates that, when including the interaction term (LOTTxCHz), the coefficient on CHz is -0.173 (the Newey–West t-statistic is -0.66). However, the interaction term (LOTTxCHz) is negative and significant, with a value of -1.388 and Newey–West t-statistic of -3.592 . Moreover, accounting for the full set of control variables does not alter the result (see C2). Therefore, the poor performance of distressed stocks is magnified by the lottery trading intensity. Distress risk on its own has little effect on subsequent returns, but when a stock exhibits stronger lottery-like characteristics, investors appear to overvalue distressed firms, leading to stronger reversal in future returns.

This finding supports the conjecture of Campbell et al. (2008) that distressed stocks may be overvalued as a result of investors seeking their positively skewed expected returns. Such demand may inflate stock prices and contribute to the lower subsequent returns observed for these firms.

It is also worth noting that the coefficient on lottery-like characteristics is significantly negative, even after controlling for financial distress. For example, Column C2 reports that the coefficient on LOTT is -1.138 and is highly statistically significant, with a Newey–West t-statistic of -4.29 . This suggests that the effect of lottery-like features on returns is not driven by financial distress but rather reflects an independent pricing pattern consistent with investors' preference for skewness, which is subsequently corrected in returns. This finding is in line with the theoretical models of skewness-seeking behaviour (see Mitton & Vorkink, 2007; Barberis & Huang, 2008) and prior empirical evidence from US and UK stocks (see Bali et al., 2011; Khasawneh et al., 2024).

Moreover, and more interestingly, the results reveal that the 52-week high effect drives the effect of lottery-like trading behaviour on the pricing of financial distress. Columns C3–C4 show that coefficients of LPH and its interaction term with distress risk (LPHxCHz) are significant and subsume the effect of LOTTxCHz. As shown in Column C3, the estimated coefficients of LPH and LPHxCHz are -1.527 and -0.859 , respectively, with a Newey–West t-statistic of -4.529 and -3.08 . The coefficient of LOTTxCHz is negative, with a value of -0.615 , but is statistically insignificant. Furthermore, Columns C5–C8 show that the impact of lottery-like trading on distress risk anomaly operates through the 52-week high channel. For example, in Column C5, the coefficients for the term LOTTxLPHxCHz is -0.941 (the Newey–West t-statistic is -2.98). This indicates a significant marginal effect of PH52. Accordingly, the 52-week high effect may mediate the influence of lottery-like trading behaviour on the financial distress risk anomaly, lending support to the conjecture proposed in this study. Meanwhile, both LOTT and LPH exhibit a negative and statistically significant effect, suggesting that they independently predict returns while jointly influencing the pricing of distress risk. Column 6 shows that accounting for the common returns predictors

does not alter these results. Columns C7–C8 report similar results; however, we employ the lottery index instead of MAX5 as a proxy for the Lottery-like characteristic.

In sum, consistent with the predictions of [Campbell et al. \(2008\)](#) and [Conrad et al. \(2014\)](#), our results suggest that investors' preference for lottery-like stocks contributes to the financial distress anomaly. Extending this argument, the effect of lottery preference may be amplified by investors' underreaction to distress signals, particularly when prices are anchored to salient reference points such as the 52-week high. Specifically, investors' attraction to lottery-like characteristics appears to divert their attention from adverse information regarding firms' financial condition. Investors in the UK market may place excessive weight on the speculative upside potential of financially distressed stocks while insufficiently incorporating the negative information conveyed by distress-related signals into prices. This interpretation is consistent with evidence showing that the relationship is stronger when stocks trade further from their 52-week highs, a pattern that may reflect the influence of anchoring effects. Drawing on the anchoring-based explanation, the proximity to a stock's 52-week high may cause investors to pay insufficient attention to distress-related information, thereby distorting their expectations of future price movements. By diverting investors' attention away from distress-related information, this mechanism may help explain the purported link between skewness-seeking behaviour and the overvaluation of the distressed stocks.

7. Conclusions

This paper offers evidence from the UK equity market regarding the distress risk anomaly, with particular focus on the role of behavioural mechanisms. Building on prior evidence that financially distressed firms tend to earn lower future returns than less distressed firms, we investigate whether this anomaly varies systematically with two widely documented behavioural effects: the 52-week high effect as a proxy for reference-point anchoring and the lottery-like effect as a proxy for skewness-seeking preferences.

The empirical results indicate that the financial distress anomaly persists in the UK market, despite its strong creditor protection framework and substantial institutional participation. This suggests that institutional features may not be able to eliminate pricing inefficiencies associated with financial distress. The results reveal that the poor performance associated with high financial distress is concentrated among stocks with high arbitrage difficulties following the period of market optimism. These results are in line with the a misvaluation explanation and help explain why the high institutional trading in UK stocks fails to eliminate the anomaly.

In addition, the findings are consistent with two complementary behavioural channels. First, the financial distress anomaly is stronger for stocks with a low 52-week high ratio. In particular, financially distressed stocks tend to exhibit worse performance when they trade further below their 52-week highs. This pattern is consistent with anchoring-based underreaction to fundamental information, suggesting that investors may update their beliefs slowly when prices are evaluated relative to salient historical reference points. Second, lottery-like features appear to be associated with the reported poor performance of financially distressed stocks, consistent with the notion that skewness-seeking preferences may contribute to the mispricing of such firms. Importantly, their interaction appears to play a role in shaping the return dynamics of distressed stocks. This implies that the distress anomaly may not be driven by a single behavioural bias, but rather by the potential joint influence of reference dependence and lottery-like demand, which together contribute to the observed return predictability. More generally, the findings highlight the importance of considering multiple behavioural channels when analysing cross-sectional return patterns in financially distressed firms.

The results have implications for broader asset pricing literature and portfolio management. They suggest that incorporating behavioural considerations alongside traditional risk-based explanations may improve our understanding of return anomalies, particularly in environments characterised by high uncertainty and valuation difficulty. From a practical perspective, the findings may also be relevant for investors and regulators seeking to better understand the sources of mispricing of financially distressed stocks. Effective portfolio construction may benefit from incorporating these dimensions when forming long-short or risk-controlled investment strategies.

The study has several limitations. First, since the analysis is based on UK-listed common stocks, further research is needed to determine whether these conditional effects are present in other equity markets. Second, because this analysis relies on single proxy of underreaction behaviour, future research could improve measurement by incorporating investor attention, analyst forecast revisions, retail trading data, short-sale constraints, information around earnings announcements, and post-stress information updates.

In summary, this study advances research on the distress risk anomaly by recasting the anomaly in terms of conditional return predictability. These findings are in line with behavioural asset pricing models, particularly the 52-week high anchor and lottery effects. However, they must be interpreted carefully as proxy evidence, not proof, of investor behaviour.

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Appendix A

Table A1. Sample Construction.

Step	Firm-Month Observations Remaining
Initial dataset	1,173,640
Exclude firms with no monthly return and less than 120 daily returns	204,457
Exclude financial firms	174,297
Exclude firms with negative book value	167,489
Exclude firms with stock price >3 pounds	162,261
Less firms with no available information	157,041

Table A2. Variables Measurements.

Variable	Definition	Expected Sign of Return Predictability	Source of Raw Data
$R_{i,t}$	Stock monthly return measured as the log return of the total return index: $R_{i,t} = \ln\left(\frac{TRI_{i,t}}{TRI_{i,t-1}}\right)$ where $TRI_{i,t}$ is the total return index.		Datastream
Charitou's z-score (CHz)	Accounting-based measure of financial distress developed by Charitou et al. (2004), measured using the following formula: $z = -7.179 + 12.39 \times TL/TA - 20.97 \times (EBIT/TL) - 3.0174 \times (CFO/TL)$ where TL/TA is the ratio of total liabilities to total asset, $EBIT/TL$ is the ratio of earnings before interest and taxes to the total liabilities, and CFO is the ratio of cash flow from operations to total liabilities.	Negative	Worldscope
Distance to default (DD)	Following Bharath and Shumway (2008), we estimate the naïve version of distance to-default (DD) measure using the following formula: $DD_{i,t} = \frac{(\ln(V/D) + (R_{t-1} - 0.5\sigma_v^2)T)}{\sigma_v \sqrt{T}}$ Then, the DD is transformed into a probability by applying the cumulative standard normal density function $DR_{i,t} = N(-DD)$ where DD is distance-to-default degree, N indicates the cumulative standard normal density function, $DR_{i,t}$ is the probability of default, V is the firm's asset value which equals the market value of firm's equity (ME) plus the face value of its debt (D) in month t . R_{t-1} is the cumulative returns over the past year. σ represents the firm's volatility of total asset returns and estimated as a weighted average of the volatilities of a firm's equity and debt. T is the time horizon which set to 1. For further details, please refer the original study.	Negative	Datastream and Worldscope
Taffler's Z-score (Taffz)	Accounting-based measure of financial distress developed by Taffler (1983), measured using the following formula: $z = 3.20 + 12.18 x_1 + 2.50 x_2 - 10.68 x_3 + 0.029 x_4$ where x_1 is profit before tax (PBT)/current liabilities, x_2 is current assets/total liabilities, x_3 is current liabilities/total assets, and x_4 is no-credit interval computed as (quick assets—current liabilities)/((sales—PBT—depreciation)/365).	Negative	Worldscope
Price-to-52 week high (PH52)	The 52-week high ratio, following George and Hwang (2004), is measured monthly using the following formula: $PH52_{i,t} = \frac{P_{i,t}}{H_{i,t}}$ where $P_{i,t}$ is the current stock price at the end of month t , and $H_{i,t}$ is the highest stock price during the previous 52 weeks. The ratio ranges from 0 to 1.	Positive	Datastream
MAX5	Following Bali et al. (2011), it is measured monthly as the average of the five highest daily returns over the past month, using the following formula: $MAX5t = \frac{1}{5} \sum_{i=1}^5 \text{Top } i \text{ daily returns in month } t - 1$	Negative	Datastream

Table A2. Cont.

Variable	Definition	Expected Sign of Return Predictability	Source of Raw Data
Beta (Beta):	The stock beta is estimated monthly using daily returns over the previous 255 trading days, based on the following formula: $R_{i,t} = \alpha_i + \beta_{i,t} * R_{m,t} + \sum_{n=1}^4 \beta_{i,t-n} * R_{m,t-n} + \varepsilon_{i,t}$ $\text{Beta} = \beta_{i,t} + \sum_{n=1}^4 \beta_{i,t-n}$ where $R_{i,t}$ is the daily stock I return, and $R_{m,t}$ is the market return at day t. β is the estimated coefficient.	Positive	Datastream
Midterm Momentum (MOM)	Following Jegadeesh and Titman (1993), midterm momentum is defined as cumulative return over the period from month $t - 13$ to month $t - 1$.	Positive	Datastream
LnBM	The natural log of Book-to-Market ratio, where, following Fama and French (1993), the Book-to-Market ratio is defined as the book value of equity divided by the market value of equity. The variable is measured on a monthly basis.	Positive	Worldscope and Datastream
LnMV	The natural logarithm of market value, where, following Fama and French (1993), the market value is defined as the monthly closing price multiplied by the number of shares outstanding.	Negative	Datastream
ROA	Return on assets, following Fama and French (2015), is defined as annual net income scaled by total assets.	Positive	Worldscope
Assets Growth (AG)	The annual change in assets, following Fama and French (2015), is measured as percentage change in total assets over the past year.	Negative	Worldscope
Short-term return (Last)	The previous month return, Following Jegadeesh (1990), is measured as the stock's return over the prior month.	Negative	Datastream
Illiquidity (Amih)	The Amihud (2002) illiquidity measure captures how much prices move in response to trading volume. It is calculated using the following formula: $Amih_{i,t} = \frac{1}{D_t} \sum_{d=1}^{D_t} \frac{ R_{i,d} }{VOL_{i,d}}$ where $R_{i,d}$ is the daily return of stock i on day d, $VOL_{i,d}$ is the daily trading volume (price $\times$ shares traded), and D_t is the number of trading days over the past 12 months. The measure is estimated on a monthly basis.	Negative/Positive	Datastream
Idiosyncratic Volatility	Measured following Ang et al. (2006), first we estimate Fama and French (1993) 3-factor model: $R_{i,d} = \alpha_i + \beta_{i,M}(R_{M,d}) + \beta_{i,S}SMB_d + \beta_{i,H}HML_d + \varepsilon_{i,d}$ where $R_{i,d}$ is the return of stock i at day t, $R_{m,d}$ is market return, SMB_t and HML_t is the size and value factors, and $\varepsilon_{i,d}$ is the estimated residual term captures idiosyncratic returns. Then, the idiosyncratic volatility is estimated by the following formula: $IVOL_{i,t} = \sqrt{\frac{1}{N-1} \sum_{d=1}^N \varepsilon_{i,d}^2}$ where N is the number of trading days in the estimation period, which is the prior 12 months	Negative	Datastream

Table A2. Cont.

Variable	Definition	Expected Sign of Return Predictability	Source of Raw Data
Idiosyncratic Skewness	Measured following Kumar (2009), similar to the idiosyncratic volatility, first we estimate Fama and French (1993) three-factor model. Then, idiosyncratic skewness is estimated as the third moment of the residuals using the following formula: $ISKEW_{i,t} = \frac{\frac{1}{N} \sum_{d=1}^N \epsilon_{i,d}^3}{\left(\frac{1}{N} \sum_{d=1}^N \epsilon_{i,d}^2 \right)^{3/2}}$ where N is the number of trading days in the estimation period, which is the prior 12 months.	Negative	Datastream
SP12M	The bid–ask spread, following Hwang and Lu (2007), is measured as the average daily bid–ask spread over the prior 12 months, using the following formula: $SP12M_{i,t} = \frac{1}{D_t} \sum_{d=1}^{D_t} \frac{Ask_{i,d} - Bid_{i,d}}{(Ask_{i,d} + Bid_{i,d})/2}$ Estimated on a monthly basis.	Negative	Datastream
Age	Number of months since the firm was listed on London Stock Exchange.	Negative	Worldscope

Notes

- Excluding delisting returns may understate extreme losses, but the study focuses on cross-sectional return patterns and pricing behaviour in tradable equity markets rather than total economic losses, emphasizing continuous return dynamics that reflect market information. Moreover, delisting returns are excluded because they require strong, potentially inconsistent assumptions about final settlement values across delisting types (e.g., liquidation, merger, suspension), which could introduce additional measurement error.
- However, to ensure that the exclusion of these stocks does not bias the results, we re-estimate the main analyses including them as part of the robustness checks. The results remain qualitatively unchanged, indicating that the main findings are not driven by their exclusion.
- Various studies employ hazard models to estimate bankruptcy risk. However, this approach relies on detailed survival and failure data for bankrupt or delisted firms. Although these models may provide more accurate predictions of bankruptcy, they perform similarly in capturing financial distress risk (Bauer & Agarwal, 2014). In this study, measuring financial distress is sufficient, as firms in distress are more likely to attract skewness-seeking traders.
- because return residuals tend to have little autocorrelation, using longer lag lengths for the Newey–West adjustment yields results similar to those obtained using a two-lag specification.
- <https://data.europa.eu/data/datasets/c04buuz6wxixqgjkhpwlug?locale=en> (accessed on 15 October 2025).
- By definition, PH52 is bounded above by 1.
- This may be attributed to the nature of DDz as a proxy for distress risk, as it is constructed using market return over the preceding 12 months.
- Lottery demand offer explanation for various pervasive pricing anomaly, for example, Idiosyncratic volatility puzzle (Bali et al., 2011) Beta anomaly (Bali et al., 2017), asset growth (Lu et al., 2022), to name a few.

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