Financial Distress and Forecast Errors

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Abstract

This paper studies the effect of distress risk on analyst forecast errors (the difference between actual and forecasted earnings), as well as how forecast errors manifest in the distress risk anomaly. Using a sample of 6,632 unique analyst-covered firms, I document a strong negative relationship between distress risk and analyst forecast errors. This effect is robust to controls for stock characteristics associated with distress risk, including profitability. Furthermore, the documented negative relationship between distress risk and forecast errors is most pronounced for firms followed by analysts with stickier expectations and firms which received negative news coverage in the period preceding the announcement of forecasts. This result provides empirical evidence of analysts under-reacting to distress risk by over-estimating the future cash flows of financially-distressed stocks. Moreover, I examine the implications of this important channel which manifests in the overpricing of financially-distressed stocks for the distress risk anomaly. The distress risk anomaly is concentrated in firms where forecast errors are most negative. The evidence reported in this paper therefore provides support for an under-reaction interpretation of the distress risk anomaly.

Keywords: Financial distress, Forecast errors, Distress risk anomaly, Under-reaction

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1. Introduction

Financial distress is a major event in the life of the firm where there is an elevated probability that the firm will fail to meet its financial obligations. When sorted into portfolios by distress risk, stocks with the highest distress risk subsequently underperform stocks with the lowest distress risk over the following twelve months (see, for example, Campbell, Hilscher & Szilagyi, 2008). This pattern, known as the distress risk anomaly, is puzzling given that financially-distressed stocks appear to be risky with reference to traditional metrics. For example, distressed stocks have high market betas, high standard deviations and load positively on common risk factors (Campbell, Hilscher, & Szilagyi, 2008). The observed negative price of distress risk is therefore outwardly incompatible with traditional risk-based explanations, with standard risk-adjustments only increasing the puzzle. Given that a positive relationship between risk and return is one of the central underpinnings of financial economics, the distress risk anomaly has received significant attention in the literature.

Of the many explanations that have been proposed for the distress risk anomaly, there are two broad streams of this literature. These explanations are that the distress risk anomaly is an instance of mispricing (see, for example, Gao, Parsons, & Shen, 2018) and that the distress risk anomaly is explained by risk (see, for example, Garlappi, Shu, & Yan, 2008). There has been substantial interest in the mispricing explanation for the distress risk anomaly. However, the arguments regarding how financially-distressed stocks become mispriced are varied. For example, it has been argued that distress risk is mispriced as a consequence of investor overconfidence (Gao et al., 2018) and limits to arbitrage (Conrad, Kapadia, & Xing, 2014). Despite the interest in the distress risk anomaly, it is commonly agreed that this pattern in returns remains unresolved. The mispricing and risk-based explanations continue to compete in the literature.

In this paper, I propose an intuitive and unexamined channel which may manifest in the mispricing of financially-distressed stocks. It is highly plausible that investors over-estimate the future cash flows of distressed firms. This is consistent with an under-reaction interpretation of the distress risk anomaly. The possibility that investors over-estimate the future cash flows of distressed stocks is in the spirit of Barberis, Shleifer, & Vishny (1998), where investors are slow to update their beliefs.[1] If there is a delay in investors incorporating financial distress in

[1] The possibility that investors over-estimate the future cash flows of distressed firms is, however, distinct from an under-reaction argument where investors do not apply an appropriate discount rate to financially-distressed firms.

their expectations, investors are likely to have optimistic expectations regarding the prospects of the most financially-distressed firms relative to firms that are least distressed. Specifically, this may be reflected in the over-estimation of the future cash flows of financially-distressed firms. This potential bias in expectations of financially-distressed firms need not necessarily be limited to newly distressed firms as, relative to other signals, distress risk is a highly complex signal. It is therefore plausible that investors under-react to distress risk over extended periods of time. Prior studies have alluded to potential under-reaction stories as interpretations for their findings (see, for example, Agarwal & Taffler, 2008). However, this promising explanation for the distress risk anomaly has not been explored in the literature due to the limitations in observing investor expectations of financially-distressed firms.

Cash flows are intrinsically related to profitability and this may assist in examining under-reaction as an explanation for the distress risk anomaly. All else equal, firms with low profitability should be expected to experience lower cash flows relative to high-profitability firms. As a result, expectations of profitability provide a useful proxy for expectations of cash flows. This is important because, unlike expectations of cash flows and distress risk, expectations of profitability are directly observable from analyst forecasts. Under-reaction to distress risk, and the over-estimation of the future cash flows of financially-distressed firms, may therefore be observed in analyst forecast errors (the difference between actual and forecasted earnings). It is a common implicit assumption in existing studies that the expectations and biases of analysts are informative of those of the representative investor (see, for example, Bouchaud, Kruger, Landier & Thesmar, 2019). Further, there is evidence that under-reaction is a behavioural bias that is not limited to individual investors, given that analysts under-react to recent information in forming their expectations (see, for example, Abarbanell & Bernard, 1992). As a result, analyst forecasts provide a useful laboratory to study under-reaction to distress risk.

In this paper, I examine the relationship between financial distress and forecast errors, and the implications of this relationship for the distress risk anomaly. The possibility that investors under-react to distress risk by over-estimating future cash flows is a simple and promising explanation for the distress risk anomaly that has not been examined in the existing literature. Using analyst forecasts as a proxy for unobservable cash flow expectations, I address this important gap in the literature by examining the relationship between financial distress and analyst forecast errors. Specifically, I hypothesise that analyst forecast errors are negatively related to distress risk since under-reaction results in excessively optimistic expectations of firms experiencing financial distress. Moreover, I examine the relationship between forecast errors and the distress risk anomaly. Should analysts be slow to update their expectations of financially-distressed stocks to reflect distress risk, then this may manifest in the temporary overpricing and subsequent low risk-adjusted returns of financially-distressed stocks. As a result, any mispricing resultant from the proposed over-estimation of cash flows will be concentrated in firms where cash flows are most over-estimated. Therefore, I hypothesise that the distress risk anomaly is concentrated in firms where forecast errors are most negative (where analyst forecasts are most positive relative to actual earnings).

Limiting the analysis to analyst-covered firms, I begin by confirming that the distress risk anomaly does indeed exist in the sample of firms that are covered by analysts. Using the Merton (1974) distance to default measure of distress risk, the long-short portfolio that is long (short) the portfolio of stocks with the highest (lowest) distress risk earns significantly negative abnormal returns of -0.55% per month with respect to the Fama-French-Carhart six-factor model. The result is similar when sorting stocks on the Campbell et al. (2008) measure of distress risk, with the long-short portfolio earning negative Fama-French-Carhart six-factor abnormal returns of -0.57% per month. This potentially mitigates the possible concern that smaller stocks of no interest to institutional investors solely drive the distress risk anomaly, given that the magnitude of the distress risk anomaly in the sample of analyst-covered firms is comparable to that reported in prior studies.[2] Additionally, in univariate sorts I confirm that there is a strong negative relationship between distress risk and profitability, where profitability monotonically decreases with distress risk. From this preliminary analysis, it is clear that the sample of analyst-covered firms is a reasonable setting to study the determinants of the distress risk anomaly.

In the first stage of analysis, I find strong support for the hypothesis that there is a negative relationship between distress risk and analyst forecast errors. I follow recent papers in the literature which examine the role of analyst forecasts in asset pricing such as Bouchaud et al. (2019) in constructing the measure of forecast errors and use the distance to default measure of distress risk in the baseline results. Using a sample of 6,632 unique analyst-covered firms, I find that when stocks are sorted on the magnitude of distress risk in the period immediately preceding the announcement of analyst forecasts, forecast errors are most negative for the

[2] For example, this magnitude of the distress risk anomaly is consistent with that reported in Campbell et al. (2008), where the annualised Fama-French-Carhart four-factor abnormal returns of the distress risk anomaly portfolio are 12.07% per annum. This is the LS1090 portfolio, as reported in Table 6 in their paper which is long (short) the decile portfolio of stocks with the lowest (highest) distress risk.

stocks with the highest distress risk. This is indicative of analysts increasingly over-estimating earnings with distress risk. Moreover, this pattern is consistent with investors under-reacting to financial distress and having optimistic expectations of firms that have high distress risk relative to firms that have low distress risk. In order to control for other characteristics distinct of financially-distressed stocks, the relationship between distress risk and forecast errors is also examined in panel regressions. I find that the relationship between financial distress and forecast errors remains strong and negative, after controlling for characteristics including leverage, momentum, idiosyncratic volatility and profitability. Furthermore, I provide evidence supporting an under-reaction interpretation of these findings. I show that the negative relationship between distress risk and forecast errors is concentrated in firms followed by analysts with stickier expectations and firms that received negative news coverage in the period preceding the announcement of analyst forecasts.

In the second stage of the analysis, I examine the implications of the relationship between financial distress and forecast errors for asset prices. I find support for the hypothesis that the distress risk anomaly is concentrated in the sample of firms where forecast errors are most negative. The long-short distress risk anomaly portfolio for the sample of firms where forecast errors are most negative earns a Fama-French-Carhart six-factor alpha that is 1.31% per month lower than the comparable portfolio in the sample of firms where forecast errors are positive. In firm-level cross-sectional regressions, I find that the result that the distress risk anomaly is concentrated in firms where forecast errors are most negative is robust to controlling for common stock characteristics. Specifically, I find that in the sample of analyst-covered firms, the distress risk anomaly is only detectable for firms in the bottom decile of forecast errors cross-sectionally. This provides evidence that the negative relationship between distress risk and analyst forecast errors that I identify in the first stage of the analysis is an important channel whereby distressed firms are mispriced.

In robustness tests, I provide further evidence in support of the forecast error interpretation of the distress risk anomaly. Under-reacting to distress risk will be most costly for firms where realised distress risk is a stronger positive signal of future distress risk. I find that the long-short distress risk anomaly portfolio for the sample of firms where distress risk is most persistent earns a Fama-French-Carhart six-factor alpha that is 0.96% per month lower than the comparable portfolio in the sample of firms where distress risk is least persistent.[3] This result provides further support for the forecast error explanation for the distress risk anomaly, since under-reacting to distress risk will lead to the greatest mispricing where distress risk is a stronger positive signal of future distress risk.

This paper contributes to the literature in several ways. The largest contribution of this paper is to the literature that examines the role of financial distress in asset pricing. There is a strong debate in this literature regarding the source of the distress risk anomaly. Particularly, there is contention regarding the extent to which this pattern in returns is explained by risk, as opposed to mispricing. Whilst prior studies have suggested under-reaction interpretations for their results (see, for example, Agarwal & Taffler, 2008), this promising explanation for the distress risk anomaly has not been examined in the literature due to the limitations in observing investor expectations. This paper addresses this important gap in the mispricing explanation for the distress risk anomaly by examining the relationship between financial distress and forecast errors. In this paper, I contribute to the literature by exploiting the relationship between profitability and cash flows to show that, relative to firms with low distress risk, analyst expectations are overly optimistic for firms that have experienced high levels of financial distress. In doing so, I provide the first direct evidence of an alternative behavioural interpretation of the distress risk anomaly, where investors over-estimate the future cash flows of financially-distressed stocks. Moreover, I show that the distress risk anomaly is concentrated in firms where earnings are over-estimated the most. This paper therefore makes a novel contribution to the growing weight of evidence that argues that the distress risk anomaly is explained by mispricing, as opposed to risk.

This paper makes a second contribution to the literature that studies analyst behaviour. This literature reports both under- and over-reaction of analysts (see, for example, Abarbanell & Bernard, 1992; and DeBondt & Thaler, 1990). Importantly, many studies argue that this under- and over-reaction behaviour of analysts is asymmetric. Specifically, it is argued that analysts over-react to positive information but under-react to negative information (Easterwood & Nutt, 1999). These studies are typically limited to studying analyst reactions to information in the context of earnings news. Although correlated, earnings news and distress risk are distinct. I

[3] Distress risk persistence is measured for each firm by regressing annual distress risk on the one-year lag of distress risk, using the entire time-series of distress risk for each firm. The coefficient of this regression is a measure of the extent to which the distress of a given firm is informative of future distress risk. This measure is consistent with the earnings persistence measure of Bouchaud et al. (2019).

contribute to this literature by showing that analyst under-reaction to information is not limited to earnings news, since I find this pattern in analyst behaviour is also observable for other information available about the firm, namely distress risk. Additionally, I extend the re-emerging literature studying the relationship between anomaly portfolio returns and analyst behaviour. Most recently, Bouchaud et al. (2019) document a relationship between analyst behaviour and the profitability anomaly.[4] This paper adds to this important literature by establishing another link between the biases of analysts and asset prices. I contribute to the existing work in this area by showing that, where analysts do not update their expectations following realisations of fundamental information, this leads to not only the mispricing of profitability, but of distress risk.

Finally, this paper makes a small contribution to the behavioural finance literature. There is debate regarding the extent to which individual and institutional investors are similarly susceptible to behavioural biases.[5] Specifically, there is scarce evidence on the parallels in under-reaction behaviour between individual and institutional investors. Studying the relationship between analyst forecast errors and asset prices, as I do in this paper, addresses this gap in the literature indirectly. Given the low institutional ownership of financially-distressed firms, the marginal investor of distressed firms is likely to be an individual investor (see, for example, Conrad, Kapadia & Xing, 2014). Furthermore, if the marginal investor does not form expectations in the same way as analysts, or at least use analyst expectations as an anchor or signal in forming expectations, there is no reason to suggest that mispricing should be concentrated in the sample of firms where analyst forecast errors are most pronounced. However, not only do I find that this is the case, but in robustness tests, I also find that the distress risk anomaly is concentrated in firms where forecast errors are most costly in the broader sample of firms that includes many firms that are not covered by analysts. The results in this paper therefore provide indirect evidence that individual investors under-react to distress risk in forming expectations at least as much as analysts, since the distress risk anomaly is

[4] Earlier papers in this literature that relates analyst forecasts to anomaly returns include studies of the post-earnings announcement drift (Ball & Brown, 1968), the accruals anomaly (Sloan, 1996) and the value anomaly (Basu, 1977).

[5] Whilst there is a broad literature that documents the impact of behavioural characteristics on the investment decisions of individual investors, there is less evidence on the institutional investor side. However, this research is developing. For example, Grinblatt and Keloharju (2009) and Brown, Lu, Ray, and Teo (2018) study sensation seeking in individual and institutional investors respectively.

concentrated in the sample of firms where under-reaction is most costly, independent of analyst coverage.[6]

This paper proceeds as follows. Section 2 provides an overview of the relevant literature and motivates the hypotheses tested. Section 3 outlines the data sources, measures and sample used in the analysis. Section 4 and 5 present the empirical findings regarding distress risk and forecast errors, and forecast errors and the distress risk anomaly respectively. In Section 6, I provide some concluding remarks.

2. Literature Review and Hypotheses

2.1 Literature Review

Where a firm has a high probability of corporate failure, it is said to be in financial distress. Corporate failure is a major event in the life of a firm where it is not able to meet its financial obligations. Given that financial distress has important implications for the firm and investors alike, there is an extensive literature that examines the role of distress risk in stock returns.

The majority of studies document that stocks with high distress risk generate anomalously low returns; making the price of distress risk very difficult to reconcile with a traditional risk-based explanation (see, for example, Dichev, 1998; Griffin & Lemmon, 2002; Campbell et al., 2008). However, some empirical studies examining the price of distress risk report conflicting results depending on the measure of financial distress employed. Using distance-to-default, *ex ante*, and systematic measures of default risk respectively, Vassalou & Xing (2004), Chava & Purnanandam (2010), and Anginer & Yildizhan (2018) document a positive price of distress risk.[7] However, some of these results have been argued to be attributable to other factors that are not specifically related with distress risk, such as short-term reversals and bid-ask bounce (Da & Gao, 2010). More recently, Gao et al. (2018) document a strong negative relation between financial distress and stock returns across thirty-eight countries over a twenty-year period.

The weight of evidence reported in the literature documents that financially-distressed stocks have abnormally low risk-adjusted returns, a result referred to as the distress risk

[6] Walther (1997) find that the weight placed on analyst forecasts increases with institutional ownership. This provides support for this interpretation that individual investors must form expectations similarly to analysts since financially-distressed firms are dominated by individual investors.

[7] Kapadia (2011) also argues that distress risk is positively priced, although this is through a mechanism where financial distress costs are positively related with common risk factors.

anomaly. Stocks with high distress risk are characterised by higher volatility, market betas, leverage, and more positive loadings on value and small-cap risk factors than stocks with low distress risk yet earn abnormally low returns. The distress risk anomaly is therefore particularly puzzling given the pricing of distressed stocks violates the assumed positive relationship between stock returns and the systematic risk factors that are included in the Fama and French (1993; 2015) models of expected returns. This disconnect between the theoretical expectation of higher returns for risky stocks and the empirically observed negative abnormal returns generated by financially-distressed stocks has resulted in there being substantial interest in the robustness of and possible explanations for the distress risk anomaly.

The existing literature has cast doubt on several plausible determinants of the distress risk anomaly as possible explanations, contributing to the puzzle of the negative price of distress risk. Although it has been previously argued that size and book-to-market factors proxy for distress risk (Chan & Chen, 1991; Fama & French, 1996), financially-distressed firms load positively on these priced factors and therefore should have higher, as opposed to lower, returns (Campbell et al., 2008; Vassalou & Xing, 2004). Additionally, Dichev (1998) and Griffin & Lemmon (2002) report that distress risk cannot explain the size or book-to-market effects, which is inconsistent with the argument that these factors might explain the distress risk anomaly. Campbell et al. (2008) demonstrate that all variables in their model predict the low returns of financially-distressed stocks and therefore the result is not solely driven by small loser stocks (Hong, Lim, & Stein, 2000) or the negative price of idiosyncratic volatility (Ang, Hodrick, Xing, & Zhang, 2006, 2009). Additionally, distressed stocks perform particularly poorly in periods of high aggregate volatility, implying distressed stocks are sensitive to increases in market wide risk or risk aversion (Campbell et al., 2008). However, this observed time-variation in returns does not assist in understanding the distress risk anomaly, given stocks that perform poorly in such times have average high returns (Ang et al., 2006).

The distress risk anomaly has continued to attract significant attention in the literature. The main explanations for the distress risk anomaly that have been proposed broadly fall into two categories. First, it has been argued, particularly in the earlier explanations offered in this literature, that the distress anomaly is able to be reconciled with risk-based interpretations. In this literature, various characteristics of financially-distressed stocks are associated with reduced systematic risk exposures, and it is proposed that the observed distress risk anomaly is a rational compensation for this. In the more recent distress risk anomaly literature, a mispricing stream of explanations is prevalent. In these studies, including that of Conrad et al. (2014) and Gao et al. (2018), characteristics of investors, financially-distressed stocks and the information environment result in the overpricing and subsequently low risk-adjusted returns of financially distressed stocks. The mispricing and risk-based explanations for the distress risk anomaly continue to compete in the literature.

The distress risk anomaly is outwardly inconsistent with standard risk-based interpretations. Despite this, there are several studies that attempt to reconcile the price of distress risk with risk-based explanations. Specifically, this literature focuses on systematic distress risk, where distress risk is dependent on market conditions.[8] It has been proposed that the low returns of financially-distressed stocks are a consequence of the correlation of default probabilities across firms. It is argued that this results in portfolios of stocks with high distress risk generating lower than expected returns during periods where there is a shock to aggregate default risk. Such unexpected shocks may not cancel each other out in small periods and hence the distress risk anomaly that is observed on aggregate may be driven by these correlated shocks to failure probabilities (Chava & Purnanandam, 2010; Duffie, Eckner, Horel, & Saita, 2009; Hackbarth, Haselmann, & Schoenherr, 2015). Furthermore, there is a literature that proposes that the systematic component of distress risk is positively priced (see, for example, Kapadia, 2011; George & Hwang, 2010; Chen, Hackbarth & Strebulaev, 2019). Financial distress is costlier for firms with higher exposure to systematic distress risk, as these costs are borne in bad economic times. As a result, firms with high systematic risk exposures therefore pre-emptively choose low leverage and have low distress risk. Whilst these studies are largely able to reconcile the price of systematic distress risk with rational models that assume a positive a relationship between risk and return, this does not resolve the distress risk anomaly. This is because the distress risk anomaly is associated with the firm-level distress risk of individual firms, as opposed to systematic distress risk exposures.[9] As a result, studies that propose explanations for the distress risk anomaly that are not risk-based have gained prominence in the literature.

Given the limitations of risk-based interpretations, the mispricing literature has developed to offer explanations for the distress risk anomaly that focus more broadly on distress risk. The

[8] Note that there is another common explanation for the distress risk anomaly that is consistent with a rational framework, that is not specific to systematic distress risk. Garlappi et al. (2008) suggest that the distress risk anomaly is consequence of shareholder expropriation. In accordance with this explanation, the low returns of highly-distressed stocks represent a level of certainty of equity holders regarding their expected payout in liquidation.

[9] Kapadia (2011) identifies that the cross-sectional correlation between systematic distress risk exposures and firm-level distress risk is negative.

mispricing explanations have the appeal of addressing the distress risk anomaly, regardless of whether the determinants of distress risk be systematic or idiosyncratic. Mispricing was first suggested by Campbell et al. (2008) as an explanation for the distress risk anomaly. Mispricing explanations for the distress risk anomaly have the broad approach of identifying features of investors, the information environment and financially-distressed stocks that potentially manifest in the overpricing of distressed stocks. For example, these features include investor overconfidence, reduced liquidity, and elevated *ex ante* skewness of financially distressed firms (see, for example, Conrad et al. 2014; Gao et al., 2018). It is proposed that these characteristics of financially-distressed stocks lead to temporary overpricing and the observed distress risk anomaly. Consistent with the mispricing explanation for the distress risk anomaly, Stambaugh & Yuan (2016) report that the returns generated by this anomaly become insignificant after controlling for a mispricing factor. Additionally, the presence of limits to arbitrage allows for instances of mispricings to persist by preventing rational investors from exploiting the opportunity (Shleifer & Vishny, 1997). The distress risk anomaly is stronger in stocks with lower institutional ownership, price per share and liquidity (Campbell et al., 2008; Conrad et al., 2014).[10] As these stocks are typically dominated by individual investors and difficult for institutional investors to arbitrage, this provides further support for the mispricing explanation.

There is a dominant underlying theme of under-reaction in the extant mispricing explanations for the distress risk anomaly. Under-reaction has a long history in the asset pricing literature. Under-reaction has been argued to explain anomalous patterns in returns including the post-earnings announcement drift (Ball & Brown, 1968), momentum (Jegadeesh & Titman, 1993), and drifts following dividend omissions (Michaely, Thaler, & Womack, 1995). This empirical evidence of under-reaction is formalised by the model of Barberis et al. (1998), where it is argued that conservatism is the behavioural bias responsible for under-reaction. The conservatism bias manifests in the slow updating of beliefs when presented with new information (Edwards, 1968). Distress risk is a complex signal and more difficult to observe relative to events such as earnings announcements and dividend omissions. Therefore, it is more plausible that reaction to distress risk is slower relative to other signals. Distress risk is often a manifestation of several characteristics including high leverage, low profitability, low past stock returns and high stock return volatility. Additionally, relative to other signals, such

[10] The distress risk anomaly is argued to still be highly significant after taking into consideration transaction costs (Novy-Marx & Velikov, 2016).

as past stock returns or market capitalisation, distress risk is not a widely reported stock characteristic. Moreover, it is possible that investors misperceive distress risk to be mean-reverting and exhibit conservatism, and this will result in the slow updating of beliefs regarding the future distress risk of the firm and under-reaction to distress risk. As a result, it is highly likely that there is a delay in investors updating their beliefs following realisations of high distress risk. Under-reaction to distress risk may manifest in the overpricing and subsequent low risk-adjusted returns of financially-distressed stocks. However, although under-reaction is a common underlying theme (see, for example, Agarwal & Taffler, 2008) of the mispricing explanations for the distress risk anomaly, the exact mechanism by which investors under-react to distress risk is not agreed upon.

Although alluded to as an interpretation for empirical evidence regarding the distress risk anomaly, direct evidence of under-reaction to distress risk is scarce. Beaver (1968) was the first to consider the reaction of investors to distress risk, reporting that financial ratios in the years prior to bankruptcy seemingly indicate that investors do not fully incorporate distress risk in valuations. Agarwal & Taffler (2008) argue that through the under-reaction channel, the distress risk anomaly is related to the momentum anomaly (Jegadeesh & Titman, 1993), whereby under-reaction to distress risk explains both patterns in returns. Although, this evidence is limited to demonstrating a relationship between distress risk and momentum. Gao et al. (2018) suggest that investors may under-react as a consequence of investor overconfidence. This overconfidence argument is broad in the sense that it suggests that investors overweight their trading ability relative to public signals, reporting that overconfidence results in a delay in the updating of beliefs and temporary mispricing of financially-distressed stocks. However, the overconfidence argument does not specify whether investors are overconfident regarding their ability in terms of returns, risk, or financial distress. The under-reaction hypothesis is consistent with prior evidence reported by Griffin & Lemmon (2002) that the largest reversals of financially-distressed stock returns occur in periods where earnings announcements are released. An intuitive determinant of the mispricing of financially-distressed stocks is that investors under-react to distress risk by under-estimating future distress risk and over-estimating the future cash flows of financially-distressed firms. However, given that expectations of financial distress are unobservable, this explanation has not been examined in the literature.

There are fundamental relationships between cash flows, profitability and distress risk which may assist in examining under-reaction as an explanation for the distress risk anomaly. Financial distress is a scenario where the cash flows of a firm are inadequate to meet its financial obligations. Given that profitability plays a large role in determining cash flows, profitability is therefore a very central determinant of distress risk. In accordance with this logic, all else equal, firms that have lower profitability should be expected to have lower cash flows and higher distress risk. Aside from the negative relationship between profitability and distress risk being intuitive, empirical evidence also suggests that this is the case. Campbell et al. (2008) consider the ability of a broad range of market and accounting variables to predict corporate failure. Of the eight variables in the Campbell et al. (2008) main model, the predictive power of profitability is of the highest statistical significance in predicting corporate failure at the twelve-month horizon. The predictive ability of profitability is higher than the leverage, stock returns, stock return volatility, market capitalisation, book-to-market, and stock price characteristics. More recently, Bali, Del Viva, Lambertides & Trigeorgis (2019) argue that growth options link the profitability and distress risk anomalies, where relative to high profitability and low distress risk firms, low profitability and high distress risk firms have more flexible real options.[11] Given the ability of low profitability to predict distress risk and the commonalities between low profitability and high distress risk firms, it is evident that information about profitability is informative about distress risk.

Unlike expectation of distress risk and cash flows, expectations of profitability for financially-distressed firms are observable in analyst forecasts. This is important as it may help to address the challenges that the under-reaction explanation for the distress risk anomaly has faced in the literature. Pertinently, the literature regarding analyst forecasts has identified several characteristics of analyst behaviour that suggest that under-reaction to distress risk is as likely to be identified in analyst expectations as it is in the expectations of other market participants, including individual investors. There is a rich literature that argues that analysts make errors in forecasting profitability. First, many argue that analysts under-react to recent information in forming their expectations (Abarbanell & Bernard, 1992; Ali, Klein, & Rosenfeld, 1992). This under-reaction is asymmetric, where analyst under-reaction to negative news is more common than under-reaction to positive news (Easterwood & Nutt, 1999). Second, there is a related but distinct stream of literature that argues that analysts have career and financial incentives to produce optimistic, as opposed to pessimistic, earnings forecasts

[11] It is argued that firms with more growth and flexible real options are less risky (see, for example, Zhang, 2005) and that the profitability, distress, lottery, and idiosyncratic volatility anomalies capture compensation for this risk.

(see, for example, Hong & Kubik, 2003; and Lim, 2001).[12] For firms that have high distress risk, under-reaction and optimistic forecasts will both manifest in the same outcome where, on average, analyst forecasts errors are negative. Whilst it is not clear that the analyst optimism channel predicts cross-sectional differences in forecast errors between firms, under-reaction would result in more optimistic forecasts for financially-distressed firms relative to low distress risk firms. As a result, this under-reaction bias in the behaviour of analysts should result in cross-sectionally very negative forecast errors (where actual earnings are lower than analyst expectations) following realisations of high distress risk.

Anomaly signals represent information that is available to analysts when forming their recommendations. There is an emerging literature that examines whether analysts use the information contained in anomaly signals in forming their recommendations. Recent evidence studying the relationship between analyst recommendations and asset pricing anomalies suggests that analysts exacerbate market inefficiencies, as opposed to playing a role in correcting mispricings. Engelberg, McLean & Pontiff (2020) show that, on average, the return forecasts for the short legs of anomaly portfolios are excessively optimistic relative to the long legs of anomaly portfolios. Moreover, Guo, Li & Wei (2020) show that the abnormally low returns of financially-distressed stocks are concentrated in firms where the consensus recommendations are most positive, indicating recommendations closer to a buy. Additionally, for financially-distressed firms where consensus recommendations are most positive, stock ownership by mutual fund increases more for these firms, relative to financially-distressed firms with less positive recommendations. The resultant upward price pressure from institutional investors on these relatively small stocks is proposed to cause financially-distressed stocks to become even more over-valued. This literature proposes that, by ignoring anomaly signals, analysts and investors that act on analyst forecasts or form expectations similarly amplify the mispricing of stocks in the short side of common anomaly portfolios, including financially-distressed stocks.

Given the relationships between profitability, cash flows and distress risk, and the under-reaction biases of analysts identified in the extant literature, analyst forecasts therefore provide a useful laboratory to study the unobservable expectations of investors regarding distress risk. Specifically, analyst forecasts are a useful proxy for expectations regarding the future cash flows of financially-distressed stocks. It is an implicit assumption in many studies that biases

[12] Grant, Jarnecic, and Su (2015) also report that there is asymmetry in broker behaviour, where relatively optimistic sell-side analysts generate more trade for their brokerage firms than pessimistic analysts.

in analyst expectations are informative of the biases in the expectations of the marginal investor. For example, Bouchaud et al. (2019) provide a discussion of the relationship between analyst forecasts and asset prices, where they argue that the biases in analyst forecasts would not be reflected in asset prices if analyst forecast errors were not correlated with the forecast errors of the marginal investor. As a result, if there is a delay in investors updating their expectations, analyst forecast errors may assist in capturing this phenomenon. Specifically, the possibility that investors under-react to distress risk by over-estimating future cash flows following realisations of high distress risk may be explored by examining analyst forecasts. If investors under-react to distress risk, this may be captured by negative forecast errors for financially-distressed firms, where the difference between actual earnings and forecasted earnings is negative. Moreover, the forecast errors of financially distressed firms would be more negative relative to other stocks in the cross-section.

In summary, the extant literature identifies the tendency of financially-distressed firms to earn abnormally low returns, a result commonly referred to as the distress risk anomaly. A stream of studies in the literature has sought to explain away the distress risk anomaly in terms of mispricing. Whilst under-reaction is a common underlying theme of these studies, empirical evidence of the exact channel by which investors under-react to distress risk is extremely limited. A plausible and unexamined channel which has the potential to manifest in the distress risk anomaly is that investors over-estimate the future cash flows of financially-distressed firms more relative to firms that are least distressed. Given the relationships between distress risk, profitability and cash flows identified in the literature, analyst forecasts therefore provide a useful laboratory to study under-reaction to distress risk and to examine the possibility that the future cash flows of financially-distressed firms are over-estimated.

2.2 Hypothesis Development

Campbell et al. (2008) were of the first to identify mispricing as a potential explanation for the anomalous, negative relationship between distress risk and risk-adjusted returns, a result commonly referred to as the distress risk anomaly. Recent studies have explored the mispricing explanation for the distress risk anomaly, where various arguments have been proposed to result in the mispricing of financially-distressed stocks. These include that investor are over-confident, over-weighting private ability relative to public signals, (Gao et al., 2018) and that financially-distressed stocks are characterised by high limits to arbitrage (Conrad et al., 2014). An alternative mispricing explanation for the distress risk anomaly is that investors under-react to distress risk, over-estimating the future cash flows of financially-distressed firms. This also has the potential to result in the observed distress risk anomaly. However, despite under-reaction to distress risk being a promising and intuitive explanation for the distress risk anomaly, this has not been examined in the literature given that investor expectations regarding financial distress are not directly observable.

Given that profitability is a key determinant of cash flows, optimistic expectations of profitability for financially-distressed firms are highly correlated with optimistic expectations of the cash flows of distressed firms. Unlike expectations of distress risk and cash flows, expectations of profitability are directly observable from analyst forecasts. Hence, analyst forecast errors provide a useful proxy to examine the under-reaction explanation for the distress risk anomaly and to test the possibility that the future cash flows of financially-distressed stocks are over-estimated. If analysts under-react to distress risk and over-estimate the future cash flows of distressed firms, this will result in optimistic expectations of the future earnings of financially-distressed firms relative to other firms. This would be reflected in higher (more positive) analyst forecasts relative to actual earnings in the forecast period following a realisation of high distress risk. However, the relationship between financial distress and analyst expectations has not been examined to date.

In this study, I address this important gap in the literature by examining the relationship between financial distress and analyst forecast errors (the difference between actual and forecasted earnings). Specifically, I hypothesise that analyst forecast errors will be negatively related to realised distress risk should analysts under-react to distress risk and over-estimate the future earnings of financially distressed stocks. The first hypothesis tested in this paper is:

H1: Analysts over-estimate earnings more for firms with high distress risk relative to firms with low distress risk.

The hypothesised negative relationship between distress risk and analyst forecast errors is a channel which has the potential to manifest in the temporary overpricing and subsequent abnormally low returns of financially-distressed stocks. It is a common implicit assumption in existing studies that the behavioural biases that affect analysts in forming expectations affect the marginal investor similarly (see, for example, Bouchaud et al., 2019). If this was not a fair assumption, it is not clear that there should be any relationship between the biases of analysts, including under-reaction to distress risk, and asset prices. However, should the expectations of analysts be informative of the expectations of the marginal investor of financially-distressed firms, the hypothesised relationship between financial distress and forecast errors has some important implications to assist in our understanding of the source of the distress risk anomaly.

I examine the possible implications of the proposed over-estimation of the future earnings of financially-distressed stocks for asset prices by examining the relationship between forecast errors and the distress risk anomaly. If the proposed relationship between financial distress and forecast errors is a promising explanation for the distress risk anomaly, the distress risk anomaly should be concentrated in firms where earnings are most over-estimated (where analyst forecasts are most positive relative to actual earnings). This is because temporary overpricing resultant from forecast errors will be most pronounced for these firms should forecast errors be reflected in asset prices. The second hypothesis tested in this paper is:

H2: The distress risk anomaly is concentrated in firms where earnings are over-estimated the most.

3. Data and Methodology

3.1 Distress Risk

Distance to default is a common measure of distress risk in both the asset pricing and corporate finance literatures. This measure is employed as the proxy for distress risk in the main results in this study, as opposed to other common measures such as the Campbell et al. (2008) measure, for several reasons. Firstly, the cross-sectional distribution of this variable is more easily interpreted as an indicator of the true values of distress risk relative to the Campbell et al. (2008) measure given that there is more cross-sectional variation in the distance to default measure. Cross-sectionally, the Campbell et al. (2008) distress risk estimates are more closely clustered around one and zero. Additionally, in some tests, the role of year-on-year persistence in distress risk in asset prices is explored. There are several accounting inputs into the Campbell et al. (2008) measure and this results in less cross-sectional variation in year-on-year persistence in distress risk relative to using the distance to default measure. This makes the Campbell et al. (2008) measure less useful for these tests. More generally, whilst it is common practice to use the estimated coefficients from the Campbell et al. (2008) estimated model, the distance to default measure of distress risk doesn't rely on the implicit assumption that the coefficients estimated by Campbell et al. (2008) are still useful in accurately predicting defaults over a decade later.

The Merton (1974) distance to default measure is used as the baseline measure of distress risk to estimate the probability that a firm is insolvent in the following twelve-month period. In order to calculate distance to default, asset value and asset volatility need to be estimated, neither of which are directly observable. Measures of these variables are constructed by solving two equations simultaneously.

First, in the Merton (1974) model, equity is valued as a European call option on the value of the firm's assets. Then:

$$\text{ME} = TA_{DD}N(d_1) - BD\exp(-R_{BILL}T)N(d_2)$$

$$d_1 = \frac{\ln\left(\frac{TA_{DD}}{BD}\right) + \left(R_{BILL} + \frac{1}{2}SIGMA_{DD}^2\right)T}{SIGMA_{DD}\sqrt{T}} \tag{1}$$

$$d_2 = d_1 - SIGMA_{DD}\sqrt{T}$$

Where N is the cumulative standard normal distribution, ME is the value of equity, TA_{DD} is the value of assets, $SIGMA_{DD}$is the volatility of assets, BD is the face value of debt maturing at time T, and $R_{BILL}$is the risk-free rate. TA_{DD} and $SIGMA_{DD}$are estimated by the model. Following Campbell et al. (2008) and Vassalou and Xing (2004), it is assumed $T = 1$ as default probability is computed over the following twelve months. Current debt plus one half of non-current debt is used to proxy for the face value of debt BD. The Federal Reserve 1-Year T-Bill rate is used to proxy for R_{BILL}.

The second equation is a relation between the volatility of equity and the volatility of assets:

$$SIGMA = N(d_1)\frac{TA_{DD}}{ME}SIGMA_{DD} \tag{2}$$

Where $SIGMA$ is the annualised standard deviation of the daily market value of equity calculated as the daily stock price multiplied by the number of ordinary shares outstanding over the prior year.

Equations 1 and 2 are solved using an iterative procedure until numerical solutions are found for the two unknown parameters, TA_{DD} and $SIGMA_{DD}$, that are consistent with the observed values of ME, BD, and $SIGMA$. As starting values for asset value and asset volatility, $TA_{DD} = ME + BD$ and $SIGMA_{DD} = SIGMA\left(\frac{ME}{ME+BD}\right)$are used. This starting value of $SIGMA_{DD}$ is used to infer TA_{DD} and this allows for new estimates of $SIGMA_{DD}$. This iterative procedure is repeated until $SIGMA_{DD}$ converges.

Once this numerical solution is obtained, distance to default (DD) is computed as:

$$DD = \frac{\ln\left(\frac{TA_{DD}}{BD}\right) + \left(\mu - \frac{1}{2}SIGMA_{DD}^2\right)T}{SIGMA_{DD}} \tag{3}$$

Where μ is an estimate of the expected annual return of the firm's assets. The return of the firm's assets is defined as the log of total firm asset value as a fraction of lagged total firm asset value where total firm asset value (TA_{DD}) is estimated by the model as described.

The corresponding implied probability of default, commonly termed expected default frequency (EDF), is then computed by substituting DD (which is a z-score) into a standard normal cumulative density function. EDF captures the probability that the value of the firm will be less than the face value of debt in the next twelve months.

$$EDF = N(-DD) \tag{4}$$

For each firm-month observation, this EDF parameter is estimated, which I refer to as the Merton (1974) distance to default measure of distress risk (*DD Distress Risk*) in this paper. To ensure the results are not sensitive to the choice of distress risk measure, the Campbell et al. (2008) measure of distress risk (*CHS Distress Risk*) is also employed to confirm that the distress risk anomaly is detectable in the I/B/E/S sample. The Campbell et al. (2008) measure of distress risk is defined in detail in Appendix 1.

3.2 Analyst Forecasts

The sample of analyst forecasts of earnings per share (EPS) and actual EPS is constructed from the I/B/E/S database. Analyst-by-analyst EPS forecasts are obtained from the I/B/E/S Detail History File (unadjusted), where I focus on EPS forecasts for the current fiscal year (one-year-ahead forecasts).[13] Consistent with the method of Bouchaud et al. (2019), all forecasts that were announced up to 45 days after an announcement of total fiscal year earnings are retained.[14] If an analyst issues multiple forecasts for the same firm and the same fiscal year during this 45-day period, only the first forecast is retained. Bouchaud et al. (2019) argue that this method of identifying analyst forecasts maximises the potential for forecast errors and biases. Additionally, this method ensures that there is minimal information regarding the forecast period reflected in the forecast, that has been released before the forecast is announced. These analyst-by-analyst forecasts from the I/B/E/S Detail History File are used to construct the median analyst forecast for each firm-fiscal year observation. The consensus forecast is constructed using this method, as opposed to using the I/B/E/S summary files, as it is not clear which analyst forecasts are included in the calculation of the pre-constructed consensus forecasts in the I/B/E/S summary files. The actual reported EPS from the I/B/E/S unadjusted actuals file are then matched with the calculated consensus forecasts.[15] The sample is filtered to exclude firms with missing actual EPS, and missing one-year-ahead and two-year-ahead median analyst EPS forecasts. This filtered annual panel of firms is comprised of 49,325 firm-year observations, before matching to the other data sources.

The Bouchaud et al. (2019) measures of forecast errors and expectation stickiness are constructed from this data. Forecast errors (FE) are measured as the difference between the actual earnings for fiscal year *t* and the consensus earnings forecast that was formed just after the announcement of fiscal year *t-1* earnings, normalised by the stock price before the announcement of fiscal year earnings *t-2*. In order to examine the under-reaction interpretation

[13] Forecasts for the different fiscal years are identified by the means of the I/B/E/S Forecast Period Indicator variable FPI. Although some I/B/E/S data is available on a quarterly basis, I focus on annual forecasts since these forecasts over longer horizons avoid potential seasonality concerns and are more likely to be susceptible to behavioural biases (Bouchaud et al., 2019).

[14] Bouchaud et al. (2019) identify 45 days as the median time across analysts between the announcement of annual earnings and the issuance of their first forecast in the I/B/E/S Detail History File.

[15] In order to address the issues identified by Diether, Malloy, & Scherbina (2002) and Robinson & Glushkov (2006) associated with stock splits occurring between the EPS forecast and the actual earnings announcement, the number of shares outstanding is adjusted using the CRSP cumulative adjustment factors.

of any observed relationship between distress risk and forecast errors, the expectation stickiness variable is also constructed. The analyst expectation stickiness measure is obtained from the estimation of the following regression of consensus forecast errors on consensus forecast revisions:

$$FE_f = \alpha_f + b_f.FR_{f,t} + \epsilon_{f,t} \tag{5}$$

Where the forecast revision (FR) of a firm is the change in the consensus earnings forecast for fiscal year *t* that was formed just after the announcement of fiscal year earnings *t-1* with respect to the consensus earnings forecast for fiscal year earnings *t* that was formed just after the announcement of fiscal year earnings *t-2*, normalized by the stock price before the announcement of fiscal year earnings *t-2*. This regression is estimated for each firm separately, using the entire history of consensus forecasts and errors. Expectation stickiness (λ_f) is simply the transformation $\lambda_f = b_f/1 + b_f$ of coefficient b_f in Equation 5.

The constructed samples of distress risk estimates and analyst forecast variables are used to investigate the relationship between distress risk and analyst forecast errors (hypothesis one).

3.3 News

To test the under-reaction interpretation, a measure of news is also collected. The 'event sentiment score' is collected from the RavenPack Full Edition database. This data is available from January 2001. All news stories over the January 2001 to December 2018 period are collected, subject to the same filters that Gao et al. (2018) apply to news stories.[16] An event sentiment score of fifty for a given news story indicates neutral sentiment, whereas a score of greater than (less than) fifty indicates positive (negative) sentiment. Firm-fiscal-year and firm-month measures of average news sentiment are calculated. The average firm-fiscal-year (firm-month) news sentiment is the simple average of all event sentiment scores for a firm in a given fiscal-year (month). If there is no news, the average news sentiment is a missing value. The

[16] Only news events that have 'relevance' and 'event novelty' scores both equal to 100 are included. This ensures that the firm name is mentioned in the headline or main title and that no similar story about the firm has been reported in the prior twenty-four hours (no duplicates). To capture firm-specific news, as opposed to market movements, news items in the following categories are excluded: stock- gain, stock-loss, market-close-buy-imbalance, market-close-sell-imbalance, no-market-close- imbalance, market-open-sell-imbalance, market-open-buy-imbalance, delay-imbalance, buy- imbalance, sell-imbalance, and no-imbalance.

RavenPack average news sentiment variable is merged to the existing sources using International Securities Identification Number (ISIN) and CUSIP identifiers.

3.4 Stock Returns and Other Signals

The sample of stock returns includes all non-financial Center for Research in Security Prices (CRSP) firms listed on major U.S. exchanges; AMEX, NYSE and NASDAQ that can be matched with Compustat.[17] Daily and monthly stock market data from CRSP and quarterly and annual company fundamental data from Compustat is also collected, as needed for the construction of other required stock characteristics. From this data, signals for market beta, size, book-to-market, momentum, investment, profitability, idiosyncratic volatility, and leverage are computed. These variables are constructed in accordance with standard definitions. Definitions of these variables are provided in Appendix 2. Monthly market excess, risk-free and factor returns are collected from Kenneth French's data library.[18]

This stock market data is used to demonstrate the implications of the findings regarding the relationship between distress risk and forecast errors for asset prices. Combining the sample of distress risk estimates with the sample of stock returns and other signals, this data is used to examine the extent to which the distress risk anomaly is concentrated in firms where forecast errors are most negative (hypothesis two).

3.5 Final Sample

The final sample is the merged sample of distress risk, analyst forecast data, and stock returns and other signals.[19] The sample period employed in the study is from January 1983 to December 2018, due to the limited availability of analyst forecast data prior to this period.[20] The main sample consists of 6,632 unique firms. In Table 1, summary statistics for the main variables employed in the following analysis are reported. The mean firm in the sample has distance to default distress risk of 14.38%, Campbell et al. (2008) distress risk of 0.06%, a mean EPS forecast error of -0.50% as a percentage of the stock price, distress risk persistence

[17] Non-financial is defined by 2-digit SIC code. Firm-month observations with 2-digit SIC codes 60, 61, 62, 63, 64, 65 and 67 are excluded.

[18] Kenneth's French data library can be accessed from this URL: https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

[19] The I/B/E/S data is merged to the other data sources by CUSIP.

[20] The tests requiring the RavenPack news data employ a restricted sample given that this data is only available from January 2001.

of 0.0416, expectation stickiness of 0.10, market beta of 1.14, log market capitalisation of 13.69, book-to-market of 0.55, momentum of 14.81%, investment of 12.71% and profitability of 38.66%. These estimates of distress risk are reasonably consistent with prior studies, despite the added constraint of requiring analyst coverage in this study. For example, Bharath and Shumway (2008) report a mean (median) Merton (1974) distress risk of 10.95% (0.01%). Furthermore, the mean forecast error is consistent with that reported by Bouchaud et al. (2019), where a mean forecast error of -0.60% is reported over the I/B/E/S sample. Moreover, recent studies using the I/B/E/S database, report average characteristics including expectation stickiness of 0.13. market betas of 1.17 and momentum of 16.13% (Bordalo, Gennaioli, Porta, & Shleifer, 2019; Bouchaud et al., 2019; Guo et al., 2020). The summary statistics reported in this paper are therefore reconcilable with recent studies that also use the sample of analyst-covered firms. Notably, the median market capitalisation in this analyst-covered sample is large relative to recent studies of financially-distressed stocks that do not require analyst coverage. For example, Gao et al. (2018) report a median market capitalisation of 442.72 million. As a result, the results in this paper are less likely to be attributable to stocks with higher limits to arbitrage.

Given this paper studies the stock returns of the most financially-distressed firms, it is imperative to identify delistings and deal with stock returns around delistings appropriately. There are 345 firm-month observations where a delisting occurs in the sample. Most delistings occur where the firm continues to trade on another major exchange or where the delisting is a consequence of merger activity. These reasons account for 87% of all delistings in the sample. Of the remaining delistings, 45 are due to reasons that may be particularly closely associated with financial distress. These reasons include the stock price falling below the acceptable level, insufficient capital, surplus, equity and float assets, and insolvency. CRSP report delisting returns for the final month of the firm's life. These are used where available.[21]

4. Distress Risk and Forecast Errors

4.1 Univariate Portfolios Sorts on Distress Risk

I begin the analysis by demonstrating that the distress risk anomaly is observed in the sample of analyst-covered firms. To demonstrate the distress risk anomaly, at the end of each month *t*,

[21] A criticism of this approach is the reported missing delisting returns in the CRSP database, particularly for firms that delist due to insolvency (Shumway, 1997). However, given that in the absence of available delisting returns the last available full-month return is used, this biases against the finding of a distress risk anomaly.

all stocks in the sample are sorted into decile portfolios based on an ascending order of distress risk, with each portfolio having an equal number of stocks. In Panel A of Table 2, stocks are sorted on the distance to default (DD) measure of distress risk. In Panel B of Table 2, stocks are sorted on the Campbell et al. (2008) (CHS) measure of distress risk. Panel A and B of Table 2 present the time-series means of distress risk, the average month *t+1* (1-month-ahead) value-weighted excess return, and, value-weighted alphas relative to the Fama-French-Carhart four-factor and six-factor models for each of the decile portfolios, and for the hedge portfolio that is long the portfolio of stocks with the highest distress risk and short the portfolio of stocks with the lowest distress risk. Newey-West adjusted *t*-statistics with six lags are reported in parentheses, testing the null hypothesis that the abnormal return is equal to zero.

By construction, the results in Table 2 show that the average DD (CHS) distress risk increases from 0% (2%) for the first decile portfolio to 78% (34%) for the tenth decile portfolio. The average 1-month-ahead excess returns of the distress risk sorted decile portfolios tend to decrease with distress risk, although this relationship is not monotonic, for either of the distress risk measures. The difference in the average monthly excess returns between the high distress risk portfolio and the low distress risk portfolios of -0.80% and -0.74% for the DD and CHS distress risk sorts are highly significant. There is therefore a clear difference in the average returns between stocks with high distress risk and stocks with low distress risk, where high distress risk stocks underperform low distress risk stocks on a raw basis.

Consistent with prior studies, the abnormal returns from sorting stocks on distress risk are concentrated in the portfolios of stocks with high distress risk. This is intuitive given that several of the low distress risk portfolios have distress risk equal to approximately zero. The six-factor abnormal returns of the highest DD and CHS distress risk portfolios of -0.46% and -0.55% per month are highly significant with corresponding *t*-statistics of -3.70 and -5.01 respectively. The abnormal returns of the DD and CHS distress risk hedge portfolios of -0.55% and -0.57% per month respectively are also highly significant. This magnitude of the distress risk anomaly is consistent with that reported in Campbell et al. (2008), where the annualised Fama-French-Carhart four-factor abnormal returns of the distress risk anomaly portfolio are 12.07% per annum. This is the LS1090 portfolio, as reported in Table 6 in their paper which is long (short) the decile portfolio of stocks with the lowest (highest) distress risk.

The main result reported in Table 2, that high distress risk stocks underperform stocks that have the lowest distress risk forms the basis for the rest of this paper. This result indicates that the distress risk anomaly is both economically and statistically significant in the sample of analyst-covered firms. It is therefore feasible to undertake a study of the determinants of the distress risk anomaly in this sample.

In order to gain a better understanding of the composition of the distress risk decile portfolios, Panel C of Table 2 reports the average values of firm characteristics for the stocks in each portfolio, averaged across the months. The differences between the high and low distress risk portfolios are also reported. The results from one-sample *t*-tests are reported in parenthesis. This *t*-test tests the null hypothesis that the time-series of the differences in the monthly mean characteristic between the high distress risk portfolio and the low distress risk portfolio is equal to zero.

Of most interest to the following analysis is the cross-sectional relationships between distress risk, and profitability and forecast errors. There is a monotonically decreasing pattern in profitability for DD distress risk sorted portfolios, where the portfolio of stocks with the highest distress risk has significantly lower profitability relative to the portfolio of stocks with the lowest distress risk.[22] This relationship is highly significant through time. This descriptive evidence that lower profitability coincides with higher distress risk is important given the unobservable nature of expectations of distress risk. As a result, expectations of low profitability may be interpreted as implicit elevated expectations of distress risk. Moreover, although not a monotonic relationship, forecast errors are also negatively related to distress risk. This relationship is also highly significant. As a percentage of the stock price, on average, the portfolio of stocks with the highest distress risk has a forecast error of -0.93% lower (more negative) than the portfolio of stocks with the lowest distress risk. Such a magnitude in the relative forecast error of sorted stocks has been reported to be an important determinant of relative mispricing. For example, Bouchaud et al. (2019) report a difference in the forecast errors between high and low profitability firms that is smaller than -0.93% and demonstrate that forecast errors are an important source of the mispricing of high profitability firms.

Distress risk has a cross-sectional relationship with other stock characteristics. These relationships are further illustrated in the correlation matrix provided in Appendix 3. Distress risk is positively related to distress risk persistence, expectation stickiness, market beta, book-to-market, idiosyncratic volatility and leverage. Distress risk is negatively related to size and momentum. These results are also consistent with evidence from the extant literature that

[22] Novy-Marx (2013) reports an average gross profitability of 21% for the portfolio of firms with the highest book-to-market ratios cross-sectionally. This may assist in addressing the potential concern that the average profitability of the high distress risk decile of 32.38% is surprisingly positive.

financially-distressed firms load positively on the market and book-to-market factors and negatively on the size and momentum factors (see, for example, Agarwal & Taffler, 2008; Griffin & Lemmon, 2002).

4.2 Distress Risk and Analyst Forecast Errors

I now formally examine the relationship between distress risk and forecast errors. This section of this paper has the objective of providing evidence of analysts over-estimating the cash flows of financially-distressed stocks. The DD measure of distress risk is used as the main measure of distress risk in these tests. The over-estimation of future cash flows is measured by computing analyst forecast errors as defined in Section 3 (the normalised difference between actual and forecasted earnings). Where the value of forecast error is negative, this indicates the over-estimation of future cash flows, since the consensus earnings forecast is higher than actual earnings.

Before running regressions, I first provide a graphical illustration of the data. In Figure 1, I show forecast error as a function of distress risk. All firm-fiscal-year observations are sorted into thirty portfolios, formed on the distress risk as at just before the announcement of fiscal year *t-1* earnings. This information is available to analysts before the announcement of their one-year fiscal year *t* earnings forecasts. For each of these portfolios, the average distress risk as at just before the announcement of fiscal year *t-1* earnings and the consensus analyst forecast error for fiscal year *t* is then computed. This Figure demonstrates a strong negative relationship between the distress risk of a firm prior to the announcement of analyst forecasts, and the subsequent analyst forecast errors. The portfolio of stocks with the highest distress risk before the announcement of analyst forecasts has an average analyst forecast error of -2.01%. On the other hand, the portfolio of stocks with the lowest distress risk before the announcement of analyst forecasts has an average analyst forecast error of just -0.38%. Also worthy of note is the distribution of forecast errors across the thirty portfolios. For all portfolios, the mean forecast error is negative, independent of whether the portfolio has high or low distress risk. This provides evidence consistent with the literature on analyst optimism (see, for example, Lim, 2001), where analysts have a bias to produce optimistic, as opposed to pessimistic earnings forecasts.

The result reported in Figure 1, that analysts increasingly over-estimate earnings with distress risk is the key finding of this paper. This provides empirical evidence in support of the under-reaction interpretation of the distress risk anomaly, without linking this pattern to asset prices. In order to further examine the relationship between distress risk and forecast errors, I next run panel regressions using the annual panel of firms.[23] It is possible that stock characteristics related to financial distress result in the observed negative relationship between distress risk and analyst forecast errors. For example, if analysts simply under-react to low profitability, then this may be driving the relationship between distress risk and forecast errors, given the earlier reported monotonic relationship between distress risk and profitability. Furthermore, it has been suggested in the literature that whether a firm is newly distressed is possibly a determinant of under-reaction to distress risk (see, for example, Gao et al., 2008). In Table 3, I address these concerns by reporting the results from regressions of analyst forecast errors on distress risk, and other stock characteristics that are closely related to financial distress, as well as the one-year change in distress risk. The following regression is estimated:

$$FE_{i,t} = \lambda_0 + \lambda_1 DD\ Distress\ Risk_{i,t-1} + \Lambda\,\mathbf{X}_{i,t-1} + \epsilon_{i,t} \tag{6}$$

Where FE is forecast error, $DD\ Distress\ Risk$ is the distance to default measure of distress risk, and **X** is a vector of control variables containing the Campbell et al. (2008) measure of distress risk, leverage, momentum idiosyncratic volatility, beta, size, book-to-market, investment, profitability, one-year change in distress risk, and the interaction of a dummy variable equal to one for firms have newly migrated to the high distress risk decile portfolio with distress risk. *i* and *t* denote firm and fiscal year respectively. All independent variables are as at just before the announcement of fiscal year *t-1* earnings and therefore available information to the analyst before the announcement of forecasts.

In the first and second specification, I begin with confirming that there is a strong and negative relationship between distress risk and analyst forecast errors. This is true for both the DD and CHS measures of distress risk. Notably, the DD measure of distress risk has a statistically stronger relationship with forecast errors. A possible reason for this is that, relative to the DD measure of distress risk, the CHS measure of distress risk is more reliant on fundamental inputs which are likely stale relative to the inputs of the DD model of distress risk. In the third and fourth specifications, the model of forecast errors on distress risk is augmented with additional variables. Specifically, the regression of forecast errors on the DD measure of distress risk is augmented with the input variables to the DD measure of distress risk (leverage,

[23] Panel regressions are used in this first stage of analysis, as opposed to cross-sectional regressions, since there is unlikely to be a time effect in the under-reaction to distress risk. Moreover, firm fixed effects are omitted as, given the persistence of distress risk over short horizons, this regression has the objective of examining the difference in forecast errors between firms with different distress risk, as opposed to the difference in forecast errors for a firm with changing distress risk.

momentum and idiosyncratic volatility). The relationship between forecast errors and distress risk remains highly significant in these specifications.

In the fifth and sixth specifications, the model is further augmented with variables attempting to capture the additional effect of newly distressed firms (one-year change in distress risk and the interaction of a dummy variable equal to one for firms have newly migrated to the high distress risk decile portfolio with distress risk) on forecast errors. The result that the one-year change in distress risk is not a significant determinant of analyst forecast errors is not entirely consistent with the results of Gao et al. (2018). Gao et al. (2018) address the under-reaction explanation for the distress risk anomaly in their study indirectly by examining the effect of the amount of time a stock has been in the high distress risk portfolio on the distress risk anomaly. The inference here is that under-reaction should only impact newly distressed stocks. If under-reaction is reflected in the over-estimation of the future cash flows of financially-distressed stocks, then consistent with this idea, it should be the case that the firms with the greatest one-year change in distress risk should be an important determinant of cross-sectional variation in forecast errors, as opposed to simply the magnitude of distress risk itself. I do not find this to be the case. Instead, I find that the over-estimation of the future cash flows of financially distressed stocks is not limited to newly-distressed stocks.[24] Distress risk is a highly complex signal for investors to detect and it is very reasonable that investors update their beliefs regarding stocks with high distress risk over extended periods of time, if at all completely.

In the seventh specification, standard asset pricing control variables are added, including market beta, size, book-to-market, investment and profitability. In this specification, there are statistically significant negative relationships between forecast errors and idiosyncratic volatility, beta, book-to-market, investment and profitability at the five percent level. However, after controlling for these additional variables, there is still a highly significant negative

[24] In the sixth specification, an alternative proxy is used to identify newly distressed stocks, which yields qualitatively similar, insignificant results. A dummy variable is used to indicate stocks that are in the high distress risk portfolio in a given fiscal year that were not in the high distress risk portfolio in the prior fiscal year. In regressions of forecast errors on distress risk, control variables and the interaction of this dummy variable with distress risk, I find no results to suggest that migration into the high distress risk portfolio is a significant determinant of forecast errors.

relationship between distress risk and forecast errors.[25] [26] Overall, this evidence indicates that the reported over-estimation of the future cash flows of financially-distressed firms is not a manifestation of relationships between forecast errors and profitability, or other characteristics distinct of financially-distressed stocks.[27] This result can be interpreted as investors under-reacting to distress risk in forming their expectations of future cash flows. This is the first empirical evidence of this important mechanism which may manifest in the mispricing of financially-distressed stocks, and the reported distress risk anomaly.

Whilst in Table 3, I report that forecast errors are negatively related to distress risk, Figure 1 indicates that, on average, the forecast errors of distress risk sorted portfolios are negative. It is therefore possible that high distress risk is a determinant of the magnitude, as opposed to the direction (sign), of forecast errors. In order to examine the extent to which distress risk predicts negative forecast errors, I run logit regressions of an indicator variable equal to one where the firm-year forecast error is less than zero on distress risk and other stock characteristics.[28] Modelled as a logistic distribution, the probability that the forecast error of a firm in year *t* is negative is given by:

$$P_{t-1}(Neg\_FE_{i,t} = 1) = \frac{\exp(\lambda_0 + \Lambda\mathbf{X}_{i,t-1})}{1 + \exp(\lambda_0 + \Lambda\mathbf{X}_{i,t-1})} \tag{7}$$

Where Neg_FE is a dummy variable equal to one if the firm's forecast error in the year *t* is less than zero and **X** is a vector of control variables known at *t-1* containing the Campbell et al. (2008) measure of distress risk, leverage, momentum idiosyncratic volatility, beta, size, book-to-market, investment and profitability.

[25] The negative relationship between profitability and forecast errors indicates that as profitability increases, investors, are more likely to over-react to this information by over-estimating future profitability. I provide a further discussion of the relationship between forecast errors and profitability in Appendix 5.

[26] In Appendix 4, this model is augmented with variables which are additional possible determinants of cross-sectional variation in forecast errors. These variables are firm-level forecast dispersion, within-industry forecast dispersion, EPS volatility, number of analysts covering the firm, change in the number of analysts covering the firm, one-year change in one-year consensus forecasts, and market capitalisation. The finding that there is a strong negative relationship between distress risk and forecast errors is robust to controlling for these characteristics.

[27] In the final two specifications, the dependent variable is the difference between actual and forecasted earnings, without normalising by price. The results from these specifications illustrate that the results documented in the main specifications are not a manifestation of the price-to-earnings ratio.

[28] An additional benefit of this analysis is that it may also alleviate possible concerns regarding the sensitivity of the findings reported in this paper to the measurement of forecast errors, since the binary indicator variable will not be affected by such issues.

In Table 4, I show that distress risk predicts not only the magnitude, but the direction of forecast errors. 54.38% of the firm-year forecast error observations are negative. The probability of a negative forecast error increases with high distress risk. This relationship is statistically significant at the one percent level in all specifications. The signs and magnitudes of the coefficients on the control variables are largely consistent with the findings from the panel regressions. Overall, the results from the logit regressions provide further evidence that cash flows are more likely to be over-estimated for firms that experienced high distress risk in the period immediately preceding the announcement of forecasts.

4.3 Examining the Under-Reaction Interpretation

The result that there is a strong negative relationship between distress risk and analyst forecast errors is consistent with under-reaction to distress risk, since this result indicates that analysts over-estimate the future cash flows of financially-distressed stocks more relative to other stocks in the cross-section. In order to further examine an under-reaction interpretation of this finding, two additional tests of the relationship between distress risk and forecast errors are undertaken. Since under-reaction describes a situation where investors are slow to update their beliefs, first it is examined whether the relationship between distress risk and forecast errors is more pronounced for firms followed by analysts with stickier expectations. Second, an under-reaction interpretation of the main finding implies that the relationship between distress risk and forecast errors will be most pronounced where there is recent information that analysts haven't fully responded to. Therefore, the implications of recent news events for the relationship between distress risk and forecast errors is also examined.

By definition, under-reaction describes a situation where there is an incomplete adjustment to available information about the firm. As a result, if it is the case that some firms are followed by analysts where the updating of beliefs is particularly slow, it is for these firms under-reaction to distress risk should be most pronounced. Bouchaud et al. (2019) provide a model for capturing just this dynamic, expectation stickiness. Expectation stickiness therefore provides a method of testing the under-reaction interpretation of the main finding. This measure of expectation stickiness is estimated for each firm separately, using the entire history of consensus forecasts and errors as described in Section 3. Where the relationship between forecast errors and forecast revisions is negative, this is indicative of analysts downward revising their expectations and under-estimating earnings (over-reacting to new information). Where the relationship between forecast errors and forecast revisions is positive, this is indicative of analysts downward revising their expectations and still over-estimating earnings (under-reacting to new information). Firms with the most positive value of expectation stickiness therefore have a higher propensity to under-react to news associated with distress risk relative to firms followed by analysts with less sticky expectations. As a result, analyst expectation stickiness is able to capture the extent to which the relationship between distress risk and forecast errors is concentrated in firms followed by analysts that are more prone to under-reacting. In order to examine the dependence of the relationship between distress risk and forecast errors on expectation stickiness, the following regression is estimated:

$$FE_{i,t} = \lambda_0 + \lambda_1 DD\ Distress\ Risk_{i,t-1} \times High\ Stickiness_i + \lambda_2 DD\ Distress\ Risk_{i,t-1} \times Low\ Stickiness_i + \lambda_3 DD\ Distress\ Risk_{i,t-1} + \lambda_4 Stickiness_i + \Lambda\,\mathbf{X}_{i,t-1} + \epsilon_{i,t} \tag{8}$$

Where $High\ Stickiness$ ($Low\ Stickiness$) is a dummy variable equal to one if a firm observation is in the top (bottom) quintile of expectation stickiness, $Stickiness$ is expectation stickiness as defined in Equation 5 and **X** is a vector of control variables containing leverage, momentum, idiosyncratic volatility, beta, size, book-to-market, investment and profitability.

In Table 5, I report that the over-estimation of the future cash flows of financially distressed stocks is concentrated in firms that are followed by analysts that have a higher propensity to under-react. This finding is firmly consistent with an under-reaction interpretation of the results reported in Tables 3 and 4. In the first three specifications, I demonstrate that the negative relationship between distress risk and forecast errors is concentrated in the firms followed by analysts with the stickiest expectations. When controlling for the interaction of high analyst expectation stickiness and distress risk, the coefficient on this variable is negative and significant at the one percent level with a corresponding *t*-statistic of -4.70. The interaction of high analyst expectation stickiness and distress risk completely subsumes the explanatory power of distress risk alone. On the other hand, the relationship between forecast errors and the interaction of low analyst expectations stickiness and distress risk is insignificant. Moreover, distress risk is highly significant in this specification. As a result, this evidence indicates that the relationship between distress risk and forecast errors only exists for firms where analysts are slow to update their beliefs.[29] This provides support for an under-reaction interpretation of the negative relationship between distress risk and forecast errors.

[29] An alternative interpretation for the relationship between distress risk and forecast errors for firms with the highest analyst expectation stickiness is that analysts are slow to update their beliefs about profitability. Specifically, it may be the case sticky expectations regarding profitability explain this result. In the final specification I show that this is not the case.

A second approach to examining the under-reaction interpretation of the finding that there is a negative relationship between distress risk and forecast errors is to consider the role of news. It is difficult to assert that the findings are a consequence of under-reaction should there be no recent information for analysts to react to. A firm can have high distress risk for an extended period of time relative to the cross-section (i.e. can persistently be in the high distress risk portfolio) but still have new, negative, information. As a result, regardless of how long a firm has had cross-sectionally high distress risk, there can still be delays in incorporating information and news related to the magnitude of distress risk. If the negative relationship between distress risk and forecast errors is found in firms with no news, or positive news in the year preceding the announcement of forecasts, it is not clear that such a relationship can be interpreted as under-reaction. On the other hand, if the negative relationship between distress risk and forecast errors is concentrated where there is recent negative news, then this is highly consistent with an under-reaction interpretation of the key finding. To define negative (positive) news, a dummy variable equal to one is assigned to firms where the average firm-fiscal-year news sentiment is less than (greater than) fifty. The average news sentiment variable constructed from the RavenPack database is employed in these tests, as described in Section 3. In order to examine the relationship between distress risk and forecast errors in sub-samples formed on news, the following regression is estimated:

$$FE_{i,t} = \lambda_0 + \lambda_1 DD\ Distress\ Risk_{i,t-1} \times Negative\ News_{i.t-1} + \lambda_2 DD\ Distress\ Risk_{i,t-1} \times Positive\ News_{i.t-1} + \lambda_3 DD\ Distress\ Risk_{i,t-1} \times News_{i.t-1} + \Lambda\,\mathbf{X}_{i,t-1} + \epsilon_{i,t} \tag{9}$$

Where $Negative\ News$ ($Positive\ News$) is a dummy variable equal to one if the average fiscal-year sentiment for a firm-fiscal-year observation is less (greater) than fifty, $News$ is a dummy variable equal to a one if the firm-fiscal year observation experienced any (positive or negative) news coverage, and $\mathbf{X}$ is a vector of control variables containing leverage, momentum, idiosyncratic volatility, beta, size, book-to-market, investment and profitability.

In Table 6, I report that the relationship between distress risk and forecast errors is only observed for firms that have had, on average, negative news in the year preceding the announcement of analyst forecasts. In the first specification, I run a univariate regression of forecast errors on the interaction of the negative news dummy variable and distress risk. I find that this relationship is strong and negative at the one percent level. On the other hand, in a univariate regression of forecast errors on the interaction of the positive news dummy variable and distress risk, I find that there is no relationship between distress risk and forecast errors. In the third specification, I find that the negative relationship between distress risk and forecast errors for firms with negative news is robust to controls for other distress risk signals. Importantly, controlling for the interaction of the negative news dummy variable and distress risk completely resolves the predictive ability of distress risk. The evidence in Table 6 is highly consistent with an under-reaction interpretation of the key finding, since the over-estimation of the future cash flows of financially-distressed stocks is only observed for firms with recent negative news.

Overall, the results in this first half of the paper provide evidence of a strong negative relationship between distress risk and analyst forecast errors (hypothesis one). Moreover, I present empirical evidence that supports the interpretation of this result as analysts under-reacting to distress risk by over-estimating the future cash flow of financially-distressed stocks. I find that the negative relationship between distress risk and forecast errors is concentrated in firms followed by analysts with stickier expectations and firms with negative news in the period immediately prior to the announcement of analyst forecasts. This is the first empirical evidence of investors under-reacting to distress risk by over-estimating the future cash flows of financially-distressed stocks and makes an important contribution to addressing this gap in the mispricing explanation for the distress risk anomaly.

5. Forecast Errors and the Distress Risk Anomaly

In the second stage of the analysis, the implications of the relationship between financial distress and forecast errors for the distress risk anomaly are examined.

5.1 Univariate Sorts on Forecast Errors

Before examining the relationship between forecast errors and the distress risk anomaly, it is first demonstrated that analysts over-estimating the earnings of firms has the potential to result in abnormally low returns. At the end of each month *t*, all stocks in the sample are sorted into decile portfolios based on an ascending order of forecast errors with each portfolio having an equal number of stocks. Table 7 presents the time-series means of forecast error, the average month *t+1* (1-month-ahead) value-weighted excess return, and, value-weighted alphas relative to the CAPM, Fama-French-Carhart four-factor and six-factor models for each of the decile portfolios, and for the hedge portfolio that is long the portfolio of stocks with the highest (most positive) forecast errors and short the portfolio of stocks with the lowest (most negative) forecast errors. Newey-West adjusted *t*-statistics with six lags are reported in parentheses, testing the null hypothesis that the abnormal return is equal to zero.

As reported in Table 7, by construction, forecast errors increase from -5.28% for the first decile portfolio to 2.99% the tenth decile portfolio. Importantly, there is a monotonically increasing relationship between forecast errors and subsequent abnormal returns relative to the Fama-French-Carhart four-factor and six-factor models. The six-factor alphas of the decile portfolios of stocks where earnings are most over-estimated and under-estimated of -0.81% per month and 0.63% respectively are highly significant with corresponding *t*-statistics of -7.89 and 7.27 respectively. The six-factor alpha of the hedge portfolio that is long (short) the portfolio of stocks with the most positive (negative) forecast errors of 1.44% per month is also highly significant. This evidence from univariate sorts on forecast errors indicates that forecast errors are an important source of mispricing and have a highly significant relationship with abnormal returns. Moreover, this result suggests that the relationship between forecast errors and distress risk reported in the first half of this paper has the potential to explain the distress risk anomaly.

5.2 Bivariate Sorts on Forecast Errors and Distress Risk

I begin by examining the distress risk anomaly in sub-samples formed on forecast errors. The value-weighted *t+1* (1-month-ahead) alphas relative to the Fama-French-Carhart six-factor model for each of the bivariate-sorted portfolios are reported in Table 8. If analyst forecast errors manifest in the overpricing and subsequent low risk-adjusted returns of financially-distressed stocks, a test of this is whether the distress risk anomaly varies depending on analyst forecast errors. Given that forecast errors are on a fiscal year basis, the annual forecast error data is aligned with the monthly distress risk and stock return data by calendar year.[30] At the end of each month *t*, stocks in the sample are sorted into quintile portfolios based on an ascending order of forecast error. I find that firms with the most negative forecast errors have lower stock returns. The relationship between analyst forecast errors and 1-month-ahead stock returns for the matching fiscal year is illustrated by the abnormally negative returns of all portfolios in the quintile where forecast errors are most negative and the abnormally positive returns of all portfolios where forecast errors are positive. This is intuitive, since firms with the most negative (positive) forecast errors underperform (outperform) analyst expectations the most. Hence, this result is consistent with the temporary overpricing and subsequent abnormally low returns of stocks in the quintile portfolio where analyst forecasts are most negative. Moreover, this provides evidence that analyst expectations are informative of those

[30] The forecast errors are lagged by one month to ensure that the forecast data is available at the beginning of the month over which forecast errors are used to predict returns.

of the marginal investor, since if this was not the case, there is no reason to suggest that forecast errors should be reflected in stock returns.

For each of the quintile portfolios formed on forecast errors, stocks are then sorted into decile portfolios based on ascending order of distress risk. If there is no relationship between forecast errors and the distress risk anomaly, we should not observe a difference in the relationship between distress risk and 1-month-ahead returns within each of the quintile portfolios formed on forecast errors. In the quintile portfolio of stocks where analysts over-estimate earnings the most, the distress risk anomaly is detectable. Although, the relationship between abnormal returns and distress risk is not monotonic. In this quintile of stocks where analyst forecast errors are most negative, the decile portfolio with the highest distress risk earns an abnormal return of -1.05% per month. This is economically larger and of greater statistical significance relative to the comparable high distress risk portfolio from the univariate sorts of -0.46%. The average monthly abnormal return of the distress risk anomaly hedge portfolio within this quintile is comparable to the abnormal returns to the distress risk anomaly portfolio from the univariate sorts. The distress risk anomaly portfolio in the quintile of stocks with the most negative forecast errors earns an abnormal return of -0.69% per month (the hedge portfolio in univariate sorts earns an abnormal return of -0.55% per month). This result indicates that the distress risk anomaly observed on aggregate is concentrated in the sample of firms where earnings are most over-estimated.

Outside of the stocks where analysts over-estimate earnings the most, the distress risk anomaly cannot be demonstrated.[31] Specifically, there is a positive price of distress risk when sorting on distress risk in the remaining four quintile portfolios. The distress risk anomaly portfolio in the quintile of stocks where forecast errors are most positive earns a monthly alpha that is 1.31% higher (more positive) than the hedge portfolio in the quintile of stocks where forecast errors are most negative. This difference is statistically significant at the one percent level. The results from bivariate sorts are consistent with the source of the distress risk anomaly

[31] In unreported tests, I also find that this result holds for alternative definitions of forecast errors. When defining forecast errors as the difference between actual and forecasted EPS (not normalised by stock price), the distress risk anomaly is only detectable in the quintile portfolio of stocks where forecast errors are most negative. Specifically, the average return of the portfolio that is long (short) the decile portfolio of stocks with the highest (lowest) distress risk in the low forecast error quintile is -0.56% per month with a *t*-statistic of -3.13. In the remaining four quintiles, the returns to this portfolio are either insignificant or positive. As such, this result is not sensitive to the measure of forecast errors employed in this paper.

being mispricing resultant from forecast errors, since the distress risk anomaly is only detectable where analysts over-estimate cash flows the most.

Next, an alternative approach is used to examine whether the distress risk anomaly can be explained by forecast errors. Value-weighted risk-adjusted month *t+1* returns are estimated for decile portfolios formed by sorting stock on distress risk at the end of each month *t*. The alphas of the value-weighted returns are presented relative to the CAPM, Fama-French-Carhart four-factor and Fama-French six-factor (FF6 α) models respectively. However, in this analysis, I augment each of these models with an additional variable. I augment each of these models with the value-weighted *t+1* returns from a long-short portfolio that is long (short) the decile portfolio of stocks with the most positive (most negative) forecast errors at the end of month *t*. Should the distress risk anomaly be explained by forecast errors, augmenting standard models with this control may be expected to reduce the significance of the distress risk anomaly.

The abnormal returns from this analysis are reported in Panel A of Table 9. As reported in Table 2, there are highly statistically negative abnormal returns of both the high distress risk portfolio and the distress risk anomaly portfolio with respect to the CAPM, Fama-French-Carhart four-factor and six-factor models. However, after augmenting each of these models with the forecast errors long-short portfolio, the returns to the high distress risk portfolio and the distress risk anomaly portfolio are not statistically different from zero. This analysis indicates that forecast errors are able to explain the distress risk anomaly. In Panel B of Table 9, the sensitivities of the distress risk anomaly portfolio to each of the portfolios included in each of the model specifications examined in Panel A are reported. These factors include the market, size, value, momentum, investment and profitability factors, and the time-series of the value-weighted returns to the portfolio that is long (short) the decile portfolio of stocks with the most positive (most negative) forecast errors. The distress risk anomaly is positively related to the size and book-to-market factors and negatively related to the momentum and profitability factors. This is consistent with expectations, as the returns of financially-distressed stocks are understandably positively correlated with the returns of small and high book-to-market, past loser and weak profitability stocks. Importantly, the negative relationship between the long-short forecast error portfolio and the distress risk anomaly portfolio is consistent with the findings reported in the first half of this paper. Since, stocks with high distress risk have the most negative forecast errors, the distress risk anomaly portfolio returns will be most negative when stocks with low forecast errors generate the lowest returns.

5.3 Firm-Level Cross-Sectional Regressions

In the next stage of analysis, I examine the relationship between the distress risk anomaly and forecast errors while controlling for other effects. Each month *t*, I run a cross-sectional regression of $t+1$ (1-month ahead) excess stock returns on distress risk and combinations of firm characteristics, including dummy variables indicating high and low forecast errors. The low forecast error variable captures observations where analyst forecasts are most positive relative to actual earnings. The specification for these regressions is as follows:

$$R_{i,t} = \lambda_0 + \lambda_1 DD\ Distress\ Risk_{i,t-1} + \lambda_2 DD\ Distress\ Risk_{i,t-1} \times Low\ Forecast\ Error_{i.t-1} + \lambda_3 DD\ Distress\ Risk_{i,t-1} \times High\ Forecast\ Error_{i.t-1} + \Lambda\,\mathbf{X}_{i,t-1} + \epsilon_{i,t} \tag{10}$$

Where R is the excess stock return, $Low\ Forecast\ Error$ ($High\ Forecast\ Error$) is a dummy variable equal to one if a firm observation is in the bottom (top) decile of forecast errors[32], and $\mathbf{X}$ is a vector of control variables containing beta, size, log book-to-market, investment and profitability.[33] *t* denotes month.

The time-series averages of the regression coefficients, along with the Newey West (1987) adjusted *t*-statistics in parentheses testing the null hypothesis that the average slope coefficient is equal to zero are reported in Table 10. To isolate the effect of controlling for forecast errors on the price of distress risk, in the first specification, excess stock returns are regressed on distress risk and other stock characteristics, without including the forecast error dummy variables as independent variables. I find that the distress risk anomaly is highly significant with a *t*-statistic of -3.06. This confirms the earlier reported findings of a negative price of distress risk in the sample of analyst-covered firms, after controlling for common stock characteristics.

In the second specification of Table 10, the baseline specification is augmented with controls for the interactions of distress risk with the forecast error dummy variables. I find that, after controlling for the interactions of distress risk with the high and low forecast error variables,

[32] Although the forecast error variable is available at an annual frequency, the dummy variables are reassigned each month. This allows for firms that enter or exit the sample.

[33] Note that the forecast error dummy variables are not included in the specification as individual independent variables, since I am interested in measuring the difference in the price of distress risk between samples of firms formed on forecast errors (as opposed to the price of forecast errors). This specification is consistent with the methodology of Gao et al. (2018). These results are, however, robust to their inclusion.

the price of distress risk unconditional on forecast error is insignificant. Consistent with the hypothesis that the distress risk anomaly is a consequence of forecast error-related mispricing, the interaction of distress risk with the low forecast error dummy variable is highly significant with a *t*-statistic of -3.67. This coefficient captures the effect of distress risk on 1-month-ahead excess stock returns, if a stock is in the bottom decile of forecast errors.[34] Most notably, distress risk is positively priced in the decile of firms where forecast errors are most positive. There is a potential look-ahead bias in examining the distress risk anomaly in sub-samples of forecast errors aligned to distress risk by calendar year. Notably, the actual earnings input to the forecast error variable is information that is not known for most firm-month observations before returns are measured. All other inputs to the forecast error variable are known in the period preceding the measurement of returns. In the final specification, I control for actual earnings to ensure that this possible look-ahead bias does not drive the relationship between forecast errors and the distress risk anomaly. I find that, although actual earnings are positively related to returns, the coefficients on the distress risk variables are very similar to the specification that does not include this control. Overall, these results provide support for the findings from the bivariate sorts reported in Table 8, since the distress risk anomaly is concentrated in firms where analysts over-estimate earnings the most, after controlling for common stock characteristics.

I next examine whether forecast errors have explanatory power beyond prior measures that have been proposed to document a link between under-reaction to distress risk and asset prices. Specifically, it has been reported in the literature that the distress risk anomaly is concentrated in firms with negative news coverage (see, for example, Gao et al., 2018). It is possible that firms with the most negative forecast errors in a given year are firms that experience new negative news after the announcement of analyst forecasts. In order to draw inferences about the relative roles of forecast errors and negative news, news is measured on an annual basis, matching the frequency of the forecast error variable. This measure of news sentiment is as described in Section 3. Each month *t*, I run a cross-sectional regression of *t+1* excess stock returns on the interactions of distress risk with the low forecast error and negative news dummy variables, and other stock characteristics. The time-series averages of the cross-sectional

[34] Controlling for the relationship between distress risk and forecast errors also resolves the beta anomaly. This indicates that, in the I/B/E/S sample, the abnormally low returns of high beta stocks are explained by controlling for the price of distress risk for firms where earnings have been over-estimated the most. This provides indirect support for a mispricing explanation for the beta anomaly.

regression coefficients for these regressions are reported in Table 11.[35] The specification for these regressions is as follows:

$$R_{i,t} = \lambda_0 + \lambda_1 DD\ Distress\ Risk_{i,t-1} + \lambda_2 DD\ Distress\ Risk_{i,t-1} \times Negative\ News_{i.t-1} \times Low\ Forecast\ Error_{i.t-1} + \lambda_3 DD\ Distress\ Risk_{i,t-1} \times Negative\ News_{i.t-1} + \Lambda\,\mathbf{X}_{i,t-1} + \epsilon_{i,t} \quad (11)$$

Where $Negative\ News$ is a dummy variable equal to one for firms where the average firm-year news sentiment is less than fifty, and **X** is a vector of control variables containing beta, size, log book-to-market, investment and profitability.[36]

In Table 11, I demonstrate that, although controlling for negative news does add additional explanatory power, controlling for news does not subsume the result that the distress risk anomaly is concentrated where analyst forecast errors are most negative. In the first specification, I report that the coefficient of the interaction of the low forecast error and negative news dummy variables with distress risk is negative and highly significant. The coefficient is larger in magnitude and of greater statistical significance relative to the interaction of the low forecast error variable with distress risk reported in Table 10. This result indicates that the distress risk anomaly is strongest for firms with both the most negative forecast errors and negative new news sentiment in a given year. However, the effect of negative news on the distress risk anomaly does not subsume the relationship between forecast errors and the distress risk anomaly. In the second specification, I demonstrate that the interaction of low forecast errors with negative news and distress risk remains negative and significant, after controlling for the interaction of negative news with distress risk.[37] Table 11 therefore provides additional support for a mispricing explanation for the distress risk anomaly since the distress risk anomaly is strongest for firms with negative news and cross-sectionally low forecast errors.

[35] It has been argued that the distress risk anomaly is driven by a period in the 1980's (Chava & Purnanandam, 2010). An unintended benefit of this analysis is that it demonstrates that the findings are not sample-specific given that the sample for this analysis begins in 2001 due to the availability of the RavenPack data.

[36] Note that the news dummy variables are not included in the specification as individual independent variables, since I am interested in measuring the difference in the price of distress risk between samples of firms formed on news (as opposed to the price of news). This specification is consistent with the methodology of Gao et al. (2018). These results are, however, robust to their inclusion.

[37] It is worthy of note that momentum is insignificant in these regression specifications that include the negative news dummy. This result is consistent with the suggestion of Agarwal & Taffler (2008) that the momentum anomaly is explained by distress risk, as opposed to the distress risk anomaly being explained by momentum.

Overall, the results in the second half of this paper demonstrate that the central result of this paper, that there is a strong negative relationship between distress risk and analyst forecast errors, has important asset pricing implications. I show that the distress risk anomaly is concentrated in firms where analysts over-estimate earnings the most (hypothesis two). This is consistent with a mispricing interpretation of the distress risk anomaly, where the over-estimation of the earnings of financially distressed firms results in temporary overpricing and subsequent abnormally low returns of firms with the high distress risk.

5.4 Robustness: Distress Risk Persistence

In firms where high distress risk in one period is a stronger positive signal of high distress risk in the next period, the mispricing resultant from under-reaction may be expected to be most pronounced. This is because under-reacting to distress risk is likely to lead to relatively larger mistakes in pricing these firms. As a result, distress risk persistence provides a useful way of identifying firms where forecast errors are likely to be most costly. Hence, if the resultant mispricing from under-reaction to distress risk is able to explain the distress risk anomaly, the distress risk anomaly should also be concentrated in firms where distress risk is most persistent year-on-year (where distress risk in one year most positively predicts distress risk in the following year). In the final set of tests, I test the robustness of the proposed relationship between forecast errors (under-reaction to distress risk) and the distress risk anomaly by examining the relationship between distress risk persistence and the distress risk anomaly.

The distress risk anomaly is examined in sub-samples formed on distress risk persistence. Distress risk persistence is the estimated coefficient from a regression of distress risk in fiscal year *t* on distress risk in year *t-1* over all annual distress risk observations for a firm.[38] [39] At

[38] Despite the surprisingly low predictive ability of distress risk at the twelve-month horizon, this measure has not been estimated in prior studies so cannot be contrasted with other estimates. I further address this issue in the appendix. Distress risk is highly persistent over periods shorter than a one-year horizon, particularly given the inputs to measures of distress risk. For example, the accounting inputs to compute leverage are available on a quarterly basis. As a result, distress risk in month *t* is highly positively correlated with distress risk in month *t+1* and month *t+2* etc. for most firms. However, there is more cross-sectional variation in the predictive ability of distress risk year-on-year. I illustrate this in Appendix 6.

[39] This notion of 'distress risk persistence' is consistent with the use of earnings persistence in the recent study of Bouchaud et al. (2019) , where the profitability anomaly is examined in sub-samples of earnings persistence. Bouchaud et al. (2019) report that the profitability is concentrated in firms where earnings are most persistent, sine this is where under-reaction to elevated profitability leads to the greatest mispricing.

the end of each month *t*, stocks in the sample are sorted into tercile portfolios based on an ascending order of distress risk persistence. For each of these tercile portfolios, stocks are then sorted into decile portfolios based on ascending order of distress risk. In Panel A of Table 12, the value-weighted *t+1* (1-month-ahead) alphas relative to the Fama-French-Carhart six-factor model are reported. Consistent with predictions, the distress risk anomaly is only observable in the portfolio where distress risk is most persistent. In the high distress risk persistence tercile portfolio, the high distress risk portfolio earns a monthly abnormal return of -0.54%. This is 0.74% per month more negative than the abnormal return of the high distress risk portfolio in the low distress risk persistence tercile. This difference is highly significant. The monthly abnormal returns to the distress risk anomaly portfolio are 0.96% per month more negative for the high distress risk persistence tercile portfolio relative to the low distress risk persistence tercile portfolio. This evidence is highly consistent with the forecast error explanation for the distress risk anomaly proposed in the first half of this paper, since forecast errors following realisations of high distress risk will result in the greatest mispricing for firms where this realisation is a stronger positive signal of high distress risk in the future periods.

In order to test whether the relationship between distress risk persistence and the distress risk anomaly is limited to analyst-covered firms, I repeat the sorts in an extended sample where the filter that requires firms to have I/B/E/S analyst coverage data is removed. This has the benefit of extrapolating the findings regarding forecast errors to firms where forecast errors are not directly observable. The results from extending the sample of firms beyond those that are analyst-covered are reported in Panel B of Table 12. Notably, the distress risk anomaly is stronger. This is somewhat by construction given that the requirement for analyst coverage likely filters out many highly distressed firms which are of no institutional interest.[40] In any case, the same pattern that is observed in the I/B/E/S sample is observed in the sample of firms that are not all covered by analysts. The distress risk anomaly portfolio in the tercile of stocks with high distress risk persistence earns a monthly alpha that is 1.05% more negative than the comparable low distress risk persistence portfolio. Consistent with expectations, this finding provides evidence that the strong negative relationship between distress risk and forecast errors reported in the first half of the paper is a sound estimate of how the marginal investor of financially-distressed stocks reacts to distress risk, since outside of the I/B/E/S sample, the distress risk anomaly is concentrated where forecast errors are most costly.

[40] This is also consistent with the results of Conrad et al. (2014), where it is reported that the distress risk anomaly is stronger in firms with lower analyst coverage.

In Appendix 8, I report results from firm-level cross-sectional regressions, examining the relationship between the interaction of distress risk persistence with distress risk and future excess stock returns. These tests address potential concerns that there is a positive cross-sectional relationship between distress risk and distress risk persistence, given that both distress risk and distress risk persistence are controlled for simultaneously in these tests. I find that in both the I/B/E/S and extended samples, the distress risk anomaly is concentrated in firms where distress risk is most persistent. Moreover, I show that this result is not subsumed by the role of negative news in determining the distress risk anomaly.

6. Conclusion

In this paper, I propose that forecast errors play an important role in generating the distress risk anomaly. Under-reaction to distress risk has been suggested as a possible explanation for earlier findings in the literature regarding the role of distress risk in stock returns. Despite this, empirical evidence of investor under-reaction to distress risk is scarce. I address this important gap in the literature by studying under-reaction to distress risk in the context of analyst forecast errors. It is plausible that under-reaction to distress risk is reflected in the over-estimation of the future cash flows of financially-distressed stocks. As a result, analysts over-estimate the earnings of financially-distressed stocks more relative to other stocks in the cross-section. This under-reaction to distress risk results in the overpricing and subsequent abnormally low returns of financially-distressed stocks.

First, I demonstrate that the over-estimation of the future cash flows of financially distressed stocks as a consequence of under-reaction is a mechanism which may result in the mispricing of distressed stocks. Defining forecast errors as the difference between actual earnings and forecasted earnings, I find strong evidence in support of this hypothesis. Univariate sorts on distress risk demonstrate that there is a strong negative relationship between distress risk and analyst forecast errors. In panel regressions, I report that the result that there is a strong negative relationship between distress risk and forecast errors is robust to controlling for other stock characteristics, including profitability. Moreover, I show that this relationship is concentrated in firms that are followed by analysts with sticky expectations and firms which received negative news coverage in the period prior to the announcement of analyst forecasts. This evidence indicates that analysts under-react to distress risk by increasingly over-estimating future cash flows with distress risk.

Finally, I show that this channel which manifests in the temporary overpricing and subsequent abnormally low returns of financially distressed stocks is reflected in asset prices.

Bivariate portfolio sorts demonstrate that the distress risk anomaly is only detectable in the portfolio of stocks where forecast errors are most negative. Firm-level cross-sectional regressions also show that the distress risk anomaly is concentrated firms where earnings are over-estimated the most, after controlling for common stock characteristics. Moreover, I demonstrate that the distress risk anomaly is strongest where forecast errors are likely to be most costly. Overall, I find evidence firmly in support of the hypothesis that the distress risk anomaly is a consequence of forecast errors.

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Tables

Table 1: Summary Statistics

This table reports summary statistics for the key variables included in this study including the mean, standard deviation (Std. Dev.), median, tenth percentile (P10) and ninetieth percentile (P90). DD Distress risk is the Merton (1974) measure of distress risk. CHS Distress risk is the Campbell et al. (2008) measure of distress risk. Forecast error (*FE*) is the difference between total fiscal year earnings reported for fiscal year *t* and the consensus forecast for total fiscal year earnings that was formed just after the announcement of fiscal year earnings *t-1*, normalized by the stock price before the announcement of fiscal year earnings *t-2*. Distress risk persistence (*Dist.P*) is the estimated coefficient from a regression of distress risk in fiscal year *t* on distress risk in year *t-1*. Expectation stickiness (*Stick.*) is the coefficient obtained from the estimation a regression of consensus forecast errors on consensus forecast revisions. Forecast revision is the change in the consensus earnings forecast for fiscal year *t* that was formed just after the announcement of fiscal year earnings *t-1* with respect to the consensus earnings forecast for fiscal year earnings *t* that was formed just after the announcement of fiscal year earnings *t-2*, normalized by the stock price before the announcement of fiscal year earnings *t-2*. Beta is the estimated market beta from weekly returns and equal-weighted market returns over the past thirty-six months. Size (*Size*) is the market capitalisation as measured by price multiplied by number of shares outstanding. In the descriptive statistics, size is reported in millions of dollars. BM is the book value of equity divided by the end of fiscal year market capitalisation. Momentum (*Mom.*) is the *t-12* to *t-2*-month cumulative return. Investment (*Invest.*) is the total of the annual change in gross property, plant and equipment plus the annual change in inventory scaled by lagged total assets. Profitability (*Profit.*) is total revenue minus cost of goods sold scaled by lagged total assets.

	DD Distress Risk	**CHS Distress Risk**	**FE**	**Dist.P**	**Stick.**	**Beta**	**Size**	**BM**	**Mom.**	**Invest.**	**Profit.**
Mean	0.1438	0.0006	-0.0050	0.0458	0.1001	1.1355	4961.0889	0.5483	0.1481	0.1271	0.3866
Std. Dev.	0.2893	0.0012	0.0207	0.2795	0.2206	0.5973	19458.2410	0.4789	0.5447	7.3417	0.2988
P10	0.0000	0.0002	-0.0299	-0.2364	-0.1217	0.4091	90.6758	0.1983	-0.3327	-0.0257	0.1121
Median (P50)	0.0001	0.0004	-0.0007	-0.0176	0.0788	1.0753	850.1625	0.4891	0.0888	0.0520	0.3392
P90	0.6693	0.0010	0.0010	0.4138	0.3497	1.8705	9953.5425	1.0004	0.6111	0.2301	0.7545

Table 2: Univariate Portfolios Sorted on Distress Risk in the I/B/E/S Sample

This table reports analyses of portfolios formed by sorting on distress risk. Panel A and B present the value-weighted risk-adjusted month *t*+1 returns for decile portfolios formed by sorting on distress risk at the end of each month *t*. Portfolio 10 (1) is the portfolio of stocks with the highest (lowest) distress risk. In Panel A, distress risk (*DD Distress risk*) is defined as the Merton (1974) measure of distress risk. In Panel B, distress risk (*CHS Distress risk*) is defined as the Campbell et al. (2008) measure of distress risk. The first two rows of each panel report the equal-weighted portfolio mean distress risk (*Distress*) and excess value-weighted returns for each portfolio (*R*). The bottom two rows present the alphas of the value-weighted returns relative to the Fama-French-Carhart four-factor (*FFC4* α) and Fama-French six-factor (*FF6* α) models respectively. Excess returns and alphas are expressed as percentages per month. Panel C presents the average firm characteristics for each portfolio. The firm characteristics are profitability (*Profit.*), forecast error (*FE*), distress risk persistence (*Dist.P*), expectation stickiness (*Stick.*), profitability persistence (*Profit.P*), market beta (*Beta*), market-capitalisation (*size*), book-to-market ratio (*BM*), momentum (*Mom.*), investment (*Invest.*), idiosyncratic volatility (*IVOL*), and leverage (*Lev*).

	Low 1	2	3	4	5	6	7	8	9	High 10	10-1
					Panel A: DD Distress Risk and Returns						
Distress	0.00	0.00	0.00	0.00	0.01	0.04	0.09	0.18	0.38	0.78	0.78
											(72.06***)
R	0.84	0.67	0.72	0.67	0.64	0.58	0.50	0.52	0.40	0.04	-0.80
											(-5.46***)
FFC4 α	0.24	0.05	0.11	0.06	0.04	0.01	-0.08	-0.03	-0.10	-0.42	-0.65
	(3.11***)	(0.70)	(1.40)	(0.85)	(0.51)	(0.09)	(-1.02)	(-0.34)	(-1.12)	(-3.42***)	(-5.12***)
FF6 α	0.09	-0.07	-0.01	-0.04	-0.08	-0.09	-0.20	-0.15	-0.18	-0.46	-0.55
	(1.21)	(-1.03)	(-0.14)	(-0.60)	(-1.14)	(-1.11)	(-2.63***)	(-1.87*)	(-2.03**)	(-3.70***)	(-4.44***)
					Panel B: CHS Distress Risk and Returns						
Distress	0.02	0.02	0.03	0.03	0.04	0.04	0.05	0.07	0.10	0.34	0.32
											(46.17***)
R	0.73	0.68	0.63	0.65	0.76	0.58	0.69	0.47	0.37	-0.02	-0.74
											(-5.46***)
FFC4 α	0.17	0.11	0.05	0.06	0.18	0.00	0.10	-0.10	-0.19	-0.57	-0.74
	(2.31**)	(1.47)	(0.56)	(0.78)	(2.35**)	(-0.01)	(1.39)	(-1.28)	(-2.11**)	(-5.28***)	(-4.83***)
FF6 α	0.02	-0.07	-0.10	-0.12	0.04	-0.09	0.01	-0.17	-0.20	-0.55	-0.57
	(0.24)	(-1.03)	(-1.24)	(-1.59)	(0.59)	(-1.01)	(0.10)	(-2.13**)	(-2.24**)	(-5.01***)	(-4.36***)
					Panel C: DD Distress Risk and Firm Characteristics						
Profit.	0.5503	0.4766	0.4423	0.4151	0.3983	0.3796	0.3746	0.3616	0.3458	0.3238	-0.2265
											(-42.35***)
FE	-0.0037	-0.0032	-0.0032	-0.0033	-0.0037	-0.0043	-0.0056	-0.0070	-0.0094	-0.0130	-0.0093
											(-38.72***)
Dist.P.	0.0371	0.0410	0.0402	0.0420	0.0432	0.0389	0.0338	0.0307	0.0338	0.0779	0.0408
											(9.04***)
Stick.	0.0588	0.0721	0.085	0.0935	0.1023	0.111	0.1143	0.1164	0.1167	0.1228	0.0072
											(34.06***)
Profit.P.	-0.0107	-0.0163	-0.0165	-0.0169	-0.0179	-0.0184	-0.0178	-0.0161	-0.016	-0.0147	-0.0040
											(-8.42***)
Beta	0.9535	1.0051	1.0473	1.0908	1.1303	1.1828	1.2249	1.278	1.3448	1.4089	0.4554
											(28.80***)
Size	12689.13	9811.84	7863.85	5694.1	4350.17	3529.28	2893.67	2342.95	2064.38	1237.18	-11451.95
											(-24.84***)
BM	0.3608	0.4102	0.4473	0.4858	0.5213	0.5524	0.5893	0.6303	0.6789	0.7346	0.3738
											(37.67***)
Mom.	0.2974	0.3216	0.3094	0.2809	0.242	0.1894	0.1124	0.0197	-0.0998	-0.3011	-0.5985
											(-43.70***)
Invest.	0.1337	0.2195	0.0844	0.1092	0.1007	0.1217	0.1688	0.1732	0.2125	0.1081	-0.0256
											(-0.63)
IVOL.	0.016	0.017	0.0177	0.0186	0.0195	0.0207	0.0222	0.0241	0.0266	0.0329	0.0169
											(47.27***)
Lev.	1.2695	1.4129	1.5231	1.6191	1.7231	1.8188	1.9362	2.1128	2.3995	3.3581	2.0886
											(48.70***)

*** Significant at the 1% level. **Significant at the 5% level. *Significant at the 10% level.

Figure 1: Forecast Errors and Distress Risk

This figure shows forecast errors as a function of past distress risk. Distress risk is the Merton (1974) measure of distress risk. Observations are sorted into 30 ordered bins of the previous financial year's distress risk. For each of the 30 ordered bins, both average previous year's distress risk and current fiscal year's average forecast error are then calculated. Forecast error is the difference between total fiscal year earnings reported for fiscal year *t* and the consensus forecast for total fiscal year earnings that was formed just after the announcement of fiscal year earnings *t-1*, normalized by the stock price before the announcement of fiscal year earnings *t-2*.

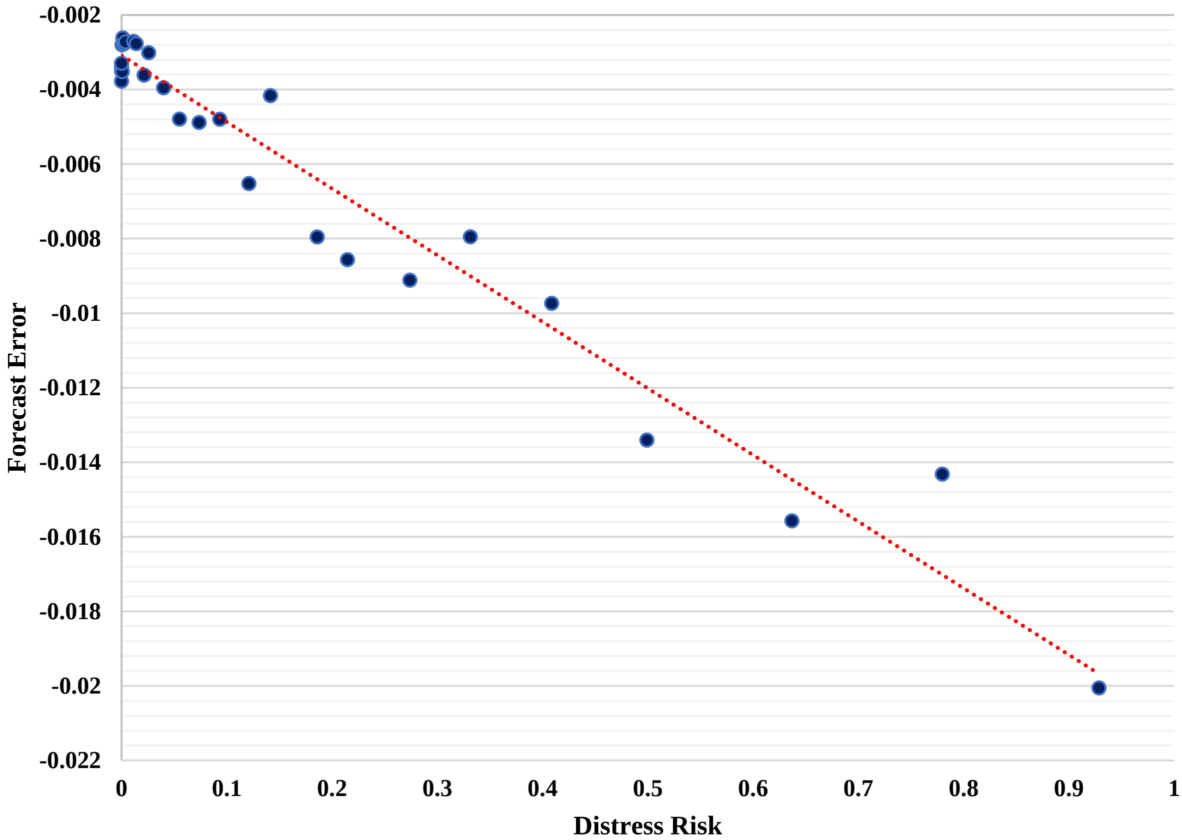

Table 3: Forecast Errors and Distress Risk Signals

This table presents the results from regressing firm-level EPS forecast errors on distress risk signals. The dependent variable in the first seven specifications is the difference between total fiscal year earnings reported for fiscal year *t* and the consensus forecast for total fiscal year earnings that was formed just after the announcement of fiscal year earnings *t-1*, normalized by the stock price before the announcement of fiscal year earnings *t-2*. DD distress risk is the Merton (1974) measure of distress risk. Δ DD distress risk is the one-year difference in the Merton (1974) measure of distress risk. CHS distress risk is the Campbell et al. (2008) measure of distress risk. Migrater is a dummy variable equal to one for firms that are in the high distress risk decile portfolio at the end of fiscal year *t*-1 that were not in the high distress risk decile portfolio at the end of fiscal year *t*-2. All other control variables are as defined in Appendix 2. All signals are as at before the announcement of fiscal year earnings *t-1*. Standard errors are double-clustered at the firm-year level. *t*-statistics are reported in parentheses. The number of firm-year observations included in the regression is presented in the row labelled *N*. The adjusted R^2 is presented in the row labelled Adj. R^2.

				Dependent variable: $(\pi_{f,t} - F_{t-1\pi f,t})/P_{f,t-2}$				*Dependent variable:* $(\pi_{f,t} - F_{t-1\pi f,t})$	
Variable	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**
DD Distress Risk	-0.0028		-0.0031	-0.0029	-0.003	-0.0036	-0.0027	-0.0509	-0.0502
	(-6.56***)		(-7.08***)	(-5.18***)	(-3.59***)	(-3.91***)	(-5.01***)	(-4.50***)	(-4.29***)
CHS Distress Risk		-0.1518	-0.1432						
		(-2.28**)	(-2.17**)						
Leverage			0.0004	0.0002	0.0006	0.0005	0.0006	0.0158	0.0115
			(2.62***)	(2.90***)	(2.99***)	(3.16***)	(3.21***)	(7.65***)	(4.88***)
Momentum				-0.0006	-0.001	-0.0006	-0.0005	-0.0011	0.0012
				(-1.76*)	(-2.73***)	(-1.74*)	(-1.48)	(-0.24)	(0.25***)
Idiosyncratic Volatility				-0.0508	-0.0519	-0.0471	-0.0281	1.2831	1.5387
				(-4.90***)	(-4.19***)	(-4.50***)	(-2.56**)	(7.37***)	(8.35***)
Beta							-0.0012		-0.0067
							(-5.52***)		(-1.59)
Size							0.0000		0.0000
							(12.09***)		(5.18***)
log(BM)							-0.0016		-0.0049
							(-9.04***)		(-1.29)
Investment							-0.0000		-0.0001
							(-3.90***)		(-1.37)
Profitability							-0.0050		-0.0955
							(-12.64***)		(-12.47***)
Δ DD Distress Risk					0.0001				
					(0.20)				
Migrater *DD Distress Risk						0.0010			
						(1.07)			
N	38,144	38,144	38,107	38,095	30,600	38,095	36,934	38,095	36,934
Adj. R^2	0.13%	0.03%	0.22%	0.31%	0.33%	0.32%	1.29%	0.16%	0.51%

*** Significant at the 1% level. **Significant at the 5% level. *Significant at the 10% level.

Table 4: Logit Regressions of Negative Forecast Error Indicator on Distress Risk Signals

This table presents the results from logit regressions of a negative forecast error indicator variable on distress risk signals. The dependent variable is a dummy variable equal to one where forecast error is less than zero and zero where forecast error is greater than zero. Forecast error is the difference between total fiscal year earnings reported for fiscal year *t* and the consensus forecast for total fiscal year earnings that was formed just after the announcement of fiscal year earnings *t-1*, normalized by the stock price before the announcement of fiscal year earnings *t-2*. DD distress risk is the Merton (1974) measure of distress risk. CHS distress risk is the Campbell et al. (2008) measure of distress risk. All other control variables are as defined in Appendix 2. All signals are as at before the announcement of fiscal year earnings *t-1*. *t*-statistics are reported in parentheses. The number of firm-year observations included in the regression is presented in the row labelled *N*. The number of firm-year observations where the negative forecast error indicator variable is equal to one is presented in the row labelled *Negative Forecast Errors*. The Cox & Snell (1989) pseudo-R^2 is presented in the row labelled Pseudo-R^2.

Variable	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**
DD Distress Risk	0.2326		0.2895	0.1817	0.1404
	(6.22***)		(7.42***)	(3.96***)	(2.95***)
CHS Distress Risk		12.3065	13.3401		
		(2.13**)	(2.27**)		
Leverage			-0.0652	-0.0517	-0.0568
			(-6.31***)	(-4.92***)	(-4.44***)
Momentum				-0.0460	-0.0682
				(-2.01**)	(-2.84***)
Idiosyncratic Volatility				4.2747	1.0417
				(5.31***)	(1.21)
Beta					0.1261
					(6.67***)
Size					-0.0000
					(-9.51***)
log(BM)					0.0972
					(6.00***)
Investment					0.2499
					(4.23***)
Profitability					0.3142
					(8.66***)
N	38,070	38,070	38,070	38,070	36,934
Negative Forecast Errors	20,702	20,702	20,702	20,702	20,156
Pseudo-R^2	0.14%	0.02%	0.29%	0.38%	1.63%

*** Significant at the 1% level. **Significant at the 5% level. *Significant at the 10% level.

Table 5: Sticky Expectations, Forecast Errors and Distress Risk

This table presents the results from regressing firm-level EPS forecast errors on analyst stickiness and distress risk signals. The dependent variable is the difference between total fiscal year earnings reported for fiscal year *t* and the consensus forecast for total fiscal year earnings that was formed just after the announcement of fiscal year earnings *t-1*, normalized by the stock price before the announcement of fiscal year earnings *t-2*. Forecast revision (FR) is the change in the consensus earnings forecast for fiscal year *t* that was formed just after the announcement of fiscal year earnings *t-1* with respect to the consensus earnings forecast for fiscal year earnings *t* that was formed just after the announcement of fiscal year earnings *t-2*, normalized by the stock price before the announcement of fiscal year earnings *t-2*. The firm-level expectation stickiness measure (*Stickiness*) is obtained from the estimation of a regression of consensus forecast errors on consensus forecast revisions ($FE_f = \alpha_f + b_f . FE_{f,t} + \epsilon_{f,t}$). This regression is estimated for each firm separately, using the entire history of consensus forecasts and errors. Stickiness (λ_f) is simply the transformation $\lambda_f = b_f / 1 + b_f$ of coefficient b_f in the above regression. High stickiness (low stickiness) is a dummy variable equal to one if a firm observation is in the top (bottom) quintile of expectation stickiness. DD distress risk is the Merton (1974) measure of distress risk. Controls is a vector of control variables including leverage, momentum, idiosyncratic volatility, beta, size, book-to-market, investment and profitability. All control variables are as defined in Appendix 2. Expectation stickiness is time-invariant. All other signals are as at before the announcement of fiscal year earnings *t-1*. Standard errors are double-clustered at the firm-year level. The number of firm-year observations included in the regression is presented in the row labelled *N*. The adjusted R^2 is presented in the row labelled Adj. R^2.

Variable	**(1)**	**(2)**	**(3)**	**(4)**
DD Distress Risk*High Stickiness	-0.0054		-0.0056	-0.0050
	(-4.70***)		(-4.82***)	(-4.21***)
DD Distress Risk*Low Stickiness		0.0001	-0.0012	-0.0009
		(0.05)	(-1.06)	(-0.78)
Profitability*High Stickiness				-0.0020
				(-2.47**)
DD Distress Risk	-0.0006	-0.0020	-0.0003	-0.0005
	(-0.95)	(-3.21***)	(-0.45)	(-0.74)
Stickiness	0.0007	-0.0004	0.0005	0.0015
	(1.01)	(-0.60)	(0.78)	(1.83*)
Controls	Yes	Yes	Yes	Yes
N	27,597	27,597	27,597	27,597
Adj. R^2	1.21%	1.01%	1.21%	1.23%

*** Significant at the 1% level. **Significant at the 5% level. *Significant at the 10% level.

Table 6: News, Forecast Errors and Distress Risk

This table presents the results from regressing firm-level EPS forecast errors on distress risk and its interactions with news dummy variables. Given the availability of the RavenPack data, this analysis is restricted to the January 2001 to December 2018 period. The dependent variable is the difference between total fiscal year earnings reported for fiscal year *t* and the consensus forecast for total fiscal year earnings that was formed just after the announcement of fiscal year earnings *t-1*, normalized by the stock price before the announcement of fiscal year earnings *t-2*. Average fiscal-year news sentiment is measured as the average event sentiment score for a firm over all news events in the fiscal-year *t-1*. Negative (positive) news is a dummy variable equal to one if the average fiscal-year sentiment for a firm-fiscal-year observation is less (greater) than fifty. News is a dummy variable equal to a one if the firm-fiscal year observation experienced any (positive or negative) news coverage. DD distress risk is the Merton (1974) measure of distress risk. Controls is a vector of control variables including leverage, momentum, idiosyncratic volatility, beta, size, book-to-market, investment and profitability. These control variables are as defined in Appendix 2. All signals are as at before the announcement of fiscal year earnings *t-1*. Standard errors are double-clustered at the firm-year level. The number of firm-year observations included in the regression is presented in the row labelled *N*. The adjusted R^2 is presented in the row labelled Adj. R^2.

Variable	**(1)**	**(2)**	**(3)**
DD Distress Risk*Negative News	-0.0049		-0.0052
	(-5.17***)		(-3.91***)
DD Distress Risk*Positive News		-0.0013	-0.0031
		(-1.87)	(-1.46)
DD Distress Risk* News			0.0011
			(0.54)
Controls	No	No	Yes
N	18,887	18,887	17,127
Adj. R^2	0.25%	0.02%	0.35%

*** Significant at the 1% level. **Significant at the 5% level. *Significant at the 10% level.

Table 7: Univariate Portfolios Sorted on Forecast Errors

This table reports the value-weighted raw and risk-adjusted month t+1 returns for decile portfolios formed by sorting on forecast errors at the end of each month t. Portfolio 10 (1) is the portfolio of stocks with the highest, most positive, (lowest, most negative) forecast errors. The first two rows report the equal-weighted portfolio mean forecast error (*FE*) and excess value-weighted returns (*R*) for each portfolio. The bottom three rows present the alphas of the value-weighted returns relative to the CAPM (*CAPM* α), Fama-French-Carhart four-factor (*FFC4* α) and Fama-French six-factor (*FF6* α) models respectively. Excess returns and alphas are expressed as percentages per month.

	Low 1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**High 10**	**10-1**
FE	-0.0528	-0.0228	-0.0114	-0.0056	-0.0022	-0.0003	0.0013	0.0035	0.0084	0.0299	0.0827 (125.35***)
R	-0.21	-0.15	0.06	0.14	0.39	0.73	0.95	1.19	1.29	1.28	1.49 (14.84***)
CAPM α	-0.78	-0.72	-0.51	-0.42	-0.14	0.19	0.40	0.63	0.74	0.72	1.50
	(-6.03***)	(-5.90***)	(-4.32***)	(-4.37***)	(-1.65*)	(2.13**)	(4.80***)	(7.40***)	(7.00***)	(6.61***)	(13.59***)
FFC4 α	-0.77	-0.71	-0.48	-0.38	-0.13	0.19	0.36	0.59	0.65	0.67	1.44
	(-7.71***)	(-7.88***)	(-5.24***)	(-5.51***)	(-1.74*)	(2.27**)	(4.75***)	(8.08***)	(7.52***)	(7.98***)	(14.27***)
FF6 α	-0.81	-0.80	-0.61	-0.50	-0.25	0.04	0.18	0.47	0.58	0.63	1.44
	(-7.89***)	(-8.82***)	(-6.68***)	(-7.39***)	(-3.69***)	(0.47)	(2.67***)	(6.64***)	(6.61***)	(7.27***)	(11.75***)

*** Significant at the 1% level. **Significant at the 5% level. *Significant at the 10% level.

Table 8: Distress Risk Anomaly Sorted by Forecast Errors

This table reports the Fama-French-Carhart six-factor alphas of the month *t*+1 value-weighted returns of portfolios formed by double-sorting on forecast errors and distress risk at the end of each month *t*. In each month *t*, stocks are sorted into quintile portfolios by sorting stocks on forecast errors. The equal-weighted average forecast error and Merton (1974) distress risk is reported for each of these quintile portfolios. In each of these quintile portfolios, stocks are then sorted into decile portfolios formed on distress risk. Portfolio Q1 is the quintile portfolio of stocks with the lowest (most negative) forecast errors. Portfolio Q5 is the quintile portfolio of stocks with the highest (most positive) forecast errors. Portfolio 10 (1) is the decile portfolio of stocks with the highest (lowest) distress risk. I also report the alphas for the 10-1 long-short portfolios, as well as the difference in the distress risk anomaly between the Q1 and Q5 portfolios. Distress risk is the Merton (1974) measure of distress risk. Forecast error is the difference between total fiscal year earnings reported for fiscal year *t* and the consensus forecast for total fiscal year earnings that was formed just after the announcement of fiscal year earnings *t-1*, normalized by the stock price before the announcement of fiscal year earnings *t-2*.

	Avg. FE	**Avg.DD Distress Risk**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**10-1**
Q1	-0.0348	24.21%	-0.37	-0.37	-0.44	-0.83	-1.10	-0.95	-1.23	-1.07	-1.01	-1.05	-0.69
			(-3.08***)	(-2.96***)	(-3.06***)	(-5.96***)	(-7.44***)	(-6.12***)	(-7.54***)	(-6.79***)	(-4.92***)	(-5.05***)	(-2.92***)
Q2	-0.0075	16.20%	-0.74	-0.78	-0.77	-0.59	-0.50	-0.50	-0.65	-0.45	-0.19	-0.05	0.69
			(-6.95***)	(-6.53***)	(-6.91***)	(-4.93***)	(-3.62***)	(-3.36***)	(-4.98***)	(-3.56***)	(-1.20)	(-0.29)	(3.77***)
Q3	-0.0011	9.89%	-0.24	-0.39	-0.07	-0.30	-0.27	-0.02	-0.06	0.16	0.37	0.43	0.68
			(-2.42**)	(-4.05***)	(-0.50)	(-2.25**)	(-2.51**)	(-0.13)	(-0.43)	(1.40)	(2.27**)	(3.21***)	(3.63**)
Q4	0.0020	8.63%	0.30	0.18	0.30	0.20	0.36	0.32	0.44	0.63	0.69	1.04	0.74
			(3.67***)	(1.22)	(3.02***)	(1.83*)	(3.55***)	(2.90***)	(3.45***)	(5.34***)	(4.19***)	(6.68***)	(4.34***)
Q5	0.0164	12.92%	0.65	0.81	0.80	0.80	0.91	0.68	1.06	1.25	1.42	1.28	0.62
			(5.95***)	(6.33***)	(6.52**)	(5.38***)	(6.58***)	(4.57***)	(7.22***)	(8.06***)	(7.71***)	(6.37***)	(2.34**)
Q1-Q5													-1.31 (-4.20***)

*** Significant at the 1% level. **Significant at the 5% level. *Significant at the 10% level.

Table 9: Abnormal Returns of Distress Risk Sorted Portfolios for Models Augmented with Forecast Errors

This table reports analyses of portfolios formed by sorting on distress risk. Panel A presents the value-weighted risk-adjusted month t+1 returns for decile portfolios formed by sorting on distress risk at the end of each month t. Portfolio 10 (1) is the portfolio of stocks with the highest (lowest) distress risk. The alphas of the value-weighted returns are presented relative to the CAPM (*CAPM* α), Fama-French-Carhart four-factor (*FFC4* α) and Fama-French six-factor (*FF6* α) models respectively. The results are also presented from augmenting these models with the time-series of the value-weighted $t+1$ returns to a portfolio that is long (short) the decile portfolio of stocks with the most positive (most negative) forecast errors (*FE*) at the end of each month t. Panel B presents the sensitivities of the value-weighted returns of the distress risk anomaly portfolio that is long (short) the decile portfolio of stocks with the highest (lowest) distress risk to each of the factors included in the model specification. These factors include the market (*MKT*), size (*SMB*), value (*HML*), momentum (*MOM*), investment (*CMA*) and profitability (*RMW*) factors. I also augment these models with the time-series of the value-weighted returns to the portfolio that is long (short) the decile portfolio of stocks with the most positive (most negative) forecast errors (*FE*).

Panel A: Abnormal Returns of Distress Risk Sorted Portfolios											
Specification	**Low 1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**High 10**	**10-1**
CAPM α	0.31	0.12	0.17	0.11	0.07	0.01	-0.08	-0.06	-0.18	-0.55	-0.86
	(3.63***)	(1.50)	(1.96**)	(1.18)	(0.75)	(0.08)	(-0.75)	(-0.51)	(-1.4)	(-3.36***)	(-5.21***)
CAPM +FEα	0.28	0.12	0.27	0.1	0.24	0.15	0.06	0.26	0.31	0.18	-0.10
	(2.78***)	(1.17)	(2.57**)	(0.86)	(2.12**)	(1.19)	(0.51)	(1.85*)	(1.99**)	(0.97)	(-0.38)
FFC4 α	0.24	0.05	0.11	0.06	0.04	0.01	-0.08	-0.03	-0.10	-0.42	-0.65
	(3.11***)	(0.70)	(1.40)	(0.85)	(0.51)	(0.09)	(-1.02)	(-0.34)	(-1.12)	(-3.42***)	(-5.12***)
FFC4 +FEα	0.24	0.06	0.18	-0.02	0.11	-0.02	-0.12	0.05	0.09	-0.04	-0.28
	(2.63***)	(0.76)	(2.08**)	(-0.24)	(1.20)	(-0.18)	(-1.35)	(0.51)	(0.89)	(-0.31)	(-1.77*)
FF6 α	0.09	-0.07	-0.01	-0.04	-0.08	-0.09	-0.20	-0.15	-0.18	-0.46	-0.55
	(1.21)	(-1.03)	(-0.14)	(-0.60)	(-1.14)	(-1.11)	(-2.63***)	(-1.87*)	(-2.03**)	(-3.70***)	(-4.44***)
FF6 +FEα	0.09	-0.05	0.06	-0.13	-0.01	-0.11	-0.24	-0.07	0.01	-0.09	-0.18
	(1.04)	(-0.65)	(0.75)	(-1.44)	(-0.13)	(-1.21)	(-2.75***)	(-0.73)	(0.13)	(-0.61)	(-1.21)

Panel B: Factor Sensitivities of Distress Risk Anomaly (10-1) Portfolio									
Specification	**α**	**MKT**	**SMB**	**HML**	**MOM**	**CMA**	**RMW**	**FE**	**Adj. R^2**
CAPM α	-0.86	0.08							1.02%
	(-5.21***)	(1.44)							
CAPM +FE	-0.10	0.08						-0.48	9.12%
	(-0.38)	(1.74*)						(-3.62***)	
FFC4	-0.65	-0.00	0.32	0.22	-0.43				42.34%
	(-5.12***)	(-0.09)	(5.91***)	(3.18***)	(-10.68***)				
FFC4 +FE	-0.28	0.00	0.31	0.22	-0.40			-0.23	45.90%
	(-1.77*)	(0.11)	(6.70***)	(3.35***)	(-9.63***)			(-2.49**)	
FF6	-0.55	-0.03	0.24	0.26	-0.42	-0.00	-0.24		44.21%
	(-4.44***)	(-0.87)	(3.90***)	(2.93***)	(-11.64***)	(-0.00)	(-3.32***)		
FF6 +FE	-0.17	-0.03	0.24	0.25	-0.39	0.02	-0.25	-0.23	47.91%
	(-1.21)	(-0.71)	(4.37***)	(2.87***)	(-10.04***)	(0.20)	(-3.63***)	(-2.70***)	

*** Significant at the 1% level. **Significant at the 5% level. *Significant at the 10% level.

Table 10: Distress Risk Anomaly and Forecast Errors

Each month, I run a cross-sectional regression of 1-month-ahead excess stock returns on distress risk, forecast errors, and other firm characteristics. This table presents the time-series averages of the monthly cross-sectional regression coefficients. Newey-West *t*-statistics using six lags are reported in parentheses. Distress risk is the Merton (1974) measure of distress risk. Forecast error is the difference between total fiscal year earnings reported for fiscal year *t* and the consensus forecast for total fiscal year earnings that was formed just after the announcement of fiscal year earnings *t-1*, normalized by the stock price before the announcement of fiscal year earnings *t-2*. Low forecast error (high forecast error) is a dummy variable equal to one if a firm observation is in the bottom (top) decile of forecast errors. Beta is the estimated market beta from weekly returns and equal-weighted market returns over the past thirty-six months. Size is market capitalisation as measured by price multiplied by number of shares outstanding. BM is the book value of equity divided by the end of fiscal year market capitalisation. Momentum is the *t-12* to *t-2*-month cumulative return. Investment is the total of the annual change in gross property, plant and equipment plus the annual change in inventory scaled by lagged total assets. Profitability is total revenue minus cost of goods sold scaled by lagged total assets. Actual earnings is the total fiscal year earnings reported for fiscal year *t*. The row labelled *N* presents the average number of observations used in the cross-sectional regressions. The average adjusted R^2 is presented in the row labelled Adj. R^2.

Variable	**(1)**	**(2)**	**(3)**
Distress Risk	-0.004	0.005	0.005
	(-3.06***)	(1.03)	(1.09)
Distress Risk*Low Forecast Error		-0.019	-0.017
		(-3.67***)	(-3.17***)
Distress Risk*High Forecast Error		0.012	0.013
		(2.43**)	(2.91***)
Beta	-0.003	-0.002	-0.000
	(-2.89***)	(-0.93)	(-0.28)
Size	0.000	0.000	-0.000
	(1.78*)	(0.46)	(-3.47***)
log(BM)	0.002	0.002	0.002
	(3.29***)	(3.66***)	(3.76***)
Momentum	0.004	0.004	0.004
	(3.48***)	(2.63***)	(2.23**)
Investment	-0.005	-0.009	-0.008
	(-4.00***)	(-5.33***)	(-4.54***)
Profitability	0.004	0.005	0.005
	(4.59***)	(4.31***)	(3.96***)
Actual Earnings			0.002
			(6.44***)
Intercept	0.008	0.008	0.04
	(4.77***)	(4.26***)	(1.77)
N	1,460	1,306	1,306
Adj. R^2	5.30%	6.80%	6.66%

*** Significant at the 1% level. **Significant at the 5% level. *Significant at the 10% level.

Table 11: Distress Risk Anomaly, Negative News and Forecast Errors

Each month, I run a cross-sectional regression of 1-month-ahead excess stock returns on distress risk, forecast errors, news and other firm characteristics. This table presents the time-series averages of the monthly cross-sectional regression coefficients. Newey-West *t*-statistics using six lags are reported in parentheses. Distress risk is the Merton (1974) measure of distress risk. Forecast error is the difference between total fiscal year earnings reported for fiscal year *t* and the consensus forecast for total fiscal year earnings that was formed just after the announcement of fiscal year earnings *t-1*, normalized by the stock price before the announcement of fiscal year earnings *t-2*. Low forecast error is a dummy variable equal to one if a firm observation is in the bottom decile of forecast errors. Average fiscal-year news sentiment is measured as the average event sentiment score for a firm over all news events in the fiscal-year *t-1*. Negative news is a dummy variable equal to one if the average fiscal-year sentiment for a firm-fiscal-year observation is less than fifty. Beta is the estimated market beta from weekly returns and equal-weighted market returns over the past thirty-six months. Size is market capitalisation as measured by price multiplied by number of shares outstanding. BM is the book value of equity divided by the end of fiscal year market capitalisation. Momentum is the *t-12* to *t-2*-month cumulative return. Investment is the total of the annual change in gross property, plant and equipment plus the annual change in inventory scaled by lagged total assets. Profitability is total revenue minus cost of goods sold scaled by lagged total assets. The row labelled *N* presents the average number of observations used in the cross-sectional regressions. The average adjusted R^2 is presented in the row labelled Adj. R^2.

Variable	**(1)**	**(2)**
Distress Risk	0.003	0.011
	(0.86)	(2.75***)
Distress Risk*Negative News* Low Forecast Error	-0.045	-0.031
	(-5.42***)	(-3.67***)
Distress Risk*Negative News		-0.023
		(-4.51***)
Beta	-0.001	-0.001
	(-0.56)	(-0.50)
Size	-0.000	-0.000
	(-3.34***)	(-3.34***)
log(BM)	0.002	0.002
	(2.20**)	(2.26**)
Momentum	-0.003	-0.003
	(-1.03)	(-1.08)
Investment	-0.004	-0.004
	(-1.41)	(-1.43))
Profitability	0.006	0.006
	(2.45**)	(2.55**)
Intercept	0.008	0.008
	(3.02***)	(2.96***)
N	874	874
Adj. R^2	7.90%	8.10%

*** Significant at the 1% level. **Significant at the 5% level. *Significant at the 10% level.

Table 12: Distress Risk Anomaly Sorted by Distress Risk Persistence

This table reports the Fama-French-Carhart six-factor alphas of the month *t*+1 value-weighted returns of portfolios formed by double-sorting on distress risk persistence and distress risk at the end of each month *t*. In each month *t*, stocks are sorted into tercile portfolios by sorting stocks on distress risk persistence. In each of these tercile portfolios, stocks are then sorted into decile portfolios formed on distress risk. Portfolio T3 (T1) is the tercile portfolio of stocks with the highest (lowest) distress risk persistence. Portfolio 10 (1) is the portfolio of stocks with the highest (lowest) distress risk. I also report the alphas for the 10-1 long-short portfolios, as well as the differences in alphas between the T3 and T1 portfolios. Distress risk is the Merton (1974) measure of distress risk. Distress risk persistence is the estimated coefficient from a regression of distress risk in fiscal year *t* on distress risk in year *t-1*. In Panel A, the sample is restricted to firms with I/B/E/S analyst coverage. In Panel B, I report the same results after removing the analyst coverage filter.

	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**10-1**
Panel A: Distress Risk Portfolios Conditional on Distress Risk Persistence – I/B/E/S Sample											
T1	-0.20	-0.09	-0.15	-0.25	-0.07	-0.03	-0.12	-0.04	-0.06	0.20	0.40
	(-2.06**)	(-0.96)	(-1.71)	(-2.57**)	(-0.72)	(-0.31)	(-1.13)	(-0.37)	(0.59)	(1.66*)	(3.02***)
T2	0.07	0.08	0.12	0.08	0.08	0.09	0.09	0.13	0.09	0.11	0.03
	(1.27)	(0.68)	(0.91)	(0.99)	(1.96**)	(0.71)	(0.93)	(0.62)	(1.02)	(-0.18)	(0.89)
T3	0.02	-0.06	-0.02	-0.09	-0.11	0.09	-0.04	-0.20	-0.32	-0.54	-0.56
	(0.30)	(-0.70)	(-0.25)	(-0.83)	(-1.25)	(0.92)	(-0.39)	(-1.80*)	(-2.86***)	(-4.18***)	(-4.23***)
T3-T1	0.22	0.03	0.13	0.16	-0.04	0.12	0.08	-0.16	-0.26	-0.74	-0.96
	(2.32**)	(0.42)	(1.50)	(1.46)	(-0.50)	(1.28)	(0.55)	(-1.29)	(-2.93***)	(-5.60***)	(-6.23***)
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**10-1**
Panel B: Distress Risk Portfolios Conditional on Distress Risk Persistence – Beyond the I/B/E/S Sample											
T1	0.07	0.04	-0.13	-0.09	-0.21	-0.03	-0.23	-0.24	-0.25	-0.10	-0.17
	(0.99)	(0.50)	(-1.73*)	(-1.15)	(-2.37**)	(-0.36)	(-2.18**)	(-2.25**)	(1.91*)	(-0.65)	(-0.95)
T2	0.13	0.12	0.14	0.09	0.07	0.09	0.00	0.04	0.04	-0.03	-0.16
	(2.02**)	(2.01**)	(2.32**)	(1.28)	(0.92)	(1.21)	(-0.02)	(0.43)	(0.43)	(-0.23)	(-1.05)
T3	0.03	0.09	-0.08	-0.06	-0.17	-0.1	-0.34	-0.38	-0.77	-1.19	-1.22
	(0.41)	(1.16)	(-1.06)	(-0.78)	(-1.78)	(-1.03)	(-3.30***)	(-3.20***)	(-5.97***)	(-7.02***)	(-6.37***)
T3-T1	-0.04	0.05	0.05	0.03	0.04	-0.07	-0.11	-0.14	-0.52	-1.09	-1.05
	(-0.66)	(0.80)	(0.78)	(0.67)	(0.53)	(-0.17)	(-0.63)	(-0.85)	(-2.86***)	(-6.35***)	(-5.97***)

*** Significant at the 1% level. **Significant at the 5% level. *Significant at the 10% level.

Appendix

Appendix 1 – Campbell et al. (2008) Measure of Distress Risk

In order to ensure the results are robust to alternative measures of distress risk, the Campbell et al. (2008) twelve-month-ahead prediction horizon model is employed in some tests. This measure is constructed following the methodology described in Campbell et al (2008). In the twelve-month-ahead Campbell et al. (2008) measure of distress risk, the probability of corporate failure in twelve months is given by:

$$DistressRisk_{i,t} = \frac{1}{1 + \exp(-Failure_{i,t})}$$

$Failure$ is specified as follows where a higher value of $Failure$ implies a higher probability of corporate failure:

$Failure_{i,t} = -9.16 - 20.26NIMTAAVG_{i,t-12} + 1.42TLMTA_{i,t-12} - 7.13EXRETAVG_{i,t-12} + 1.41SIGMA_{i,t-12} - 0.045RSIZE_{i,t-12} - 2.13CASHMTA_{i,t-12} + 0.075MB_{i,t-12} - 0.058PRICE_{i,t-12}$

The independent variables in this model relate to profitability ($NIMTAAVG$), leverage ($TLMTA$), excess return ($EXRETAVG$), volatility ($SIGMA$), relative size ($RSIZE$), liquidity ($CASHMTA$), market-to-book (MB), and price ($PRICE$).41 The predictor variables included in the Campbell et al. (2008) model of failure probability are defined as follows:[42]

Profitability ($NIMTAAVG$)

The profitability predictor variable is a lagged average of a ratio of net income to the market value of total assets as follows:

$$NIMTA_{i,t} = \frac{Net\ Income_{i,t}}{(Firm\ Market\ Equity_{i,t} + Total\ Book\ Liabilities_{i,t})}$$

This variable is adjusted to reflect lagged information about profitability by imposing geometrically declining weights on lagged $NIMTA$, denoted as $NIMTAAVG$. When lagged

41 Following Campbell et al. (2008), all explanatory variables are winsorised at the fifth and ninety-fifth percentiles.

42 Following Campbell et al. (2008), each firm-fiscal year observation is aligned to calendar time and accounting data is lagged by two months to ensure the accounting data is available at the beginning of the month over which bankruptcy is measured.

observations are missing, they are replaced with their cross-sectional means to avoid losing observations.

$$NIMTAAVG_{t-1,t-12} = \frac{1-\emptyset^3}{1-\emptyset^{12}}\left(NIMTA_{t-1,t-3} + \cdots + \emptyset^9 NIMTA_{t-10,t-12}\right)$$

where $\emptyset = 2^{-\frac{1}{3}}$, implying the weight is halved each quarter.

Leverage ($TLMTA$)

The leverage predictor variable is a ratio of total liabilities to the market value of total assets as follows:

$$TLMTA_{i,t} = \frac{Total\ Book\ Liabilities_{i,t}}{(Firm\ Market\ Equity_{i,t} + Total\ Book\ Liabilities_{i,t})}$$

Excess Return ($EXRETAVG$)

The excess return predictor variable is a lagged average of the monthly log excess return on each firm's equity relative to the to the S&P500 index, defined as follows:

$$EXRET_{i,t} = \log\left(1 + R_{i,t}\right) - \log\left(1 + R_{S\&P500,t}\right)$$

As with profitability, this variable is adjusted to reflect lagged information from excess returns by imposing geometrically declining weights on lagged $EXRET$, denoted as $EXRETAVG$. When lagged observations are missing, they are replaced with their cross-sectional means to avoid losing observations.

$$EXRETAVG_{t-1,t-12} = \frac{1-\emptyset}{1-\emptyset^{12}}\left(EXRET_{t-1} + \cdots + \emptyset^{11} EXRET_{,t-12}\right)$$

Volatility ($SIGMA$)

The volatility predictor variable measures the daily variation of returns computed as an annualised three-month rolling sample standard deviation of each firm's daily stock return, centred around zero as follows:

$$SIGMA_{i,t-1,t-3} = \left(252 \times \frac{1}{N-1} \sum_{k \in [t-1,t-2,t-3]} r_{i,k}^2\right)^{\frac{1}{2}}$$

$SIGMA$ is coded as missing if there are fewer than five non-zero observations over the three months used in the rolling window computation.

Relative Size ($RSIZE$)

The relative size predictor variable measures the log of the ratio of firm market capitalisation to market capitalisation of the S&P500 index as follows:

$$RSIZE_{i,t} = \log\left(\frac{Firm\ Market\ Equity_{i,t}}{Total\ S\&P500\ Market\ Value_{t}}\right)$$

Liquidity ($CASHMTA$)

The liquidity predictor variable is a ratio of a company's cash and short-term assets to the market value of its assets as follows:

$$CASHMTA_{i,t} = \frac{Cash\ and\ Short\ Term\ Investments_{i,t}}{(Firm\ Market\ Equity_{i,t} + Total\ Book\ Liabilities_{i,t})}$$

Market-to-Book (MB)

The market-to-book predictor variable is a ratio of the firm market equity as a ratio of the book value of equity as follows:

$$MB_{i,t} = \frac{Firm\ Market\ Equity_{i,t}}{(Total\ Book\ Assets_{i,t} - Total\ Book\ Liabilities_{i,t})}$$

Following Campbell et al. (2008), where there are negative of book equity, these negative values are replaced with small positive values of $1 to ensure that the market-to book ratios for these firms are in the right tail, not the left tail, of the distribution.

Price ($PRICE$)

Price per share is truncated at above $15 in order to capture the tendency for distressed firms to trade at low prices per share, without reverse-splitting to bring price per share back into a more normal range. Price is defined of the log of firm price per share as follows:

$$PRICE_{i,t} = \log(Price\ Per\ Share_{i,t})$$

Appendix 2 – Variable Definitions

Table A1 – Variable Definitions

This Table presents definitions of the variables included in the analysis in this paper. The variable definitions are in alphabetical order.

Variable	Definition
Analyst expectation stickiness (*Stick*)	The firm-level expectation stickiness measure is obtained from the estimation of a regression of consensus forecast errors on consensus forecast revisions ($FE_f = \alpha_f + b_f . FE_{f,t} + \epsilon_{f,t}$). This regression is estimated for each firm separately, using the entire history of consensus forecasts and errors. Stickiness (λ_f) is simply the transformation $\lambda_f = b_f / 1 + b_f$ of coefficient b_f in the above regression.
Beta	Following Fama & Macbeth (1973), the beta of a firm in month *t* is the estimated market beta from a regression of weekly stock returns on equal-weighted weekly market returns over the past thirty-six months ending month *t-1* with at least 52 weeks of returns.
Book-to-market (*BM*)	Following Rosenberg, Reid & Lanstein (1985), the book-to-market ratio of a firm is the book value of equity divided by the end of fiscal year market capitalisation.
Campbell et al. (2008) distress risk (*CHS Distress risk*)	This is the Campbell et al. (2008) measure of distress risk. This is defined in detail in Appendix 2.
Change in Forecast	Following Hawkins, Chamberlin & Daniel (1984), change in forecast is the mean one-year analyst forecast in the month prior to the forecast period end date from the I/B/E/S summary file minus the same mean one-year forecast for the prior forecast period.
Change in Number of Analysts	Change in number of analysts is the difference in the number of analyst forecasts for a firm from the most recently available I/B/E/S summary files relative to the number of analyst forecasts relative to three months prior.
Distance to default distress risk (*DD Distress risk*)	This is the Merton (1974) distance to default measure of distress risk. This is defined in detail in Appendix 1.
Δ DD distress risk	Δ DD distress risk is the one-year difference in the Merton (1974) distance to default measure of distress risk. I.e. Δ DD distress risk for a firm in month *t* is the distance to default measure of distress risk in month *t* minus the distance to default measure of distress risk in month *t-1*. This value is not scaled by distress risk in month *t-1* as many firm-month estimates of distress risk are approximately equal to zero.
Distress risk persistence (*Dist.P*)	The distress risk persistence of a firm is the estimated coefficient from a regression of distress risk at the end of fiscal

	year *t* on distress risk at the end of fiscal year *t-1* over all fiscal year-end distress risk observations for a firm. This is consistent with the Bouchaud et al. (2019) measure of earnings persistence.
EPS Volatility	The EPS volatility of a firm is the standard deviation of EPS (actual reported EPS) of a firm over the sample period.
Firm-level forecast dispersion	The firm-level forecast dispersion of a firm is the time-series average of the standard deviations of all one-year analyst forecasts issued for the firm for each forecast period over the sample period.
Forecast error (*FE*)	The forecast error for a firm in fiscal year *t* is the difference between total fiscal year earnings reported for fiscal year *t* and the consensus forecast for total fiscal year earnings that was formed just after the announcement of fiscal year earnings *t-1*, normalized by the stock price before the announcement of fiscal year earnings *t-2*. This is consistent with the Bouchaud et al. (2019) measure of forecast error.
Forecast revision (*FR*)	The forecast revision of a firm is the change in the consensus earnings forecast for fiscal year *t* that was formed just after the announcement of fiscal year earnings *t-1* with respect to the consensus earnings forecast for fiscal year earnings *t* that was formed just after the announcement of fiscal year earnings *t-2*, normalized by the stock price before the announcement of fiscal year earnings *t-2*.
Idiosyncratic volatility (*IVOL*)	The idiosyncratic volatility of a firm in month *t* is the standard deviation of the daily residuals of a regression of daily stock returns on the Fama-French-Carhart four-factors in month *t.*
Investment (*Invest.*)	Investment is the total of the annual change in gross property, plant and equipment plus the annual change in inventory scaled by lagged total assets.
Leverage (*Lev.*)	Leverage is total firm assets, the sum of total liabilities and market equity, divided by market equity at fiscal year-end.
Momentum (*Mom.*)	Momentum is defined as intermediate-term momentum. Following Jegadeesh & Titman (1993), the momentum of a firm in month *t* is the cumulative return from month *t-12* to month *t-2*.
Negative News	Average fiscal-year (calendar month) news sentiment is measured as the average event sentiment score for a firm over all news events in the fiscal-year (month) *t-1*. Negative news is a dummy variable equal to one if the average fiscal-year (calendar month) news sentiment for a firm -fiscal-year (firm-month) observation is less than 50.

Number of Analysts	Number of analysts is the number of analyst forecasts for a firm from the most recently available I/B/E/S summary files.
Positive News	Average fiscal-year (calendar month) news sentiment is measured as the average event sentiment score for a firm over all news events in the fiscal-year (month) *t-1*. Positive news is a dummy variable equal to one if the average fiscal-year (calendar month) news sentiment for a firm -fiscal-year (firm-month) observation is greater than 50.
Profitability (*Profit.*)	Following Novy-Marx (2013), profitability is total revenue minus cost of goods sold scaled by lagged total assets.
Profitability persistence (*Profit.P*)	The profitability persistence for a firm is the estimated coefficient from a regression of profitability in fiscal year *t* on profitability at the end of fiscal year *t-1* over all fiscal year-end profitability observations for a firm. This is consistent with the Bouchaud et al. (2019) measure of earnings persistence.
Size	The size of a firm in month *t* is the market capitalisation as measured by price multiplied by number of shares outstanding as at end of month *t-1*.
Within-Industry Forecast Dispersion	The within-industry forecast dispersion of a firm is the time-series average of the standard deviations of all one-year analyst forecasts issued within an SIC2 industry for each forecast period over the sample period.

Appendix 3 – Correlations Between Firm Characteristics

Table A2 – Correlations Between Firm Characteristics

This table reports the Pearson correlation coefficients between the Merton (1974) measure of distress risk (*DD Distress* Risk), Campbell et al. (2008) measure of distress risk (*CHS Distress* Risk), forecast error (*FE*), profitability (*Profit.*), distress risk persistence (*Dist.P*), expectation stickiness (*Stick.*), profitability persistence (*Profit.P*), market beta (*Beta*), market-capitalisation (*Size*), book-to-market ratio (*BM*), momentum (*Mom.*), investment (*Invest.*), idiosyncratic volatility (*IVOL*), and leverage (*Lev*).

	DD Distress Risk	**CHS Distress Risk**	**FE**	**Profit.**	**Dist.P.**	**Stick.**	**Profit.P.**	**Beta**	**Size**	**BM**	**Mom.**	**Invest.**	**IVOL.**	**Lev.**
DD Distress Risk	1.00	0.14	-0.13	-0.09	0.04	0.06	0.00*	0.10	-0.08	0.28	-0.39	0.00*	0.33	0.30
CHS Distress Risk		1.00	-0.02	-0.06	0.00*	0.02	0.01	0.15	-0.06	0.16	0.08	0.00*	0.22	0.21
FE			1.00	-0.04	0.00*	0.00*	-0.02	-0.03	0.05	-0.06	0.08	0.00*	-0.09	-0.01
Profit.				1.00	-0.04	-0.06	0.05	0.05	-0.02	-0.21	0.04	0.00*	0.06	-0.20
Dist.P.					1.00	0.02	0.03	-0.02	-0.00*	0.03	-0.01	0.00*	-0.04	0.06
Stick.						1.00	-0.05	0.01	-0.04	0.09	-0.01	0.00*	0.02	0.06
Profit.P.							1.00	0.04	-0.01	-0.01	0.00*	0.00*	0.04	-0.03
Beta								1.00	-0.10	-0.01	0.03	0.00*	0.31	-0.05
Size									1.00	-0.32	0.09	0.01	-0.42	-0.08
BM										1.00	-0.06	0.00*	0.12	0.46
Mom.											1.00	0.00*	-0.05	-0.02
Invest.												1.00	0.00*	0.00*
IVOL.													1.00	0.05
Lev.														1.00

* Denotes correlation coefficients that are not significant at the one percent level of significance.

Appendix 4– Additional Firm-Level Determinants of Forecast Errors

It is possible that there are additional characteristics associated with financial distress which manifest in the result that there is a strong negative relationship between distress risk and forecast errors. It is plausible that there is more disagreement between analysts regarding the expected EPS of financially-distressed stocks (*firm-level forecast dispersion*), greater variance in the expected EPS within industries where there is high financial distress (*within-industry forecast dispersion*), and greater variance in the actual EPS of financially-distressed stocks (*EPS volatility*).[43] Moreover, it is highly likely that financially-distressed firms are followed by fewer analysts (*number of analysts*) and that the number of analysts following a financially-distressed firm is decreasing (*change in number of analysts*). It is also possible that recent changes in one-year forecasts (*change in forecast*) and market capitalisation (*size*) are determinants of cross-sectional differences in consensus forecast errors. I test the relationship between each of these variables and forecast errors and examine whether the documented relationship between distress risk and forecast errors is robust to controlling for these firm characteristics.

The univariate relationships between forecast errors and the above-identified potential firm-level determinants of forecast errors are reported in Table A3. In Table A4, I report the results from combining these variables in panel regressions. In the multivariate specification, there are statistically significantly positive relationships between forecast errors and within-industry forecast dispersion, EPS volatility, number of analysts and size. There are statistically significantly negative relationships between forecast errors and firm-level forecast dispersion and changes in forecasts. Given that it is highly likely that financially-distressed firms are followed by fewer analysts, have reduced market capitalisation and experience elevated firm-level forecast dispersion, it is possible that the negative relationship between distress risk and forecast errors is a manifestation of these characteristics. In Table A4, the model of distress risk signals reported in Table 3 is augmented with these firm-level characteristics which may manifest in cross-sectional differences in forecast errors. I find that the central result, that analysts over-estimate the earnings of financially-distressed stocks, is robust to controlling for these characteristics.

[43] Bouchaud et al. (2019) propose that analysts may be more likely to make systematic forecast errors for firms where EPS volatility is higher since analysts “give up” on making accurate forecasts.

Table A3: Additional Firm-Level Determinants of Forecast Errors

This table presents the results from regressing firm-level EPS forecast errors on possible firm-level determinants of forecast errors. The dependent variable is the difference between total fiscal year earnings reported for fiscal year *t* and the consensus forecast for total fiscal year earnings that was formed just after the announcement of fiscal year earnings *t-1*, normalized by the stock price before the announcement of fiscal year earnings *t-2*. Firm-level forecast dispersion is the time-series average of the standard deviations of all one-year analyst forecasts issued for the firm for each forecast period. Within-industry forecast dispersion is the time-series average of the standard deviations of all one-year analyst forecasts issued within an SIC2 industry for each forecast period. EPS volatility is the standard deviation of EPS (actual reported EPS) of a firm. Number of analysts is the number of one-year analyst forecasts from the most recently available I/B/E/S summary files. Change in number of analysts is the difference in the number of one-year analyst forecasts for a firm from the most recently available I/B/E/S summary files relative to the number of analyst forecasts relative to three months prior. Change in forecast is the mean one-year analyst forecast in the month prior to the forecast period end date from the I/B/E/S summary file minus the same mean one-year forecast for the prior forecast period. Size is the log of the market capitalisation as measured by price multiplied by number of shares outstanding. All signals are as at before the announcement of fiscal year earnings *t-1*. Standard errors are double-clustered at the firm-year level. The number of firm-year observations included in the regression is presented in the row labelled *N*. The adjusted R^2 is presented in the row labelled Adj. R^2.

Variable	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**
Firm-Level Forecast Dispersion	-0.0004						
	(-1.27)						
Within-Industry Forecast Dispersion		0.0000					
		(6.68***)					
EPS Volatility			0.0005				
			(5.87***)				
Number of Analysts				0.0002			
				(13.70***)			
Change in Number of Analysts					0.0000		
					(0.01)		
Change in Forecast						-0.0000	
						(-1.47)	
Size							0.0000
							(15.49***)
N	37,978	38,069	38,070	33,387	33,261	33,253	38,070
Adj. R^2	0.00%	0.05%	0.15%	0.47%	0.00%	0.00%	0.25%

*** Significant at the 1% level. **Significant at the 5% level. *Significant at the 10% level.

Table A4: Forecast Errors and Distress Risk Signals with Additional Determinants of Forecast Errors

This table presents the results from regressing firm-level EPS forecast errors on distress risk signals and additional possible firm-level determinants of forecast errors. The dependent variable is the difference between total fiscal year earnings reported for fiscal year *t* and the consensus forecast for total fiscal year earnings that was formed just after the announcement of fiscal year earnings *t-1*, normalized by the stock price before the announcement of fiscal year earnings *t-2*. All explanatory variables are as defined in Appendix 2. All signals are as at before the announcement of fiscal year earnings *t-1*. Standard errors are double-clustered at the firm-year level. The number of firm-year observations included in the regression is presented in the row labelled *N*. The adjusted R^2 is presented in the row labelled Adj. R^2.

Variable	**(1)**	**(2)**
DD Distress Risk		-0.0029
		(-3.41***)
Leverage		0.0003
		(1.52)
Momentum		-0.0009
		(-2.52***)
Idiosyncratic Volatility		-0.0329
		(-2.58***)
Profitability		-0.0035
		(-7.80***)
Δ DD Distress Risk		0.0001
		(0.01)
Firm-Level Forecast Dispersion	-0.0019	-0.0023
	(-4.60***)	(-4.96***)
Within-Industry Forecast Dispersion	0.0000	0.0000
	(5.25***)	(3.16***)
EPS Volatility	0.0006	0.0006
	(5.96***)	(5.49***)
Number of Analysts	0.0001	0.0001
	(10.22***)	(6.39***)
Change in Number of Analysts	-0.0001	0.0000
	(-1.03)	(0.14)
Change in Forecast	-0.0000	0.0000
	(-2.33**)	(0.37)
Size	0.0000	0.0000
	(8.61***)	(8.38***)
N	33,063	27,485
Adj. R^2	0.74%	1.12%

*** Significant at the 1% level. **Significant at the 5% level. *Significant at the 10% level.

Appendix 5 – Forecast Errors and Profitability

Although the results reported in Table 3 support the hypothesis that investors under-react to financial distress by over-estimating the future cash flows of firms with high distress risk, the sign on the profitability coefficient is outwardly difficult to reconcile with the findings of a recent study regarding analyst forecast errors following realisations of high profitability. Bouchaud et al. (2019) argue that the profitability anomaly can be explained by under-reaction to high profitability, which results in the under-estimation of the future profitability of high profitability stocks. If this were the case, we would expect to see a positive relationship between profitability and forecast errors where, all else equal, higher profitability results in a positive forecast error, where actual profitability is higher than forecasted profitability. Instead, the negative coefficient on profitability in the baseline results indicate that analysts over-react to increasing profitability. To explore this, I test for the relationship between profitability and forecast errors conditional on a firm being in the highest quintile of profitability cross-sectionally. In Table A5, I report that the relationship between profitability and forecast errors is non-linear. The relationship between the interaction of profitability and a dummy variable equal to one if a firm is in the top quintile of profitability, and forecast errors is positive and significant. The results from this model indicate that, although on aggregate analysts over-react to increasing profitability, firms under-react to high profitability when profitability is cross-sectionally very high.

I also examine whether this non-linearity is a potential problem for the findings regarding the negative relationship between distress risk and forecast errors. I find that the strong negative relationship between forecast errors and distress risk is concentrated in the firms with high distress risk, with an insignificant relationship between forecast errors and distress risk for low distress risk firms This result is likely driven by the minimal cross-sectional variation in distress risk for firms with below-median distress risk. However, this addresses the possible concern that low distress risk firms drive the negative relationship between distress risk and forecast errors. Furthermore, unlike high profitability, low distress risk is interpretable as a neutral signal, as opposed to a positive signal given that the median firm has distress risk of approximately zero. Hence, it is intuitive that we do not observe over or under-reaction to low distress risk. On the other hand, high distress risk is a negative signal. This finding that analysts under-react to high distress risk is therefore consistent with earlier papers in the analyst literature arguing that under-reaction is a stronger phenomenon for negative information (Easterwood & Nutt, 1999).

Table A5 – Forecast Errors and Profitability

This table presents the results from regressing firm-level EPS forecast errors on distress risk signals. The dependent variable is the difference between total fiscal year earnings reported for fiscal year *t* and the consensus forecast for total fiscal year earnings that was formed just after the announcement of fiscal year earnings *t-1*, normalized by the stock price before the announcement of fiscal year earnings *t-2*. DD distress risk is the Merton (1974) measure of distress risk. Δ DD distress risk is the one-year difference in the Merton (1974) measure of distress risk. Leverage is the sum of the market capitalisation and total liabilities divided by the market capitalisation at fiscal year-end. Momentum is the 11-month cumulative return starting two months ago. Idiosyncratic volatility is the standard deviation of the residual of a regression of daily stock returns on the Fama-French-Carhart four factors. Profitability is total revenue minus cost of goods sold scaled by lagged total assets. All signals are as at before the announcement of fiscal year earnings *t-1*. Low distress risk is a dummy variable equal to one if a firm observation is in the bottom quintile of distress risk. High profitability is a dummy variable equal to one if a firm observation is in the top quintile of profitability. Standard errors are double-clustered at the firm-year level. The number of firm-year observations included in the regression is presented in the row labelled *N*. The adjusted R^2 is presented in the row labelled Adj. R^2.

Variable	**(1)**	**(2)**
DD Distress Risk	-0.0034	-0.0033
	(-4.11***)	(-4.07***)
Leverage	0.0002	0.0002
	(0.98)	(0.90)
Momentum	-0.0009	-0.0009
	(-2.70***)	(-2.70***)
Idiosyncratic Volatility	-0.0329	-0.0361
	(-2.94***)	(-3.21***)
Profitability	-0.0040	-0.0059
	(-9.89***)	(-8.72***)
Δ DD Distress Risk	0.0003	0.0003
	(0.52)	(0.50)
DD Distress Risk* Low Distress risk		-0.0000
		(-0.41)
Profitability* High Profitability		0.0021
		(3.89***)
N	33,799	33,799
Adj. R^2	0.59%	0.63%

*** Significant at the 1% level. **Significant at the 5% level. *Significant at the 10% level.

Appendix 6– Distress Risk Persistence over Varying Time Horizons

In the final tests of this paper, I examine whether the distress risk anomaly is concentrated in firms where distress risk is most positively related with distress risk in future periods. I measure distress risk persistence at the twelve-month horizon. This measures the relationship between distress risk at month *t* and distress risk at month *t+12* for each stock in the sample.

Distress risk is highly persistent for most firms at horizons shorter than twelve-months. Specifically, 82.57% (85.92%) of firm-month observations that were in the high (low) distress risk portfolio in month *t* fall into the high (low) distress risk portfolio in month *t+1*. However, at horizons of twelve-months and longer, the serial dependence of cross-sectional distress risk rankings is less pronounced. For example, just 32.37% (44.08%) of firm-month observations that were in the high (low) distress risk portfolio in month *t* fall into the high (low) distress risk portfolio in month *t+12*. Consequently, the twelve-month horizon of the distress risk persistence measure that is applied in the analysis results in more cross-sectional variation in distress risk persistence relative to estimating this measure over shorter horizons. In Table A6, I provide an illustration of cross-sectional distress risk persistence (i.e. the persistence of cross-sectional rankings of distress risk) at the one-, three-, six-, twelve-, and twenty-four-month horizons.

Table A6 – Transition Matrices for Distress Risk Sorted Portfolios

At the end of each month *t*, all stocks are sorted into decile portfolios on an ascending sort of distress risk. Stocks are then independently sorted into ascending probability of solvency decile portfolios as at months *t+1*, *t+3*, *t+6*, *t+12*, *t+24*. This table reports the percentage of firm-month observations that fall into a given probability of solvency decile at time *t+1* (Panel A), *t+3* (Panel B), *t+6* (Panel C), *t+12* (Panel D), *t+24* (Panel E) provided falling into a given probability of solvency decile in month *t*. These values are in percentage terms. Distress risk is the Merton (1974) distance to default measure of distress risk.

Panel A: One-Month Transition Probabilities (%)

Distress Risk Decile Month *t*	Distress Risk Decile Month *t+1*									
	1 (Low)	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10 (High)**
1 (Low)	85.92	11.67	1.40	0.51	0.24	0.12	0.04	0.03	0.04	0.03
2	10.60	68.71	15.74	3.14	0.98	0.40	0.21	0.11	0.06	0.05
3	1.61	14.26	60.87	16.85	4.18	1.28	0.50	0.23	0.15	0.07
4	0.71	2.62	16.11	56.39	16.89	5.00	1.46	0.51	0.20	0.1
5	0.38	1.23	3.09	16.73	54.07	17.20	5.27	1.43	0.45	0.14
6	0.22	0.70	1.31	3.70	17.21	53.15	17.50	4.87	1.09	0.25
7	0.22	0.39	0.82	1.43	4.02	17.41	53.78	17.07	4.22	0.64
8	0.12	0.22	0.40	0.79	1.48	3.90	17.16	56.7	17.04	2.18
9	0.08	0.15	0.18	0.32	0.58	1.26	3.37	17.01	63.15	13.91
10 (High)	0.08	0.08	0.09	0.14	0.26	0.35	0.75	2.00	13.69	82.57

Panel B: Three-Month Transition Probabilities (%)

Distress Risk Decile Month *t*	Distress Risk Decile Month *t+3*									
	1 (Low)	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10 (High)**
1 (Low)	70.04	20.33	5.39	2.19	0.92	0.47	0.22	0.19	0.13	0.12
2	18.20	41.36	23.42	9.22	4.05	1.86	1.05	0.47	0.22	0.16
3	5.38	20.55	32.56	21.91	10.77	4.77	2.17	1.05	0.55	0.28
4	2.50	8.33	19.42	27.88	21.18	11.40	5.47	2.43	1.02	0.36
5	1.36	3.92	9.06	19.05	25.73	20.99	11.81	5.18	2.19	0.71
6	0.82	2.57	4.77	9.83	18.35	25.24	21.39	11.17	4.64	1.21
7	0.63	1.43	2.79	5.27	9.97	18.71	25.70	21.59	10.89	3.01
8	0.44	0.81	1.48	2.80	5.60	10.30	18.97	28.7	23.21	7.69
9	0.29	0.45	0.79	1.28	2.46	4.72	10.07	21.67	35.69	22.57
10 (High)	0.23	0.30	0.38	0.59	0.84	1.65	3.21	7.49	21.55	63.75

Panel C: Six-Month Transition Probabilities (%)

Distress Risk Decile Month *t*	Distress Risk Decile Month *t+6*: 1 (Low)	2	3	4	5	6	7	8	9	10 (High)
1 (Low)	56.81	22.52	9.76	4.83	2.64	1.44	0.77	0.59	0.37	0.26
2	19.94	27.64	21.01	13.24	8.16	4.55	2.86	1.42	0.77	0.41
3	8.81	18.79	21.58	17.83	13.46	8.78	5.32	2.97	1.65	0.80
4	5.05	11.47	16.41	18.50	16.77	12.93	8.97	5.69	3.10	1.12
5	3.00	7.17	11.26	15.56	16.80	16.28	13.15	9.48	5.07	2.22
6	2.19	4.75	7.78	11.42	14.65	16.97	16.56	13.09	8.66	3.94
7	1.54	3.31	5.24	8.01	11.30	15.01	17.93	16.92	13.85	6.89
8	1.16	2.24	3.61	5.47	8.43	11.72	15.46	19.67	19.88	12.36
9	0.76	1.42	2.32	3.50	5.21	8.14	12.20	18.46	24.90	23.10
10 (High)	0.58	0.76	1.09	1.67	2.47	4.30	6.88	11.68	21.86	48.70

Panel D: Twelve-Month Transition Probabilities (%)

Distress Risk Decile Month *t*	Distress Risk Decile Month *t+12*: 1 (Low)	2	3	4	5	6	7	8	9	10 (High)
1 (Low)	44.08	20.75	12.40	7.92	5.10	3.60	2.51	1.66	1.18	0.81
2	18.74	19.62	16.45	13.39	10.65	7.93	5.58	3.84	2.46	1.33
3	11.14	15.24	15.42	14.03	12.45	10.7	8.29	6.25	4.23	2.25
4	7.27	12.03	13.44	13.42	13.06	12.39	10.31	8.54	5.95	3.58
5	5.58	9.15	11.23	12.49	12.51	12.58	11.99	10.48	8.53	5.45
6	3.93	7.26	9.43	10.88	11.89	12.40	12.69	12.53	10.89	8.10
7	3.14	5.72	7.73	9.41	10.88	11.81	13.18	13.77	13.46	10.89
8	2.63	4.51	6.14	8.04	9.72	11.29	13.10	14.32	15.69	14.56
9	1.90	3.59	4.75	6.24	7.99	9.78	12.13	15.03	18.17	20.41
10 (High)	1.36	2.18	3.09	4.22	5.67	7.68	10.34	13.56	19.53	32.37

Distress Risk Decile Month *t*	Panel E: Twenty-Four-Month Transition Probabilities (%) Distress Risk Decile Month *t+24*									
	1 (Low)	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10 (High)**
1 (Low)	36.04	20.05	13.08	9.07	6.48	4.94	3.68	2.74	2.20	1.73
2	17.93	17.15	14.89	12.83	10.42	8.42	6.69	5.08	3.95	2.64
3	11.77	13.96	13.75	12.85	11.91	10.64	8.77	7.34	5.50	3.52
4	8.23	11.30	12.39	12.48	12.08	11.26	10.54	8.98	7.49	5.26
5	6.63	9.38	10.68	11.47	11.68	11.93	11.20	10.52	9.47	7.04
6	5.41	8.06	9.61	10.26	11.00	11.42	11.87	12.06	11.08	9.22
7	4.49	6.40	8.09	9.56	10.43	11.26	12.33	12.91	12.64	11.88
8	3.59	5.59	7.09	8.53	9.77	10.82	11.94	13.34	14.31	15.01
9	3.13	4.61	6.08	7.11	8.85	10.37	11.95	13.54	15.79	18.57
10 (High)	2.51	3.55	4.42	5.90	7.32	9.11	11.15	13.49	17.67	24.87

Appendix 7– Distress Risk and Distress Risk Persistence

In the analysis, I document that the distress risk anomaly is concentrated in firms where distress risk is most persistent. I first examine this in bivariate sorts, by showing that the distress risk anomaly is only observable in the sample of stocks where distress risk is most persistent. It is very possible that distress risk persistence is positively correlated with distress risk, and that this manifests in the observed relationship between distress risk persistence and the distress risk anomaly documented in the bivariate sorts. In Table A7, I examine this by documenting the average distress risk of bivariate sorted portfolios formed by sorting on distress risk persistence and distress risk.

I confirm that the tercile portfolio of stocks with the highest distress risk persistence, on average, has higher distress risk than the tercile portfolio of stocks with the lowest distress risk persistence. However, in each of the tercile portfolios, there is substantial cross-sectional variation in distress risk. For example, in the extended sample of firms, the difference in the mean distress risk of the high and low distress risk decile portfolios in the tercile portfolio of stocks with the lowest (highest) distress risk persistence is 86.96% (91.26%). Consistent with the anomaly literature, the distress risk anomaly captures the difference in returns between stocks with high distress risk cross-sectionally and stocks with low distress risk cross-sectionally (as opposed to the absolute magnitude of distress risk). As a result, it is highly unlikely that the relationship between distress risk persistence and the distress risk anomaly observed in the bivariate sorts is completely driven by the positive correlation of distress risk persistence with distress risk. Moreover, this is confirmed in the firm-level cross-sectional regressions reported in Appendix 8. The finding that the distress risk anomaly is most pronounced in firms where distress risk is most persistent is not a mechanical consequence of the relationship between distress risk persistence and distress risk, since the distress risk anomaly is most pronounced in firms where distress risk is most persistent, after controlling for both distress risk and distress risk persistence.

Table A7 – Average Distress Risk of Bivariate Distress Risk Persistence and Distress Risk Sorted Portfolios

This table reports the average distress risk in month *t* of portfolios formed by double-sorting on distress risk persistence and distress risk at the end of each month *t*. In each month *t*, stocks are sorted into tercile portfolios by sorting stocks on distress risk persistence. In each of these tercile portfolios, stocks are then sorted into decile portfolios formed on distress risk. Portfolio T3 (T1) is the tercile portfolio of stocks with the highest (lowest) distress risk persistence. Portfolio 10 (1) is the portfolio of stocks with the highest (lowest) distress risk. I also report the difference in the average distress risk between the high distress risk and low distress risk portfolios within each tercile, as well as the difference in the average distress risk between the high distress risk persistence and low distress risk persistence portfolios within each decile. These values are in percentage terms. Distress risk is the Merton (1974) measure of distress risk. Distress risk persistence is the estimated coefficient from a regression of distress risk in fiscal year *t* on distress risk in year *t-1*. In Panel A, I restrict the sample to firms with I/B/E/S analyst coverage. In Panel B, I report the same results after removing the analyst coverage filter.

	1 (Low)	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10 (High)**	**10-1**
	Panel A: Distress Risk Portfolios Conditional on Distress Risk Persistence in the I/B/E/S Sample										
T1	0.00	0.04	0.31	0.97	2.00	4.20	8.32	17.47	35.37	73.50	73.50 (63.72***)
T2	0.00	0.01	0.08	0.28	0.79	2.28	5.11	11.50	24.54	64.92	64.92 (50.60***)
T3	0.00	0.07	0.37	1.12	3.03	6.41	12.34	24.18	44.12	80.77	80.77 (76.46***)
T3-T1	0.00 (-1.36)	0.03 (-1.81)	0.06 (1.73*)	0.15 (2.10**)	1.03 (4.39***)	2.21 (5.46***)	4.02 (6.48***)	6.71 (8.09***)	8.75 (8.67***)	7.27 (11.28***)	7.27 (2.38**)
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**10-1**
	Panel B: Distress Risk Portfolios Conditional on Distress Risk Persistence in All Firms										
T1	0.00	0.02	0.25	1.12	3.30	7.94	17.00	32.73	56.68	86.96	86.96 (106.36***)
T2	0.00	0.01	0.08	0.41	1.49	4.48	11.29	24.70	47.54	82.33	82.33 (81.27***)
T3	0.00	0.05	0.45	2.08	6.07	13.34	25.03	42.91	67.02	91.26	91.26 (126.34***)
T3-T1	0.00 (2.35**)	0.03 (3.87***)	0.20 (6.41***)	0.96 (7.14***)	2.77 (8.24***)	5.40 (9.67***)	8.03 (10.95***)	10.18 (13.55***)	10.34 (15.84***)	4.30 (12.58***)	4.30 (11.85***)

Appendix 8– Firm-Level Cross-Sectional Regressions: Distress Risk Persistence

It is possible that the abnormal returns to the distress risk anomaly portfolios from double sorts on distress risk persistence and distress risk are capturing exposure to another risk premium, as opposed to distress risk. Additionally, it is possible that distress risk is a more persistent characteristic for highly distressed stocks.[44] To examine the impact of distress risk persistence on the distress risk anomaly while controlling for other effects, I run firm-level cross-sectional regressions of future excess stock returns on distress risk and combinations of firm characteristics, including distress risk persistence. Each month *t*, I run a cross-sectional regression of *t+1* (1-month ahead) excess stock returns on distress risk and combinations of firm characteristics, including distress risk persistence. The time-series averages of the regression coefficients, along with the Newey West (1987) adjusted *t*-statistics in parentheses testing the null hypothesis that the average slope coefficient is equal to zero are reported. In order to ascertain whether the dependence of the distress risk anomaly on distress risk persistence is reliant on analyst coverage, these tests are run both restricted and unrestricted to I/B/E/S analyst-covered firms. The results to these regressions are reported in Table A8.

In the first specification, the model of stock returns and characteristics is augmented with a control for distress risk persistence and the interaction of distress risk with a dummy variable that is equal to one if the stock is in the top quintile of distress risk persistence. In the I/B/E/S sample, the distress risk anomaly is no longer significant. However, the interaction of distress risk with the high distress risk persistence dummy variable is highly significant. This coefficient captures the effect of distress risk on 1-month-ahead excess stock returns, if a stock is in the highest quintile of distress risk persistence. This result therefore indicates, that in the I/B/E/S sample, the distress risk anomaly is concentrated in firms where distress risk is most year-on-year persistent. The distress risk anomaly is much larger in magnitude and statistically

[44] If it is true that distress risk persistence is higher (more positive) for more financially-distressed stocks, the most distressed stocks (which earn abnormally negative returns) are concentrated in the tercile portfolio of high distress risk persistence. This will result in the distress risk anomaly being detected only in the tercile of high distress risk persistence stocks. In Appendix 7, I demonstrate that whilst the high distress risk portfolio in the tercile portfolio of stocks with high distress risk persistence has higher average distress risk than the the high distress risk portfolio in the tercile portfolio of stocks with low distress risk persistence, there is still reasonable cross-sectional variation in distress risk in each of the tercile portfolios. As a result, it is unlikely that the dependence of the distress risk anomaly on distress risk persistence reported in Table 12 is driven solely by the relationship between distress risk and distress risk persistence.

more significant in the extended sample. However, controlling for the interaction of distress risk with the high distress risk persistence dummy variable reduces the magnitude and statistical significance of the distress risk anomaly. The distress risk anomaly is larger in magnitude and far more statistically significant when a firm is in the top quintile of distress risk persistence, relative to outside of the top quintile of distress risk persistence.[45] In both specifications, distress risk persistence alone is not a strong predictor of returns. This result provides further evidence that the distress risk anomaly is indeed most significant where forecast errors are most costly.

In the second specification, I examine whether distress risk persistence has explanatory power beyond negative news. Negative news simply captures information that can impact the beliefs of investors regarding a firm's future distress risk. However, for firms where negative news is informative of future negative news, a delay in updating beliefs will lead to greater mispricing. As a result, it is highly plausible that there is variation across firms regarding the extent to which negative news manifests in the distress risk anomaly. This variation will be captured by the measure of distress risk persistence. As a result, it should be the case that the previously reported relationship between the distress risk anomaly and negative news should be most pronounced where distress risk is most persistent. In report that distress risk persistence explains the distress risk anomaly beyond what is captured by negative news. In the I/B/E/S sample, I find that the distress risk anomaly is only detectable in firms with both negative news and where distress risk is highly persistent. I.e. Negative news only manifests in the distress risk anomaly where high distress risk is highly informative of high distress risk in future periods. The economic magnitude and statistical significance of the distress risk anomaly is also much larger when the controlling for high distress risk persistence. Moreover, outside of the I/B/E/S sample, I also demonstrate that the distress risk anomaly is concentrated in firms that have both negative news and where distress risk is a stronger positive signal of future distress risk. This evidence further indicates that the distress risk anomaly is strongest where under-reaction and forecast errors are most costly; where distress risk is most persistent.

[45] In Appendix 9, I show that the documented relationship between the distress risk anomaly and distress risk persistence reported in Table 10 is not a manifestation of forecast errors resultant from under-reaction to low profitability. I report that the relationship between the distress risk anomaly and distress risk persistence is robust to controlling for profitability persistence.

Table A8: Distress Risk Anomaly, Distress Risk Persistence and News

Each month, I run a cross-sectional regression of 1-month-ahead excess stock returns on distress risk, distress risk persistence, and other firm characteristics. This table presents the time-series averages of the monthly cross-sectional regression coefficients. Newey-West *t*-statistics using six lags are reported in parentheses. Distress risk is the Merton (1974) measure of distress risk. Distress risk persistence is the estimated coefficient from a regression of distress risk in fiscal year *t* on distress risk in year *t-1*. High distress risk persistence is a dummy variable equal to one if a firm observation is in the top quintile of distress risk persistence. Average calendar month news sentiment is measured as the average event sentiment score for a firm over all news events in the month *t-1*. Negative news is a dummy variable equal to one if the average calendar month news sentiment for a firm-month observation is less than fifty. Given the availability of the RavenPack data, specification two is restricted to the January 2001 to December 2018 period. Beta is the estimated market beta from weekly returns and equal-weighted market returns over the past thirty-six months. Size is the log of the market capitalisation as measured by price multiplied by number of shares outstanding. BM is the book value of equity divided by the end of fiscal year market capitalisation. Momentum is the *t-12* to *t-2*-month cumulative return. Investment is the total of the annual change in gross property, plant and equipment plus the annual change in inventory scaled by lagged total assets. Profitability is total revenue minus cost of goods sold scaled by lagged total assets. The row labelled *N* presents the average number of observations used in the cross-sectional regressions. The average adjusted R^2 is presented in the row labelled Adj. R^2.

Variable	*Panel A* *I/B/E/S Sample*		*Panel B* *Beyond the I/B/E/S Sample*	
	(1)	**(2)**	**(3)**	**(4)**
Distress Risk	0.747	0.001	-0.005	-0.002
	(1.01)	(0.30)	(-2.94***)	(-0.59)
Distress Risk*High Distress Risk Persistence	-0.011		-0.014	
	(-5.44***)		(-9.79***)	
Distress Risk*Negative News*High Distress Risk Persistence		-0.020		-0.016
		(-4.08***)		(-4.85***)
Distress Risk*Negative News		-0.002		-0.011
		(-0.70)		(-4.09***)
Distress Risk Persistence	-0.037		0.001*	
	(-1.02)		(1.96)	
Beta	-0.042	-0.002	-0.001	-0.002
	(-0.94)	(-1.63)	(-0.99)	(-0.80)
Size	-0.000	-0.000	0.000	-0.000
	(-0.77)	(-2.32**)	(0.78)	(-1.81*)
BM	0.001	0.001	0.003	0.002
	(2.48**)	(1.69*)	(5.78***)	(2.52**)
Momentum	0.002	0.000	0.004	0.001
	(0.66)	(0.27)	(4.27***)	(0.53)
Investment	-0.006	-0.003	-0.005	-0.004
	(-3.34***)	(-1.37)	(-5.89***)	(-2.93***)
Profitability	0.004	0.004	0.005	0.005
	(3.20***)	(2.85***)	(5.16***)	(3.75***)
Intercept	0.051	0.009	0.008	0.008
	(1.08)	(3.34***)	(4.23***)	(2.68***)
N	960	1,010	2,311	1,973
Adj. R^2	6.20%	0.64%	4.30%	0.49%

*** Significant at the 1% level. **Significant at the 5% level. *Significant at the 10% level.

Appendix 9– Distress Risk Persistence vs. Profitability Persistence

It is plausible that the finding that the distress risk anomaly is concentrated in firms where distress risk is most persistent is driven by biases in investor reactions to the low profitability of financially-distressed firms, as opposed to under-reaction to distress risk. To examine this, I run a regression of excess stock returns on distress risk and other stock characteristics, augmented with a control for profitability persistence, a dummy variable that is equal to one if the stock is in the top quintile of profitability persistence, and an interaction of distress risk with the profitability persistence dummy variable.[46] I then re-introduce the distress risk persistence controls, to isolate the effect of controlling for distress risk persistence, as opposed to profitability persistence. The time-series averages of the cross-sectional regression coefficients for these regressions are reported in Table A9. Given the reduced sample of I/B/E/S-covered firms for which there are estimates of distress risk persistence and profitability persistence, I report these results for the extended sample that is not limited to analyst-covered firms.

I find the result that the distress risk anomaly is concentrated in firms where distress risk is most persistent is robust to controlling for profitability persistence. There is a strong statistically significantly negative relationship between distress risk and 1-month-ahead stock returns where distress risk persistence is high. The economic magnitude and statistical significance of the coefficient on the interaction of distress risk with the high distress risk persistence dummy variable is equivalent to specifications without controls for profitability persistence. As a result, it is evident that the relationship between the distress risk anomaly and distress risk persistence is not a manifestation of under-reaction to profitability. Although profitability persistence does not mitigate the relationship between distress risk persistence and the distress risk anomaly, biases in expectations with respect to profitability do appear to play an additional role in understanding the distress risk anomaly in the extended sample. However, its importance is smaller in economic magnitude and statistical significance relative to the role of distress risk persistence. The distress risk anomaly is less significant in specifications that

[46] The profitability persistence for a firm is the estimated coefficient from a regression of profitability in fiscal year *t* on profitability at the end of fiscal year *t-1* over all fiscal year-end profitability observations for a firm. This is consistent with the Bouchaud et al. (2019) measure of earnings persistence.

control for profitability persistence.[47] The relationship between the interaction of distress risk with the high profitability persistence dummy variable and 1-month-ahead stock returns is negative and statistically significant. This result is consistent with the under-reaction interpretation of the distress risk anomaly presented in this paper. If investors are slow to update their beliefs, then the distress risk anomaly will be most significant where signals associated with distress risk are a stronger signal of future distress risk. Specifically, if low profitability is a strong signal of low profitability in future periods, then under-reacting to realisations of low profitability experienced by financially-distressed firms will lead to relatively greater mispricing for these securities.

[47] Notably there is a strong positive relationship between profitability persistence and 1-month-ahead stock returns that is not explained by controlling for profitability. This is beyond the scope of this paper. However, it is not clear what drives this price of profitability persistence.

Table A9: Distress Risk Persistence vs. Profitability Persistence

Each month, I run a cross-sectional regression of 1-month-ahead excess stock returns on distress risk, distress risk persistence, and other firm characteristics. This table presents the time-series averages of the monthly cross-sectional regression coefficients. Newey-West *t*-statistics using six lags are reported in parentheses. The row labelled *N* presents the average number of observations used in the cross-sectional regressions. The average adjusted R^2 is presented in the row labelled Adj. R^2. Distress risk is the Merton (1974) measure of distress risk. Distress (profitability) persistence is the estimated coefficient from a regression of distress risk (profitability) in fiscal year *t* on distress risk (profitability) in year *t-1*. High distress risk persistence (low distress risk persistence) is a dummy variable equal to one if a firm observation is in the top (bottom) quintile of distress risk persistence. High profitability persistence (low profitability persistence) is a dummy variable equal to one if a firm observation is in the top (bottom) quintile of profitability persistence. Beta is the estimated market beta from weekly returns and equal-weighted market returns over the past thirty-six months. Size is the log of the market capitalisation as measured by price multiplied by number of shares outstanding. BM is the book value of equity divided by the end of fiscal year market capitalisation. Momentum is the *t-12* to *t-2*-month cumulative return. Investment is the total of the annual change in gross property, plant and equipment plus the annual change in inventory scaled by lagged total assets. Profitability is total revenue minus cost of goods sold scaled by lagged total assets. The sample is all firms, without the analyst coverage filter.

Variable	**(1)**	**(2)**
Distress Risk	-0.007	-0.004
	(-4.27***)	(-2.19**)
Distress Risk*High Distress Risk Persistence		-0.013
		(-9.51***)
Distress Risk Persistence		0.001
		(1.06)
Distress Risk*High Profitability Persistence	-0.007	-0.006
	(-3.75***)	(-3.37***)
Profitability Persistence	0.005	0.005
	(5.92***)	(6.01***)
Beta	-0.001	-0.001
	(-0.87)	(-0.87)
Size	0.000	0.000
	(0.23)	(0.20)
BM	0.003	0.003
	(5.68***)	(5.70***)
Momentum	0.004	0.004
	(4.29***)	(4.31***)
Investment	-0.005	-0.005
	(-5.63***)	(-5.58***)
Profitability	0.005	0.005
	(5.12***)	(5.02***)
Intercept	0.005	0.005
	(2.66***)	(2.60***)
N	2,311	2,311
Adj. R^2	4.70%	4.90%

*** Significant at the 1% level. **Significant at the 5% level. *Significant at the 10% level.