What drives the distress risk-return puzzle?

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DOI:
10.1002/ijfe.2608

What Drives the Distress Risk-Return Puzzle? A Perspective on Limits of Arbitrage

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Empirical research has documented a negative relationship between distress risk and stock returns. This negative risk-return trade-off, known as the distress puzzle, poses a challenge to asset pricing models. In this study, we provide a new explanation of the distress puzzle by considering the effect of arbitrage asymmetry. We find that the negative distress risk-return relation is stronger in stocks that have higher limits of arbitrage. The investors are virtually unable to short sell mispriced high distress risk stocks due to the low supply of lendable stocks from institutions and that arbitrage is costly. In addition, we show that the limits of arbitrage effect is distinct from liquidity effect in explaining the distress puzzle.

Keywords: Distress risk, Anomalies, Limits of arbitrage, Market efficiency

Subject classification codes: G12, G14, G3

We thank Professor David Newton and Dr Xiafei Lei for their support and the UCLA-LoPucki Bankruptcy research centre for providing defaulted firm database, Yezhou would also like to acknowledge the financial support provided by China Scholarship Council. All errors are our own.

1. Introduction

Financial distress risk is perceived to be a result of size and value premium in the cross-section of stock returns (Chan & Chen, 1991; Fama & French, 1996). If the financial distress risk is indeed a systematic risk, the rational investor should demand a positive risk premium (Choi, Kim, & Park, 2020). However, studies show that stocks with high financial distress risk earn abnormally low returns (Dichev, 1998; Campbell, Hilscher, & Szilagyi (hereafter CHS), 2008; Avramov, Chordia, Jostova, & Philipov, 2013; Auer & Hiller, 2019; Nedumparambil & Bhandari, 2020; Sha, Kang, & Wang, 2020). The return premium, generated by long low distress risk stocks and short high distress risk stocks, is persistent and the capital asset pricing model (CAPM) and the Fama-French three-factor (FF-3) models have failed to explain it. Such types of return premium are commonly referred to the "distress puzzle".

This study contributes to the literature by providing a new explanation of the distress puzzle through arbitrage asymmetry channel. We find that the distress risk premium is stronger among stocks with higher limits of arbitrage. We argue that this is due to the short-sale constraints for investors who wish to short high distress risk stocks. Our explanation is inspired by the work of Da and Gao (2010), who find that illiquidity is positively associated with high distress risk. However, low liquidity stocks are associated with high returns (Amihud, 2002) and high distress stocks are associated with low returns (CHS, 2008). These established relationships challenge the liquidity-distress risk relation found by Da and Gao (2010). To reconcile these conflicts, we show that the high distressed stocks are associated with higher arbitrage costs, which coincides with low liquidity. It is the limits of arbitrage effect, not the liquidity effect, that drives the distress puzzle.

It is important to note that previous literature has used different proxies of distress risk and this could potentially yield different distress risk-return relations and explanations of the distress puzzle. This study analyses the distress puzzle proposed by CHS (2008) where the distress risk is calculated using a hazard model. Shumway (2001) claims that the hazard model is superior to static models (e.g. the O-score and the Z-score) and provides superior out-of-sample forecasts. This is because the static model only uses a firm’s financial data from the year before failure while the hazard model takes into account all information prior to the failure of the firm. Furthermore, we follow CHS (2008) to calculate the failure probability (FP) using annually updated parameters; that is, we estimate a default forecasting model for each year with data available prior to that year. The advantage of such an estimation strategy is to avoid look-ahead bias, which could potentially exist in a fixed parameter model. Thus, our explanation of the distress puzzle relies on a dynamic FP, which is claimed to be a better measurement of distress risk (Hilscher & Wilson, 2017). This contrasts with explanations of the distress puzzle which are based on the Z-score/O-score (Avramov, Chordia, Jostova, & Philipov, 2013, Goldfrey & Brooks 2015) or use FP assuming fixed parameters (Stambaugh, Yu, & Yuan, 2012). Furthermore, this study advances other similar studies by providing a straightforward and independent driver of the distress puzzle. This contrasts with Goldfrey and Brooks (2015), whose work is based on a mixed story containing both limits of arbitrage effect and momentum effect.

Our main conjecture is that the return spreads between low and high distress risk stocks are positively associated with limits of arbitrage. To measure the limits of arbitrage, we use a stock's monthly bid-ask spread, dollar volume, and the Amihud (2002) illiquidity ratio as proxies of transaction cost (Ali, Hwang, & Trombley, 2003; Asquith, Pathak, & Ritter, 2005). We use the idiosyncratic volatility relating to the FF-3 model as the holding cost (Pontiff, 1996, Ang, Hodrick, Xing, & Zhang, 2006).

We form five-by-five portfolios that rank stocks by distress risk and a proxy of limits of arbitrage independently. Consistent with our conjecture, the distress risk premium, measured as the long-short portfolio return from holding the lowest distress risk quintile portfolio and shorting the highest distress risk quintile in each limits of arbitrage quintile, is positively related to limits of arbitrage proxies. Compared to the distress risk premium (0.62% per month) among all stocks, the distress risk premium is only -0.08%−0.45% per month and is statistically insignificant from zero in the lowest limits of arbitrage quintile. In the highest limits of arbitrage quintile, the distress risk premium is as high as 1.19%-1.74% per month. The distress risk premium is even larger if portfolio return is risk-adjusted. The FF-3 alpha of the above portfolio is 0.45%−1.03% per month in low limits of arbitrage stocks and 1.51%-2.27% per month in high limits of arbitrage stocks. These results are in line with the limits of arbitrage theory such that anomalies are more pronounced in high arbitrage costs stocks. Similar conclusions are reached by using the Fama and MacBeth (1973) cross-sectional regression.

Since our transaction cost proxies for limits of arbitrage are also the proxies for liquidity, we disentangle the liquidity effect from the limits of arbitrage effect. We find evidence that the relationship between the distress risk premium and the proxies of limits of arbitrage is not a tautology of the stock liquidity effect. In the five-by-five portfolio sorts, for instance, the average portfolio return is positively related to stocks' monthly bid-ask spread in low distress risk quintiles. However, the average portfolio return is negatively related to stocks' monthly bid-ask spread in high distress risk quintiles. This is inconsistent with the liquidity effect since illiquidity should be associated with high returns. The reversed illiquidity-return relationship in high distress risk stocks is due to the high costs for short selling. Thus, we conclude that it is the limits of arbitrage, not the liquidity effect, that drives the distress risk premium. We observe similar patterns when using other transaction cost proxies.

We further investigate why costly arbitrage is strongly associated with the distress puzzle, i.e. why high distress risk stocks carry a high bid-ask spread, small dollar volume, extreme illiquidity and volatile returns? A plausible explanation is that for high distress risk stocks, short-selling is impeded. If distress risk eventually evolves into a distress event, institutional investors may suffer substantial losses for holding those stocks. To minimise the loss, institutions will tend to release their positions to retail investors when distress risk increases (Li & Zhong, 2013). It follows that high distress risk stocks are associated with a continuous low institutional ownership, resulting in a shortfall of short-selling supply. We find evidence supporting the short-sale constraints explanation that low supply of short selling (low institutional ownership) is associated with high distress risk stocks. This indicates that the investors are virtually unable to short sell mispriced high distress risk stocks due to the low supply of lendable stocks from institutions and that arbitrage is costly (Stambaugh, Yu, & Yuan, 2012; Beneish, Lee, & Nichols 2015).

The remainder of the paper is organised as follows. Section 2 presents the background and hypotheses. Section 3 describes the data and the variable. Section 4 presents our empirical results while Section 5 contains robustness test outcomes. Section 6 concludes.

2. A Review of the Literature

There are two types of resolution to the question of the existence of the distress puzzle. The first viewpoint is that the asset pricing model is not accurate; based on this, a new risk factor should be added to the model to explain the negative distress risk-return relationship. This assumes that the market is efficient (Chan & Chen, 1991; Vassalou & Xing, 2004; Kapadia, 2011). The second opinion notes that efficient market theory does not reflect real market behaviour; investors with different risk appetites make different choices, and idiosyncratic firm characteristics can draw investors' attention to certain distressed firms more than others (Griffin & Lemmon, 2002; Garlappi, Shu, & Yan, 2008; CHS, 2008; Avramov, Chordia, Jostova, &

Philipov., 2009; Avramov, Chordia, Jostova, & Philipov, 2013).

The rational explanation asserts the effectiveness of existing equilibrium asset pricing models; naturally, anomalies are defined as missing risk exposures that correlate to either firm characteristics or systematic risk (Tang, Wu, & Zhang, 2013). Given the existence of the distress anomaly, it is reasonable to assume that financial distress is a missing part of systematic risk or is correlated with a firm's characteristics such as size and leverage. This is also the conclusion of Chan and Chen (1991). Vassalou and Xing (2004) and Kapadia (2011) find that distress risk is associated with macroeconomic conditions and firm characteristics.

Schwert (2003) argues that most anomalies are due to temporary investor behaviour, and notes that their impact on asset pricing declines over time. CHS (2008) start from an assumption based on the experience of industrial investors who favour financial distressed stocks, which they argue that institutional holders with high levels of risk-aversion drive down the prices of distressed stocks, as active investors could participate in firms' operational running and reduce high-risk investments and sell poison assets, releasing positive signals to market participants. However, these are merely assertions and lack empirical examination or evidence. A more common explanation is that investor sentiment leads to mispricing during the earning announcement. Stambaugh, Yu, and Yuan (2012) find that anomalies, especially those excess returns generated from the short-side portfolio, are due to investors' sentiment. Such sentiment damages the accuracy of pricing in the market, and hence unexpected events such as financial distress generate considerable opportunities for obtaining excess returns.

Corporate finance theory also explains the relationship between distress risk and stock returns, which argues that a firm's capital structure and its dynamic change results in complex effects on stock returns. George and Hwang (2010) find that the distress anomaly is connected with a firm's debt structure, the distress anomaly only appears when firms have low distress cost, which is co-determined by its debt level and tax benefit. Gomes and Schmid (2010) document that highly levered firms are also mature firms with more (safe) book assets and fewer (risky) growth opportunities. Hence, a premium is charged for low-levered firms resulting in a negative risk-return relationship when the distress risk is measured by a firm's leverage. This point of view is supported by some interesting findings in their cross-sectional regression analyses, but the main drawback, according to Gomes and Schmid (2010), is that their theoretical explanation is "more complex than static textbook examples suggest" (p.467), and their proposed explanation has not presented a good reason why Fama and French three-factor model and Fama-French-Carhart four-factor model is not capturing the pricing power of distress risk.

Exploiting anomalies as profitable investment strategies are subject to frictions in trading stocks. In the survey by Shleifer and Vishny (1997), it is found that investors may give up investing opportunities due to the limits of arbitrage, despite the presence of anomalies. The relationship between the effect of limits of arbitrage and anomalies has been found in some well-known anomalies, including the book-to-market anomaly (Ali, Hwang, & Trombley, 2003), asset growth anomaly (Lam & Wei, 2011), cash holdings effect (Li & Luo, 2016), and the idiosyncratic volatility puzzle (Duan, Hu, & Mclean, 2010; Han & Lesmond, 2011; Qu, Liu, & He, 2018). Since anomaly-driven trading involves holding and rebalancing portfolios, it is natural to test if the distress risk premium also carries costs that make arbitrage difficult.

Financial distress is value-destroying. Andrade and Kaplan (1998) find that the ex-post cost of financial distress is 10%-20% of total firm value, and the cost largely absorbs the potential benefits from the tax-shield effect (Almeda & Philippon, 2007). Glover (2016) argues the expected loss for investors can be as large as 45% of firm value in financial distress. The cost of financial distress is multidimensional, such as suspending ongoing R&D schemes (Opler & Titman 1994; Franzen, Rodgers, & Simin, 2007), reducing profitability and investment opportunities (Fama & French, 2006), and incurring liquidation costs (Altman & Hotchkiss, 2010; George & Hwang, 2010). In extreme cases, distressed stocks could have zero value because the residual value, which equity represents, cannot be reclaimed until debtholders are satisfied (Li & Zhong, 2013). Therefore, sophisticated investors, such as financial institutions may lack interest in holding distressed stocks. Even if there are sufficient supply of stocks for short-selling, short-sell distressed stocks can be costly (Nagel, 2005), unlikely to happen (Stambaugh, Yu, & Yuan, 2012) or even unprofitable (Novy-Marx & Velikov 2016). However, the value-destroying nature of financial distress can be mitigated by stringent regulation. For example, Bose, Filomeni, and Mallick (2021) show that distressed firms are able to improve their performance relative to non-distressed firms after the introduction of new Insolvency and Bankruptcy Code in India.

3. Data and Variable

3.1. Key Variables

Following CHS (2008), we measure a stock's distress risk by its FP from the hazard model, that is predicting financial distress using accounting-based and market-based data. The parameters of the default forecasting model are updated annually; that is, we estimate a default forecasting model for each year with data available prior to that year[1]. The advantage of such an estimation strategy is to avoid look-ahead bias, which could potentially exist in a fixed parameter model. The supreme predictive accuracy of FP on default compared to other accounting-based or market-based measures has been verified by the literature (e.g. CHS, 2008; Campbell, Hilscher, & Szilagyi, 2011; Charitou, Dionysiou, Lambertides, & Trigeorgis, 2013; Tinoco & Wilson, 2013).

Following Duan, Hu, and Mclean (2010) and Li and Luo (2016), we adopt proxies for limits of arbitrage, namely: (a) bid-ask spread, dollar trading volume, and illiquidity ratio for transaction cost (Lesmond, 2002); (b) idiosyncratic volatility

[1] For brevity, the estimated parameters for the default forecasting model are not reported. When estimating the parameters, the list of financially distressed firms includes US bankruptcy initial filings from Thomson's SDC Platinum, the UCLA-LoPucki Bankruptcy Research Database, Compustat, Moody's Default Research Database, and CRSP Event files. All filings include common corporate identifiers, exact dates of declared bankruptcy, default, and performance-related delisting events. In cases of duplicate records, the record with the earliest event date is stored and the rest are dropped.

resulting from the FF-3 model for holding cost (Ang, Hodrick, Xing, and Zhang, 2006); and (c) institutional ownership and short interest ratio for short-sale constraints (Asquith, Pathak, & Ritter, 2005). All measures are calculated on a monthly basis, while transaction cost measures are calculated as a 12-month averaged daily value at the end of month $t-1$ to overcome short-term market reactions (Li & Luo 2016).

In discovering the relationship between the distress puzzle and firm characteristics, we present the link between limits of arbitrage and the distress puzzle in Table 1. We sort all US stocks by FP into deciles at the beginning of the month and rebalance the portfolio in the following month from 1981 to 2014; see Section 4 for details. The results are consistent with CHS (2008). In panel A, high FP stocks have lower returns than low FP stocks. The spread of returns between the top 10% and the bottom 10% of stocks is 0.61% per month without risk-adjusting or 0.90%-1.42% per month with risk-adjusting. The high distress risk portfolio tends to have higher bid-ask spread, illiquidity, and idiosyncratic volatility, and lower dollar volume and institutional ownership, as well as a lower short interest ratio than the low distress risk portfolio. In short, our findings are consistent with the argument of CHS (2008) by showing the presence of the distress puzzle, and the spread of the costly arbitrage across distress risk sorted portfolios.

<Insert Table 1 Here>

3.2. Summary statistics

The relationship between distress risk and limits of arbitrage is reported in Table 2.

Panel A shows the distribution of the key variables. Panel B shows the Spearman correlations of all variables. Consistent with Novy-Marx and Velikov (2016), Stambaugh, Yu, and Yuan (2015) and Broggard, Li, and Xia (2017), FP is positively related to stock bid-ask spread (*BA*), Amihud's illiquidity ratio (*ILLIQ*), and idiosyncratic volatility (*IVOL*), and FP is negatively related to dollar volume (*DV*), and institutional ownership (*IO*). This provides evidence that a stock's distress risk is associated with these well-documented limits of arbitrage effects. We also find that FP is negatively associated with a stock's short interest ratio (*SIR*), suggesting that the demand of short selling is low (Asquith, Pathak, & Ritter, 2005). The definitions of variables used in this study are proved in the Appendix.

<Insert Table 2 Here>

4. Empirical Findings

4.1. The distress risk premium

We calculate the distress risk premium as follows. At the beginning of every month, all stocks are sorted by FP into deciles. The distress risk premium is defined as the long-short portfolio that holds stocks in the first decile of FP (low distress risk firms) and shorts stocks in the tenth decile (high distress risk firms). Inspired by CHS (2008), Li and Luo (2016) and Hackbarth, Haselmann, and Schoenherr (2015), we measure the distress risk premium using the portfolio's value-weighted return, the portfolio's alpha relating to the FF-3 model (Fama & French, 1993), and the portfolio’s alpha relating to the Fama-French five-factor (FF-5) model (Fama & French, 2015). Stocks that had a SIC code of 6000-6999 (Finance, Insurance or Real Estate), or did not have a common stock identifier on the day of forming portfolios were dropped. The Newey-West adjusted standard error with 12 lags was used when calculating *t*-statistics. The NYSE breakpoints were applied to the NYSE-AMEX-NASDAQ samples to further eliminate size effects. The final dataset contains 2,271,552 firm-month observations covering 408 months.

Distressed returns were addressed by using the CRSP delisting return (CRSP code dlret) where available. We follow Hillegeist, Keating, Cram, and Lundstedt (2004) and use the initial filling for financial distress as the distress indicator, and the return of the month filling first financial distress event as the firm’s delisting return. All observations after the initial filling are then dropped. These adjustments represent a conservative estimation of returns from distressed firms and do not sharpen the distress risk premium according to CHS (2008).

The performance of the distress risk premium from 1981-2014 is provided in Table 3. The results highlight three interesting aspects. First, consistent with CHS (2008), the distress risk premium is persistent at 0.62% per month over the sample. We also estimate the portfolio performance by excluding the 1981-1989 period, and using the post-2003 period. We find the distress risk premium remains large and significant in the remaining sample period and becomes more pronounced after 2004. The distress premium in Panel E is enlarged by 19 bps and over 3 times than in Panel

A, suggesting that the distress premium is not subsumed by time-variation in risk-factor loadings.

Second, the distress puzzle is more pronounced when working with risk-adjusted returns. This is because the monthly alpha from the FF-3 and the FF-5 models are higher than its raw excess returns (α_{FF-3}=1.43%, α_{FF-5}=0.98% against excess returns of 0.62%). The reason for the superior risk-adjusted distress risk premium over raw excess returns is the portfolio's covariance relating to risk factors. We find the default risk strategy carries a significant negative factor loading from the FF-3 model, meaning the performance is negatively related to market performance, size and value effects.

Third, the distress risk premium comes mainly from the short-side of the long-short portfolio, where the short side contributes 62.90% to the raw returns, 77.62% to the α_{FF-3}, and 70.70% to the α_{FF-5} in the sample period. This is consistent with Stambaugh, Yu, & Yuan (2012), who find that the premium of the anomaly relies on the performance of the short side portfolios. The return asymmetry implies that short-sale impediments, if they exist, will greatly affect the overall performance (Stambaugh, Yu, & Yuan, 2015).

<Insert Table 3 Here>

4.2. Double-Sorts portfolio analyses

We use double-sort portfolio analysis to further examine how variation in the limits of arbitrage can affect the distress risk premium. Using the same sample period as above, at the beginning of each month, we sort all stocks in the full sample dataset into five quintiles according to their distress risk. Independently, the stocks are sorted into five quintiles according to one of the limits of arbitrage proxies. The proxies of limits of arbitrage are transaction cost (measured by *BA*, *DV*, and *ILLIQ* respectively), holding cost (measured by *IVOL*), and short selling constraints (measured by *IO* and *SIR*). The two-way method generates 25 independent double-sorted portfolios. Based on these portfolios, we form five long-short portfolios, and denote Low-High, representing a distress risk trading strategy, whereby holding stocks in the first FP quintile and shorting stocks in the fifth FP quintile controls for the effects of limits of arbitrage. Using the same method, another five long-short portfolios are constructed to examine the return premium associated with limits of arbitrage proxies controlling for distress risk effect.

4.2.1. Trading costs and the distress risk premium

Table 4 shows portfolio returns independently sorted by distress risk and transaction costs. The transaction cost proxies are *BA*, *DV* and *ILLIQ* and are reported in panels A, B and C respectively. To correct the potential bias from a firm's size, value-weighted excess returns are reported, together with the corresponding FF-3 alpha.

<Insert Table 4 Here>

Panel A of Table 4 reports the average portfolio returns sorted by FP and bid-ask spread independently. The distress risk premium, measured as the average return from Low-High FP quintile, is stronger when the average *BA* is high. When the average *BA* declines, the corresponding distress risk premium is reduced. In the lowest *BA* quintile, the distress risk premium (FF-3 alpha) is 0.38% (*t*-statistic = 1.06) per month or 0.84% (*t*-statistic = 2.54). These abnormal returns constitute the worst performance among all the five long-short distress risk portfolios.

The fact that the distress risk premium is small in low *BA* stocks is mostly due to the outstanding performance from stocks with a high FP and a low *BA*. On one hand, high FP stocks present a monotonic pattern, yielding from 0.96% per month in the lowest *BA* quintile to 0.20% per month in the highest *BA* quintile. On the other hand, in each *BA* quintile, the low FP stocks perform consistently well, with monthly excess returns varying from 1.24%-1.64%. This is a much narrower range for returns compared to high FP stock returns. The difference in performance between low and high distress risk stocks is consistent with the univariate sort in Table 4 where the short-side portfolio drives the overall performance. This further shows how the distress risk premium is positively associated with a stock's bid-ask spread.

Although bid-ask spread is a proxy for limits of arbitrage, it is also a proxy for liquidity. Thus, we need to disentangle liquidity effect from limits of arbitrage effect. If the bid-ask spread is the liquidity proxy in this study, we should find that spread is positively priced in stock returns. The returns of low-high *BA* portfolios in the first and second FP quintiles are -0.29% and -0.16% per month respectively. This indicates that the bid-ask spread (illiquidity) is positively priced in returns (Amihud, 2002). However, the returns of low-high *BA* portfolio in the fifth FP quantile is 0.76%, which is positive. This implies that bid-ask spread (illiquidity) is negatively priced in returns when the FP is high and challenge the liquidity explanation of the distress risk premium. The reserved illiquidity-return relationship in high distress risk stocks is due to the high costs for short selling. Thus, we conclude that it is the limits of arbitrage, not the liquidity effect, that drives the distress risk premium.

When stock's dollar volume and Amihud's illiquidity ratio are used as the proxy variables for trading costs, a similar conclusion as in the FP-*BA* sorted portfolio is drawn. The distress risk premium monotonically declines as the transaction cost decreases[2], the decline in the distress risk premium is due to the relatively strong performance of the short-side (high FP) portfolios. Furthermore, in the fifth FP quintile, returns are -0.24% per month (-0.01% for the FF-3 alpha model) for the low-high *DV* portfolio, and 0.63% per month (0.44% for the FF-3 alpha model) for low-high *ILLIQ* portfolio, indicating that illiquidity is not positively priced in the stock returns in the high FP quintile. Those results again indicate that it is not the liquidity effect that drives the distress risk premium.

Our results are consistent with the literature in explaining the cash holding anomaly, momentum effect, and idiosyncratic volatility puzzle where the portfolio's performance from these anomalies is not significant among low transaction cost firms (Li & Luo, 2016; Han & Lesmond, 2011). However, our findings do not support the view that liquidity risk is responsible for the distress puzzle. The reversed relationship

[2] Note that high *DV* indicates low transaction costs.

between stock return and the liquidity effect in high distress risk stocks is not consistent with Da and Gao (2010). The variation in the distress risk premium across transaction cost quintiles should be viewed as a result of costly arbitrage among high distress risk stocks.

4.2.2. Holding costs, short-sale constraints, and the distress risk premium

Holding costs are incurred every period the arbitrage position is held (see Pontiff, 1996). The costs include the borrowing costs of short sale and holding risk exposure that cannot be hedged. Thus, we expect that the distress risk premium is more pronounce for stocks with larger holding costs. We use idiosyncratic volatility as the proxy for holding cost and the pattern of the distress risk premium across idiosyncratic volatility quintiles is shown in panel A of Table 5.

<Insert Table 5 Here>

Consistent with this justification, the distress risk premium gets larger as *IVOL* increases, and the distress risk premium is concentrated in the fifth *IVOL* quintile (1.74% per month, *t*-statistic = 4.11), in sharp contrast to the premium in low *IVOL* firms (-0.08% per month, *t*-statistic = -0.33).

The spread between low idiosyncratic volatility and high idiosyncratic volatility portfolios also carries a premium that cannot be explained by the asset pricing model, as reported in Ang, Hodrick, Xing, and Zhang (2006). In the last row of panel A in Table 5, the returns of all low-high *IVOL* portfolios across FP quintiles are positive and significant at 10% level, showing that, even when controlling for FP, high *IVOL* stocks pervasively underperform.

Thus, the combined reading of results in Tables 4 and 5 suggests that the distress risk premium, like other anomalies such as cash holding effect (Li & Luo, 2016), idiosyncratic volatility puzzle (Han & Lesmond, 2011), is greater in stocks that suffer from high transaction and holding costs, proxied by a high bid-ask spread, a high Amihud’s illiquidity ratio, a high idiosyncratic volatility, and a low trading volume.

It is not clear why high distress risk stocks are more difficult to trade. One plausible explanation is the short-selling constraints. Two short-sale constraint variables are therefore applied to test if limits of arbitrage could explain the distress puzzle. According to Nagel (2005), Beneish, Lee, and Nichols (2015), institutional ownership can represent the supply of short-selling stocks, and short interest ratio can represent the demand for short-selling. Panels B and C of Table 5 shows portfolio returns independently sorted by distress risk and short-sale constraints.

We find evidence that the distress risk premium is clustered in stocks that are difficult to short-sell. Specifically, for stocks sorted by FP and *IO*, the distress risk premium generally decreases in low to high institutional ownership quintiles, from 2.62% (*t*-statistic = 5.07) to -0.19% (*t*-statistic = -0.62) per month, which suggests that the ease of short selling significantly reduces profits in the distress puzzle. Moreover, the positive relationship between *IO* and stock returns becomes negative in the high

FP quintile. Portfolios sorted by FP and *SIR* have different patterns: the distress risk premium is V-shaped in *SIR*, where both the low and high *SIR* quintiles yield around 0.7% per month, which is higher than the intermediate quintiles. The relation between FP and two constraint proxies is largely following the pattern of asset growth anomaly (Lam & Wei, 2011), which is also driven by the short-selling constraints. We, thus, interpret our results by the same underlying mechanism.

4.3. Distress risk, limits of arbitrage and the cross-sectional returns

To cross-check our portfolio-sorted results and, more importantly, to examine the relationship between the distress risk and limits of arbitrage, we run Fama and MacBeth (1973) cross-sectional regressions.

We first investigate the effect of distress risk and limits of arbitrage on stock returns. We regress stock monthly excess returns on a set of explanatory variables, including firms' FP, the proxy of limits of arbitrage (*Arbitrage Limit*), a vector of the lagged control variables ($\boldsymbol{X_{i,t}}$), including the natural logarithm of a firm's market capitalisation at the end of June (*lnME*), the natural logarithm of a firm's book-to-market ratio (*lnBEME*) and the cumulative compounded stock returns over the last 12 months (*MOM12*). The proxy of limits of arbitrage is one of the following: *BA*, *DV*, *ILLIQ*, *IVOL*, *IO*, or *SIR*. Specifically, the regression has the form of:

$$R_{i,t} - r_{f,t} = \lambda_0 + \lambda_1 FP_{t-1} + \lambda_2 Arbitrage\ Limit_{t-1} + \lambda_3 \boldsymbol{X_{i,t-1}} + \varepsilon_{i,t}, \tag{1}$$

where $\boldsymbol{X_{i,t-1}} = \begin{bmatrix} lnME_{i,t-1} & lnBM_{i,t-1} & MOM12_{i,t-1} \end{bmatrix}$.

Table 6 provides the results of the regression analysis. In general, the distress risk is negatively priced in expected stock returns. The coefficient of *FP* is negative in all regressions and is statistically significant at 10 percent level in 11 out of 12 regressions. All proxies measuring limits of arbitrage have predictive power for expected returns. When control variables are included, all coefficients of limits of arbitrage proxies, except *DV*, show the sign expected from the portfolio analysis, and all are statistically significant at 5 percent level. The coefficient of *DV* is positive, which should have been negative according to the portfolio analysis. The inconsistency of *DV* in the portfolio analysis and the regression analyses was also found by Lam and Wei (2011) and Li and Luo (2016), suggesting that the predictive power of *DV* is sensitive to the estimation method. Overall, the significance of limits of arbitrage proxies is consistent with Asquith, Pathak, and Ritter (2005) and Hou and Loh (2016), showing that the variation of arbitrage costs is associated with subsequent stock returns.

<Insert Table 6 Here>

To examine whether the distress risk - equity returns relation depends on firm's limits of arbitrage status, an interaction term between the firm's distress risk and status of limits of arbitrage is added in the regression.

We classify the status of limits of arbitrage into two categories, namely low limits of arbitrage and high limits of arbitrage. We combine all six limits of arbitrage proxies (*BA*, *DV*, *ILLIQ*, *IVOL*, *IO*, and *SIR*) to produce an indicator of limits of arbitrage[3]. The limit of arbitrage indicator is calculated by using the average of standardised proxies and the steps are the following. First, all limits of arbitrage proxies are standardized, ranging from zero to one. Second, all the standardized proxies are added together. We specify the limits of arbitrage indicator such that a high value means high limits of arbitrage. Since *DV*, *IO*, and *SIR* are proxies such that high value means low limits of arbitrage, we change the sign of these standardized proxies when adding up all proxies. Finally, the sum of all standardized proxies is divided by six to ensure that the value of the indicator is still between zero and one. Based on the limits of arbitrage indicator, we define dummy variable *High Aribitrage Limit* such that it takes a value of 1 if the value of limits of arbitrage indicator is above its yearly cross-sectional average and otherwise 0.

To examine whether the distress risk - returns relation depends on firm's arbitrage limit status, equation (2) is estimated. The coefficient of the interaction term between *FP* and the *High Arbitrage Limit* depicts the difference in the pricing power of distress risk between high arbitrage limit firms and low arbitrage limit firms. Specifically, the regression has the following form:

$$\begin{aligned} R_{i,t} - r_{f,t} &= \lambda_0 + \lambda_1 FP_{t-1} + \lambda_2 High\ Arbitrage\ Limit_{t-1} \\ &+ \lambda_3 FP_{t-1} \times High\ Arbitrage\ Limit_{t-1} + \lambda_4 \boldsymbol{X_{i,t-1}} + \varepsilon_{i,t}. \end{aligned} \quad (2)$$

Table 7 reports the regression results. The coefficients of *FP* are significant and negative. The coefficient of the interaction term between *FP* and *High Arbitrage*

[3] We also used each individual limits of arbitrage proxy to form dummy variable, the conclusion remains the same.

Limit is negative and highly significant (λ_3=-2.535, *t*-statistic = -3.64). This gives direct evidence that the predictive power of distress risk is greater for high limits of arbitrage limit stocks than for low limits of arbitrage stocks. The results also provide a cross-check on our portfolio-level analysis, where the scale of distress risk premium is significant in the highest limits of arbitrage quintile while in the lowest limits of arbitrage quintile it is only marginally significant or even vanishes.

<Insert Table 7 Here>

5. Robustness tests

5.1. Do penny stocks matter?

Research has identified that penny stocks are associated with positive returns, and therefore numerous research has identified anomalies using a market-wide sample without these stocks. Some studies are interested in whether the penny stock positively contributes to the distress risk premium, since high distress risk stocks typically have a low price. We re-estimate the two-way sort portfolios by dropping all stocks that have price below one dollar to see if the distress risk premium vanishes, and the results are reported in Table 8.

We find the distress risk premium maintains the same pattern as in section 4.2, i.e. the premium still increases from low to high limits of arbitrage quintiles. The premiums in the highest limits of arbitrage quintile are even higher than the results including penny stocks. This is because depending on the distress risk, penny stock could either yield positive returns as a compensation of low liquidity, or yield negative returns as the effect of the distress puzzle. Thus, excluding penny stocks will strengthen our conclusion section 4.2.

<Insert Table 8 Here>

5.2. Distress risk premium across limit of arbitrage in longer holding period

If the limits of arbitrage effect convey more information about short-term market impacts than a stock's fundamental conditions, then one might argue that the distress risk premium is another type of short-term return pattern rather than a persistent and long-term market anomaly. This is because short-term impact in the market is usually unstable and reversed in the subsequent month. To determine whether the distress puzzle is driven by short-term market drift or by the underlying fundamental of the market, we extend the holding period of the characteristic-sorted portfolios in section 4.2 from 1 to 12 months. This gives sufficient time to examine the persistence of the distress risk premium and its relationship to limits of arbitrage.

We use 12-months as the holding period to mimic the method of CHS (2008) and Hackbarth, Haselmann, and Schoenherr (2015). The portfolios are constructed using the same methodology as in earlier sections. The weight of stock returns included in the portfolio is determined by the date of forming portfolio and remains constant over the following 12 months for calculating the value-weighted returns. Because institutional holding is also a proxy for corporate governance in the long holding period (Gompers, Ishii, & Metrick, 2003), we do not incorporate IO as well as

SIR in the 12-month holding period when interpreting the results. We find the 12-month distress risk premium, reported in Table 9, remains quantitatively unchanged and is positively related to limits of arbitrage.

<Insert Table 9 Here>

6. Conclusion

In this paper, we undertake an extensive investigation of the relationship among a firm's distress risk, limits of arbitrage, and the cross-section of stock returns. We first revisited the CHS (2008) failure probability and its associated distress risk premium and find evidence of persistence of the distress risk premium in our updated sample period. We further show that the distress risk premium is stronger among stocks with higher limits of arbitrage. This is due to the short-sale constraints for investors who wish to short high distress risk stocks. Our conclusions are insensitive when changing the sampling method, holding portfolios for a longer period, and using the FF-3 alpha as a measurement of the portfolio's performance.

Our paper contributes to the literature by providing a new explanation of the distress puzzle as documented by CHS (2008) and dissecting anomalies (Barahona, Driessen, & Frehen, 2021; BenMabrouk, & Souayeh, 2021; Jiang, Du, An, & Zhang, 2021). Da and Gao (2010) found that illiquidity was positively associated with high distress risk. However, low liquidity stocks should be associated with higher returns (Amihud, 2002) and high distress stock with lower returns (CHS, 2008). To reconcile the conflicting evidence in the literature, we show that high distress stocks are associated with higher arbitrage costs, which coincides with low liquidity. It is the limits of arbitrage effect, not the liquidity effect, we argue, that drives the distress puzzle.

Chu, Hirshleifer, and Ma (2020) document that limits of arbitrage change over time. Liquidity shortfall happened in the US and international markets as a consequence of implementing the circuit breaker (Sharma, Narayan and Thuraisamy, 2015). The market nature of liquidity and short-selling has changed accordingly that is independent from any long-term market risks. However, as Westerlund, Karabiyik, Narayan, and Narayan (2021) shown, such phenomenon has at least two possible explanations: structural break, or time-varying risks. This will be an interesting question for future research.

Data Availability Statement

The data that support the findings of this study are available from Compustat, CRSP, Thomson's SDC platinum, Moody and UCLA-LoPucki. Restrictions apply to the availability of these data, which were used under license for this study. Data are available at https://wrds-www.wharton.upenn.edu/ with the permission of Wharton Research Data Services, and https://www.moodysanalytics.com/ with the permission of Moody. Data from UCLA-LoPukci Bankruptcy Research Database is provided by the UCLA-LoPucki Bankruptcy Research Centre.

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and https://lopucki.law.ucla.edu/ with the permission of UCLA-LoPucki Bankruptcy

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Appendix: Variable Definitions

Bid-ask spread (*BA*): The bid-ask spread is the difference between quoted closing ask price (CRSP code ask) and closing bid price (CRSP code bid) divided by the bid-ask average value. The highest (CRSP code $askhi$) or lowest (CRSP code $bidlo$) trading price is used as the alternative for missing values of ask or bid. The spread is estimated on a daily basis and reported as the average value in the past 12 months. We required at least 15 effective observations in each month.

Dollar trading volume (*DV*): The dollar trading volume is the number of shares traded (CRSP code vol) in a day multiplied by the closing price (CRSP code prc). Similar to the calculation of *BA*, we require at least 15 effective price data observations in each month and calculate the average value in the past 12 months. If the closing price is missing, the bid-ask average on the day is used. A low value of *DV* indicates high limits of arbitrage.

Stock illiquidity (*ILLIQ*): The stock illiquidity ratio is the average ratio of the daily absolute return (CRSP code ret) to its dollar trading volume (*DV*) in the past 12 months.

$$ILLIQ_t = \frac{1}{D}\sum_{D=1}^{D}\frac{|ret|}{DV}$$

Idiosyncratic volatility (*IVOL*): Idiosyncratic volatility is measured as the standard deviation of residual returns relating to the FF-3 model (Ang, Hodrick, Xing, & Zhang, 2006).

$$R_{i,\tau} - r_{f,\tau} = \alpha_{i,t} + \beta_{mkt}MKT_{i,\tau} + \beta_{SMB}SMB_{i,\tau} + \beta_{HML}HML_{i,\tau} + \varepsilon_{i,\tau}$$

$$IVOL_{i,t} = Std.Dev(\varepsilon_{i,\tau}) \times \sqrt{D}$$

Every month t, the daily stock returns $R_{i,\tau}$ in excess of US one-month T-bill rate $r_{f,\tau}$, are regressed by MKT, SMB, and HML. This data is available on a daily basis from Professor Kenneth French’s website. The monthly idiosyncratic risk for firm i is thus defined as the standard deviation of the FF-3 model residual $\varepsilon_{i,\tau}$. We convert the daily standard deviation to monthly value by multiplying the square root of number of trading days (D) in the month t.

Institutional ownership (*IO*): Institutional ownership is calculated as the total number of shares held by all institutions in the Thomson Reuters 13-F Filings database, divided by the total number of shares outstanding on the CRSP monthly file (CRSP code shrout). We use CRSP cumulative adjustment factors to adjust the number of stocks held by institutions for confounding corporate events. Thomson Reuters updates the institutional held stocks at the end of every quarter. We match the share information known at the quarter-end month t with CRSP stock information known at month t, $\mathrm{t}-1$ and $\mathrm{t}-2$ respectively and assume the ownership is unchanged within the quarter.

Short interest ratio (*SIR*): The short interest ratio is calculated as the short position on the mid-month date (as reported on the NASDAQ or NYSE monthly short interest files that are recorded in Compustat) divided by the number of shares outstanding on the same date (the 15th of each month, or the previous business day if the 15th is not a business day) as reported on the CRSP daily stock file. This is then multiplied by 100 to express it as a percentage. We use the Morningstar Short Interest Database where the short interest information is not available in Compustat. We use CRSP cumulative adjustment factors to adjust the number of stocks for confounding corporate events such as stock splits.

Firm size (*ME*): A firm's size and is measured by the market value of its equity (CRSP code prc times shrout) in millions of U.S. dollars.

Book-to-market ratio (*BEME*): Following Davis, Fama, and French (2000), a firm's book-to-market ratio is the market value of a firm's equity divided by the book value of its equity. *ME* is the market capitalisation, defined as the December-end closing price multiplied by shares outstanding in millions of US dollars. *BE* is the shareholder’s equity plus deferred taxes and investment credit using the method of Davis, Fama, and French (2000). The definition of book equity (*BE*) is the total shareholders' equity plus deferred taxes and investment tax credit (Compustat item TXDITC), minus the book value of preferred stock (Compustat item PSTK). Depending on the data availability, we use the shareholders' equity as reported by Compustat (Compustat item SEQ). In cases where SEQ is not available, we calculate shareholders' equity as the sum of common and preferred equity (Compustat items CEQ and PSTK). If neither of these two is available, we define shareholders' equity as the difference between total assets and total liabilities (Compustat items AT and LT).

12-month Return Momentum (*MOM12*): This is the cumulative value of stock returns (CRSP code ret) from the past 12 months until 2 months prior to month t.

Table 1: Motivation of linking limits of arbitrage to the distress puzzle

Portfolio	0010	1020	2030	3040	4050	5060	6070	7080	8090	9000
Panel A: Portfolio Performance										
Excess Return	0.23	0.27	-0.06	-0.06	-0.02	-0.02	0.15	0.08	0.33	-0.39
CAPM Alpha	0.12	0.23	-0.09	-0.08	-0.02	-0.06	0.07	-0.06	0.05	-0.78
FF-3 Alpha	0.31	0.39	0.04	0.01	-0.08	-0.12	-0.12	-0.29	-0.25	-1.11
FF-5 Alpha	0.28	0.27	0.00	-0.02	-0.12	0.04	0.04	-0.10	0.12	-0.70
Panel B: Limits of Arbitrage										
BA	1.606	1.237	1.164	1.288	1.592	1.675	2.504	2.725	3.875	5.085
DV	9630.6	20931.3	20732.1	17784.1	13285.9	10773.7	8976.1	5931.2	3764.0	2724.8
ILLIQ	2.701	1.869	2.137	2.216	2.429	3.025	4.404	5.370	9.259	30.581
IVOL	0.025	0.024	0.024	0.024	0.025	0.027	0.030	0.034	0.040	0.055
IO	0.377	0.425	0.429	0.416	0.398	0.376	0.355	0.323	0.296	0.260
SIR	0.058	0.049	0.049	0.055	0.036	0.033	0.034	0.030	0.031	0.029
Panel C: Portfolio Characteristics										
FP	0.009	0.015	0.020	0.027	0.035	0.046	0.061	0.085	0.132	0.469
ME	921.5	2361.5	3075.9	3372.7	3058.9	2769.1	2104	1775.4	1005.6	322.8
BEME	0.686	0.550	0.544	0.574	0.623	0.695	0.767	0.828	0.861	0.889
MOM12	0.333	0.321	0.279	0.230	0.193	0.156	0.123	0.076	-0.022	-0.300

Note: From January 1981, we sort all stocks based on their failure probability into ten deciles and hold them for one month. Panel A reports portfolio average monthly excess returns as well as alphas from CAPM, the Fama-French three-factor model, and the Fama-French five-factor model. All returns are value-weighted and are reported as a percentage. Panel B reports the time-series average value of all limits of arbitrage proxies in each portfolio. *BA* is the 12-month averaged quoted bid-ask spread expressed as a percentage. *DV* is the 12-month averaged dollar volume divided by 106. *ILLIQ* is the 12-month averaged Amihud (2002) illiquidity measure multiplied by 106. *IVOL* is a firm's idiosyncratic volatility related to the Fama-French 3-factor adjusted returns as in Ang, Hodrick, Xing, and Zhang (2006). *IO* is the ratio of common shares held by institutions divided by the total common shares available in the market. *SIR* is the ratio of common shares that are available to short divided by the total common shares available in the market. Panel C reports the time-series average value of a firm's characteristics. *FP* is the month-end failure probability as in CHS (2008), expressed as a percentage. *ME* is the log value of a firm's market value of equity in millions of US dollars. *BEME* is the firm's book-to-market ratio as in Davis, Fama, and French (2000). *MOM12* is the cumulative return of (*t-12, t-2*). The data range is from January 1981 to December 2014, covering a total of 408 months.

Table 2: Summary statistics

Panel A: Distribution of firm characteristics											
Variable	*RET*	*FP*	*ME*	*BEME*	*MOM12*	*BA*	*DV*	*ILLIQ*	*IVOL*	*IO*	*SIR*
Obs.	1368942	1368942	1368942	1368942	1368942	1368941	1355239	1314938	1355763	1220494	902740
Mean	0.007	0.059	2041.0	0.737	0.179	3.256	14.074	2.860	0.028	0.411	0.032
Std.dev	0.326	0.113	12084.4	15.881	0.786	4.195	90.431	16.131	0.022	0.304	0.077
Skewness	754.648	8.964	18.6	1166.644	11.927	3.808	39.506	47.506	3.939	0.581	18.196
P1	-0.384	0.000	3.0	0.038	-0.755	0.025	0.002	0.000	0.004	0.002	0.000
P25	-0.072	0.016	36.5	0.314	-0.198	0.747	0.081	0.006	0.014	0.140	0.001
P50	-0.003	0.030	150.4	0.562	0.062	2.078	0.542	0.084	0.022	0.367	0.009
P75	0.072	0.059	726.0	0.935	0.359	4.051	4.135	1.007	0.036	0.650	0.035
P99	0.518	0.525	34222.3	3.043	2.867	20.341	248.810	46.114	0.107	1.087	0.273
Panel B: Correlation between firm characteristics											
	RET	*FP*	*ME*	*BEME*	*MOM12*	*BA*	*DV*	*ILLIQ*	*IVOL*	*IO*	*SIR*
RET	1.000										
FP	-0.029	1.000									
ME	0.001	-0.047	1.000								
BEME	0.023	0.198	-0.074	1.000							
MOM12	0.022	-0.227	0.020	-0.068	1.000						
BA	0.001	0.195	-0.126	0.243	-0.027	1.000					
DV	-0.001	-0.048	0.593	-0.091	0.023	-0.139	1.000				
ILLIQ	0.008	0.133	-0.054	0.173	-0.007	0.575	-0.062	1.000			
IVOL	-0.033	0.309	-0.146	0.057	-0.089	0.373	-0.126	0.289	1.000		
IO	0.010	-0.155	0.148	-0.128	0.035	-0.497	0.198	-0.253	-0.333	1.000	
SIR	-0.006	-0.013	-0.009	-0.098	0.031	-0.131	0.057	-0.077	-0.022	0.216	1.000

Note: Panel A reports the distribution of all variables and panel B reports the time-series averages of cross-sectional correlations. The sample period is from January 1981 to December 2014, covering a total of 408 months. RET is a stock's monthly return. *FP* is measured as the month-end failure probability as in CHS (2008), expressed as a percentage. *ME* is the log value of the firm's market value of equity in millions of US dollars. *BEME* is the firm's book-to-market ratio as in Davis, Fama, and French (2000). *MOM12* is the cumulative returns of (t-12, t- 2). *BA* is the 12-month averaged quoted bid-ask spread expressed as a percentage. *DV* is the 12-month averaged dollar volume divided by 106. *ILLIQ* is the12-month averaged (Amihud, 2002) illiquidity measure multiplied by 106. *IVOL* is a firm's monthly idiosyncratic volatility related to the Fama-French 3-factor adjusted return as in Ang, Hodrick, Xing, and Zhang (2006). *IO* is the ratio of common shares held by institutions divided by the total common shares available in the market at the month t-1. *SIR* is the ratio of common shares that are available to short divided by the total common shares available in the market at the month t-1.

Table 3: The Distress risk premiums and factor loadings

Portfolio	Alpha	MKT	SMB	HML	RMW	CMA
Panel A: Long-short Portfolio Returns (%)						
Value-weighted Excess Return	0.62					
	(1.38)					
FF-3 Model	1.43	-0.61	-0.44	-1.02		
	(4.09)	(-5.41)	(-2.21)	(-3.28)		
FF-5 Model	0.98	-0.49	-0.29	-1.42	0.65	0.71
	(2.24)	(-4.26)	(-1.63)	(-4.48)	(1.48)	(1.08)
Panel B: Long Leg Monthly Excess Returns (%) – stocks in the lowest distress risk decile						
Value-weighted Excess Return	0.23					
	(1.30)					
FF-3 Model	0.31	1.00	0.39	-0.42		
	(2.17)	(25.39)	(5.34)	(-4.54)		
FF-5 Model	0.28	1.01	0.36	-0.50	-0.04	0.19
	(1.73)	(24.89)	(5.89)	(-6.19)	(-0.33)	(0.87)
Panel C: Short Leg Monthly Excess Returns (%) – stocks in the highest distress risk decile						
Value-weighted Excess Return	-0.39					
	(-1.10)					
FF-3 Model	-1.11	1.61	0.83	0.60		
	(-3.94)	(17.26)	(5.29)	(2.47)		
FF-5 Model	-0.70	1.50	0.66	0.91	-0.69	-0.52
	(-2.11)	(16.31)	(4.01)	(3.28)	(-2.02)	(-1.05)
Panel D: Long-short Portfolio Returns Excluding 1980s (%)						
Value-weighted Excess Return	0.81					
	(1.83)					
FF-3 Model	1.56	-0.71	-0.40	-0.99		
	(3.41)	(-4.96)	(-1.74)	(-2.67)		
FF-5 Model	0.99	-0.49	-0.23	-1.56	0.74	0.92
	(1.95)	(-3.20)	(-1.11)	(-4.52)	(1.66)	(1.18)
Panel E: Long-short Portfolio Returns Since 2004 (%)						
Value-weighted Excess Return	2.11					
	(2.30)					
FF-3 Model	2.82	-0.74	-0.20	-1.33		
	(4.37)	(-4.92)	(-0.62)	(-4.70)		
FF-5 Model	2.64	-0.67	-0.12	-1.39	0.45	0.21
	(3.68)	(-4.13)	(-0.31)	(-4.97)	(1.25)	(0.38)

Note: From January 1981, we sort all stocks based on their FP into deciles, and then hold for one month. The distress risk premium is calculated as the long-short portfolio that result from buying the safest 10% of stocks and shorting the riskiest 10% of stocks. We report the portfolio's monthly value-weighted excess returns (in excess of the one-month U.S. T-bill rate) and risk-adjusted returns by the FF-3 and FF-5 models with corresponding factor loadings. All *t*-statistics (in parentheses) are based on Newey and West (1987) adjusted with a 12-month lag. Panel A reports the monthly performance of the distress risk premium from January 1981 to December 2014. Panel B reports the long side portfolio performance of the distress risk strategy, and panel C reports the performance of the short side in the same sample period. Panel D reports the distress risk premium excluding the 1981-1990 period. Panel E reports the distress risk premium since 2004.

Table 4: Portfolio returns from distress risk-transaction cost double-sort

Panel A: FP-BA Group							
Bid-Ask Spread(BA)	Low FP	2	3	4	High FP	FP Low-High	Low-High FF-3
Low BA	1.35	0.97	0.88	0.94	0.96	0.38	0.84
	(4.38)	(4.15)	(3.49)	(2.98)	(1.92)	(1.06)	(2.54)
2	1.36	1.15	1.11	1.00	0.75	0.61	1.19
	(4.55)	(4.55)	(4.95)	(3.53)	(1.60)	(1.64)	(3.76)
3	1.24	0.80	0.82	1.09	0.54	0.71	1.38
	(4.10)	(2.64)	(2.91)	(3.41)	(0.97)	(1.58)	(3.55)
4	1.47	0.85	0.60	0.66	0.18	1.29	1.95
	(4.18)	(2.75)	(1.94)	(1.88)	(0.36)	(3.38)	(6.45)
High BA	1.64	1.13	0.69	0.82	0.20	1.43	1.85
	(4.44)	(3.20)	(1.90)	(1.73)	(0.45)	(4.69)	(6.14)
BA Low-High	-0.29	-0.16	0.19	0.12	0.76		
	(-0.97)	(-0.49)	(0.52)	(0.29)	(1.61)		
Low-High FF-3	-0.21	0.02	0.37	0.17	0.80		
	(-0.84)	(0.08)	(1.44)	(0.43)	(2.11)		
Panel B: FP-DV Group							
Dollar Volume (DV)	Low FP	2	3	4	High FP	FP Low-High	Low-High FF-3
Low DV	1.81	1.40	1.36	1.57	0.62	1.19	1.51
	(5.51)	(4.56)	(4.53)	(3.62)	(1.39)	(3.22)	(4.28)
2	1.63	1.20	1.18	1.12	0.56	1.07	1.48
	(6.22)	(4.4)	(3.87)	(3.28)	(1.27)	(3.32)	(6.26)
3	1.37	1.19	1.11	1.14	0.58	0.79	1.33
	(5.31)	(4.56)	(4.22)	(3.89)	(1.31)	(2.37)	(5.34)
4	1.25	1.06	1.08	1.19	0.94	0.31	0.93
	(4.5)	(4.64)	(5.01)	(4.66)	(2.21)	(0.92)	(3.41)
High DV	1.30	0.92	0.88	0.96	0.87	0.43	1.03
	(4.06)	(4.09)	(4.00)	(3.29)	(1.80)	(1.22)	(3.39)
DV Low-High	0.51	0.48	0.49	0.62	-0.24		
	(1.48)	(1.72)	(1.72)	(1.77)	(-0.68)		
Low-High FF-3	0.47	0.33	0.39	0.68	-0.01		
	(1.39)	(1.58)	(1.92)	(1.90)	(-0.05)		
Panel C: FP-ILLIQ Group							
Amihud Illiquidity (ILLIQ)	Low FP	2	3	4	High FP	FP Low-High	Low-High FF-3
Low ILLIQ	1.33	0.91	0.92	0.95	0.88	0.45	1.03
	(4.29)	(4.06)	(4.24)	(3.42)	(1.81)	(1.26)	(3.29)
2	1.28	0.99	1.02	1.15	0.86	0.42	1.08
	(4.51)	(4.04)	(4.46)	(4.04)	(1.95)	(1.16)	(3.52)
3	1.50	1.24	1.00	1.04	0.59	0.90	1.43
	(5.08)	(4.39)	(3.64)	(3.30)	(1.29)	(2.52)	(5.18)
4	1.57	1.31	1.19	1.12	0.50	1.07	1.50
	(5.80)	(4.07)	(3.93)	(3.08)	(1.08)	(3.17)	(6.01)
High ILLIQ	1.92	1.43	1.26	1.01	0.25	1.67	1.95
	(5.76)	(4.11)	(3.77)	(2.56)	(0.55)	(6.08)	(8.52)
ILLIQ Low-High	-0.59	-0.51	-0.34	-0.05	0.63		
	(-2.01)	(-1.66)	(-1.11)	(-0.18)	(1.64)		
Low-High FF-3	-0.48	-0.36	-0.19	0.00	0.44		
	(-2.32)	(-1.59)	(-0.91)	(0.01)	(1.40)		

Note: From January 1981 to December 2014, stocks are independently sorted by the firm's distress risk, measured by monthly failure probability (*FP*) and the proxy of transaction cost (measured as the 12-month averaged bid-ask spread (*BA*) in Panel A; monthly dollar volume (*DV*) in Panel B; and monthly Amihud (2002) illiquidity ratio (*ILLIQ*) in Panel C) into quintiles and then held for one month. The performance of the portfolio is measured by the value-weighted returns and FF-3 alpha expressed as a percentage. Standard errors are Newey and West (1987) adjusted.

Table 5: Portfolio returns from distress risk-holding cost/ short selling constraints double-sort

Panel A: FP-IVOL Group Idiosyncratic Volatility (IVOL)	Low FP	2	3	4	High FP	FP Low-High	Low-High FF-3
Low IVOL	1.25	1.09	1.04	1.18	1.33	-0.08	0.45
	(4.56)	(5.44)	(5.21)	(5.29)	(4.13)	(-0.33)	(1.87)
2	1.43	0.89	0.98	0.95	1.27	0.16	0.77
	(4.66)	(3.02)	(4.17)	(3.12)	(3.50)	(0.58)	(3.12)
3	1.34	1.09	0.63	0.79	0.66	0.68	1.29
	(3.65)	(3.31)	(1.98)	(2.00)	(1.26)	(1.68)	(3.52)
4	1.23	0.83	0.48	0.55	0.11	1.12	1.84
	(2.83)	(2.11)	(1.22)	(1.18)	(0.18)	(2.30)	(4.12)
High IVOL	0.90	0.10	-0.03	0.15	-0.85	1.74	2.27
	(2.04)	(0.23)	(-0.06)	(0.29)	(-1.40)	(4.11)	(6.03)
IVOL Low-High	0.35	0.98	1.07	1.03	2.18		
	(1.08)	(2.52)	(2.77)	(2.30)	(4.21)		
Low-High FF-3	0.46	1.05	1.15	1.19	2.27		
	(1.72)	(3.48)	(3.70)	(3.84)	(6.00)		
Panel B: FP-IO Group Institutional Ownership (IO)	Low FP	2	3	4	High FP	FP Low-High	Low-High FF-3
Low IO	2.59	0.82	0.93	1.02	-0.02	2.62	2.89
	(7.06)	(2.61)	(3.61)	(3.45)	(-0.05)	(5.07)	(5.98)
2	1.57	1.27	0.95	1.29	0.41	1.16	1.81
	(4.84)	(4.46)	(3.83)	(4.60)	(0.89)	(3.36)	(5.80)
3	0.92	0.74	0.74	0.49	0.65	0.27	0.83
	(3.34)	(3.36)	(3.34)	(1.80)	(1.56)	(0.73)	(2.53)
4	0.76	0.45	0.43	0.69	0.76	0.00	0.62
	(2.56)	(1.87)	(1.78)	(2.06)	(1.81)	(0.01)	(1.67)
High IO	0.20	0.19	0.20	0.36	0.39	-0.19	0.43
	(0.64)	(0.70)	(0.76)	(1.22)	(0.90)	(-0.62)	(1.82)
IO Low-High	2.40	0.64	0.73	0.65	-0.41		
	(7.32)	(3.01)	(4.50)	(2.77)	(-1.30)		
Low-High FF-3	2.43	0.70	0.84	0.87	-0.03		
	(7.38)	(3.22)	(4.64)	(3.80)	(-0.10)		
Panel C: FP-SIR Group Short Interest Ratio (SIR)	Low FP	2	3	4	High FP	FP Low-High	Low-High FF-3
Low SIR	1.17	0.44	0.53	0.58	0.47	0.70	1.24
	(4.83)	(1.67)	(2.01)	(2.00)	(1.19)	(2.18)	(4.50)
2	0.96	0.55	0.42	0.71	0.62	0.35	0.89
	(3.87)	(2.25)	(1.67)	(2.76)	(1.56)	(1.04)	(2.76)
3	0.50	0.62	0.53	0.85	0.43	0.07	0.57
	(1.76)	(2.51)	(2.14)	(2.97)	(1.17)	(0.23)	(1.78)
4	0.94	0.62	0.54	0.74	0.21	0.73	1.35
	(3.05)	(2.31)	(2.17)	(2.56)	(0.51)	(2.01)	(3.84)
High SIR	1.31	0.83	0.71	0.61	0.52	0.79	1.45
	(3.84)	(2.66)	(2.42)	(1.78)	(1.14)	(2.20)	(4.20)
Low-High	-0.14	-0.39	-0.18	-0.02	-0.04		
	(-0.55)	(-1.70)	(-0.81)	(-0.12)	(-0.15)		
Low-High FF-3	-0.21	-0.42	-0.17	0.06	-0.01		
	(-0.90)	(-1.47)	(-0.73)	(0.30)	(-0.04)		

Note: From January 1981 to December 2014, stocks are independently sorted into quintiles by the firm's distress risk, measured by monthly failure probability (*FP*) and the proxy of holding costs, monthly idiosyncratic volatility (*IVOL*) or the proxy of short-sale constraints *IO* and *SIR*, and then held for one month. The performance of the portfolio is measured by the value-weighted return and FF-3 alpha as a percentage. Standard errors are Newey-West adjusted.

Table 6: Cross-sectional regression: distress risk and limits of arbitrage

Variable	Transaction Cost						Holding Cost		Short-selling Constraint			
	Bid-ask Spread		Dollar Volume		Illiquidity		Idiosyncratic Volatility		Institutional Ownership		Short Interest Ratio	
FP	-4.427***	-4.529***	-3.063*	-4.547***	-5.697***	-5.421***	-1.997	-2.951**	-2.733*	-4.017**	-5.386***	-6.047***
	(-2.99)	(-3.20)	(-1.88)	(-3.00)	(-3.51)	(-3.46)	(-1.50)	(-2.27)	(-1.77)	(-2.19)	(-2.85)	(-3.30)
BA	0.143***	0.133***										
	(5.00)	(3.96)										
DV			-0.019*	0.019***								
			(-1.66)	(2.65)								
ILLIQ					0.087***	0.064***						
					(7.09)	(5.36)						
IVOL							-6.753	-13.313***				
							(-1.04)	(-2.59)				
IO									-0.206	-0.866***		
									(-0.68)	(-3.46)		
SIR											-10.900***	-5.160**
											(-3.47)	(-2.17)
Ln(BEME)		0.524***		0.529***		0.474***		0.487***		0.494***		0.426***
		(4.61)		(4.68)		(4.11)		(4.84)		(4.20)		(4.02)
Ln(ME)		-0.0475		-0.225***		-0.056		-0.196***		-0.234***		-0.117**
		(-0.81)		(-3.31)		(-0.99)		(-4.66)		(-4.35)		(-2.15)
MOM12		0.592***		0.641***		0.579***		0.639***		0.773***		0.654***
		(2.87)		(3.25)		(2.87)		(3.23)		(3.57)		(3.13)
Intercept	0.687***	1.136**	1.007***	2.227***	0.829***	1.323***	1.006***	2.376***	1.016***	1.976***	1.093***	1.740***
	(2.80)	(2.43)	(3.68)	(4.72)	(3.30)	(2.90)	(4.44)	(6.43)	(3.09)	(4.63)	(4.18)	(3.95)
Observations	1475496	1475496	1460255	1460255	1406851	1406851	1459784	1459784	1300916	1300916	948072	948072

Note: For each month from January 1981 to December 2014, we regress a stock's monthly excess returns (CRSP monthly return in excess of the one-month T-bill rate) on a set of independent variables using the regression of Fama and MacBeth (1973). The independent variables included a proxy of stock distress risk, which is measured as the percentage of a firm's failure probability (*FP*) as devised by CHS (2008); a proxy of limits of arbitrage: bid-ask spread expressed as a percentage (*BA*), dollar volume (*DV*), Amihud (2002) illiquidity ratio (*ILLIQ*), idiosyncratic volatility relating to the FF-3 factor model (*IVOL*), percentage of institutional ownership (*IO*), and short interest ratio (*SIR*). For each limits of arbitrage proxy, we also run a regression that includes a set of control variables, namely the log value of book-to-market ratio (*BEME*), the log value of market capitalisation (*ME*), and the 12-month momentum (*MOM12*). Time-series averages of cross- sectional estimated coefficients (×100) are reported. The t-statistics are adjusted by the Newey-West standard error with a 12-month lags. Finally, *, **, and *** indicate that the significance level is 10%, 5%, and 1%, respectively.

Table 7: Cross-sectional regression: distress risk in high and low arbitrage limit stocks

	(1)	(2)	(3)
FP	-4.162***	-4.134***	-2.981***
	(-6.32)	(-6.32)	(-3.95)
High Arbitrage Limit		-0.185***	-0.105
		(-2.72)	(-1.50)
FP High Arbitrage Limit*			-2.535***
			(-3.64)
Control variables	Yes	Yes	Yes
Observations	1475505	869851	869851

Note: For each month from January 1981 to December 2014, we regress a stock's monthly excess returns (CRSP monthly return divided by the one-month T-bill rate) on a set of independent variables using the regression of Fama and MacBeth (1973). The independent variables include a proxy of stock distress risk, which measured as the percentage of firm's failure probability (*FP*) devised by CHS (2008); *High Arbitrage Limit* (dummy variable takes a value of 1 if the value of limits of arbitrage indicator is above its cross-sectional average of the year, otherwise 0) and a set of control variables including the log value of a stock's book-to-market ratio (*BEME*), the market value of equity (*ME*), and the 12-month momentum (*MOM12*). The t-statistics are adjusted by the Newey-West standard error with a 12-month lag. Finally, *, **, and *** indicate that the significance level is 10%, 5%, and 1%, respectively.

Table 8: Portfolio returns from distress risk-limits of arbitrage double-sort without penny stocks

	BA as limits of arbitrage		*DV* as limits of arbitrage		*ILLIQ* as limits of arbitrage		*IVOL* as limits of arbitrage		*IO* as limits of arbitrage		*SIR* as limits of arbitrage	
	Raw Return	FF-3 Alpha	Raw Return	FF-3 Alpha	Raw Return	FF-3 Alpha	Raw Return	FF-3 Alpha	Raw Return	FF-3 Alpha	Raw Return	FF-3 Alpha
Low limits of arbitrage	0.66	0.95	0.43	0.96	0.50	0.96	-0.05	0.27	-0.14	0.56	0.75	1.46
	(1.97)	(2.70)	(1.72)	(3.57)	(1.77)	(3.56)	(-0.23)	(1.59)	(-0.44)	(1.84)	(1.83)	(4.05)
2	0.78	1.33	0.34	0.92	0.43	1.00	0.42	1.02	-0.11	0.55	0.20	0.98
	(2.49)	(4.43)	(1.27)	(3.53)	(1.57)	(3.68)	(1.54)	(3.99)	(-0.32)	(1.67)	(0.52)	(3.09)
3	1.21	1.69	0.51	0.97	0.75	1.25	0.80	1.37	0.23	0.91	-0.34	0.19
	(3.79)	(5.23)	(2.29)	(4.21)	(3.00)	(4.45)	(2.66)	(4.97)	(0.66)	(2.79)	(-1.02)	(0.54)
4	1.15	1.65	0.91	1.30	0.98	1.39	1.12	1.78	1.13	1.85	0.37	1.03
	(3.61)	(5.82)	(4.46)	(5.68)	(4.23)	(6.12)	(3.17)	(3.54)	(2.86)	(5.03)	(0.98)	(2.85)
High limits of arbitrage	1.69	2.12	1.31	1.63	1.45	1.77	1.53	2.16	2.17	2.58	0.63	1.14
	(6.32)	(8.64)	(5.54)	(6.28)	(7.02)	(8.85)	(4.20)	(5.84)	(5.18)	(6.20)	(1.90)	(3.56)

Note: From January 1981 to December 2014, stocks with a stock price over one US dollar are independently sorted by monthly failure probability (*FP*) and the proxy of limits of arbitrage, bid-ask spread expressed as a percentage (*BA*), dollar volume (*DV*), Amihud (2002) illiquidity ratio (*ILLIQ*), idiosyncratic volatility relating to the FF-3 factor model (*IVOL*), percentage of institutional ownership (*IO*), or short interest ratio (*SIR*). The performance of the portfolio is measured by value-weighted excess return as well as FF-3 alpha as a percentage. Standard errors are Newey-West adjusted.

Table 9: 12-month returns from distress risk-limits of arbitrage double-sort

	BA as limits of arbitrage		*DV* as limits of arbitrage		*ILLIQ* as limits of arbitrage		*IVOL* as limits of arbitrage	
	Raw Return	FF-3 Alpha	Raw Return	FF-3 Alpha	Raw Return	FF-3 Alpha	Raw Return	FF-3 Alpha
Low limits of arbitrage	0.23	0.77	0.29	0.81	0.27	0.79	0.04	0.86
	(0.93)	(2.03)	(0.80)	(2.89)	(0.75)	(2.23)	(0.10)	(2.18)
2	-0.59	-0.26	0.18	0.89	0.38	0.99	0.42	1.07
	(-1.48)	(-0.67)	(0.60)	(3.52)	(1.12)	(3.14)	(1.22)	(3.41)
3	-0.58	-0.04	0.50	0.89	0.18	0.76	0.54	1.00
	(-1.69)	(-0.13)	(1.63)	(3.47)	(0.56)	(2.51)	(1.89)	(3.66)
4	0.24	0.81	0.33	0.80	0.14	0.76	0.20	0.67
	(0.72)	(2.56)	(1.21)	(3.45)	(0.46)	(2.74)	(0.66)	(2.30)
High limits of arbitrage	0.67	1.38	1.54	0.84	1.33	1.80	0.47	0.75
	(1.93)	(3.31)	(3.88)	(2.19)	(2.84)	(3.09)	(1.96)	(3.19)

Note: From January 1981 to December 2014, stocks are independently sorted by monthly failure probability (*FP*) and the proxy of limits of arbitrage, bid-ask spread expressed as a percentage (*BA*), dollar volume (*DV*), Amihud (2002) illiquidity ratio (*ILLIQ*), or idiosyncratic volatility relating to the FF-3 factor model (*IVOL*). The performance of the portfolio is measured by value-weighted 12-month holding period excess return as well as FF-3 alpha as a percentage.. Standard errors are Newey-West adjusted.