Idiosyncratic Risk, Financial Distress and the Cross Section of Stock Returns

Finance
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Henri Kotiaho
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ABSTRACT
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IDIOSYNCRATIC RISK, FINANCIAL DISTRESS AND THE CROSS SECTION OF STOCK RETURNS

PURPOSE OF THE STUDY

This study examines the asset pricing impact of idiosyncratic risk and financial distress on cross sectional stock returns. Specifically, I investigate whether financial distress can explain the correlation between conditional idiosyncratic volatility and return and vice versa. Idiosyncratic volatility is defined as standard deviation of the firm return that cannot be explained by the Fama French (1993) three factor model. This study is the first to investigate the interaction between idiosyncratic risk and financial distress by employing generalized autoregressive conditional heteroskedasticity GARCH models to measure conditional idiosyncratic volatility and in addition to unpublished working paper by Song (2008), first to employ Campbell et al. (2008) measure of financial distress using both market and accounting variables.

DATA

This study targets all common shares that are traded in NYSE, AMEX and NASDAQ during the period between 1971 and 2008. The market data is obtained from Center for Research in Security Prices (CRSP) and the accounting data from COMPUSTAT database. The sample consists of 18 795 unique stocks.

RESULTS

The results indicate a positive relation between idiosyncratic risk and expected stock returns, which like many other anomalies is mainly driven by smaller stocks. The relation between distress risk and expected stock returns is found to be negative.

I find that both idiosyncratic volatility and financial distress maintain their explanatory power when both variables are included in the cross-sectional regression. In the multivariate independent sort, the positive relation between idiosyncratic volatility and stock returns is shown to be conditional on low distress risk. A positive relation is found in low distress risk quintiles but in high distress risk quintiles the idiosyncratic volatility spread is insignificant. The negative effect of distress risk persists after controlling for idiosyncratic volatility across idiosyncratic volatility quintiles in multivariate independent sort. The findings indicate that financials distress risk has a more fundamental asset pricing impact than idiosyncratic volatility.

KEYWORDS

Asset pricing, idiosyncratic risk, financial distress, expected returns

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TIIVISTELMÄ
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IDIOSYNKRAATTINEN RISKI, KONKURSSIRISKI JA ODOTETUT OSAKETUOTOT

TUTKIELMAN TAVOITE

Tutkielman tavoitteena on selvittää idiosynkraattisen riskin ja konkurssiriskin vaikutusta osaketuottoihin. Tavoitteena on erityisesti tutkia selittääkö konkurssiriski idiosynkraattisen riskin ja osaketuottojen korrelaatiota ja päinvastoin. Idiosynkraattisen riskin mittarina on osaketuottojen volatiliteetti, joka ei selity Faman ja Frenchin (1993) kolmen faktorin mallilla. Tutkielma on ensimmäinen, jossa idiosynkraattisen riskin ja konkurssiriskin interaktion tutkimisessa ehdollista idiosynkraattista volatiliteettiä mallinnetaan GARCH –prosessilla.

AINEISTO

Tutkielman aineisto koostuu NYSE, AMEX ja NASDAQ pörsseissä listattujen yritysten osaketuotoista vuosien 1971 ja 2008 välillä. Osakemarkkinadata on haettu Center for Research in Security Prices (CRSP) tietokannasta ja tilinpäätösinformaation COMPUSTAT tietokannasta. Lopullinen aineisto sisältää 18 195 yksittäistä osaketta.

TULOKSET

Tulokset osoittavat että idiosynkraattinen riskin ja osaketuottojen välillä on positiivinen suhde, joka keskittyy lähinnä pienten yritysten osakkeisiin. Konkurssiriskin ja osaketuottojen välinen suhde on puolestaan negatiivinen.

Regressioanalyysin tulokset osoittavat että idiosynkraattinen riski ja konkurssiriski säilyttävät merkitsevyytensä, kun molemmat muuttajat ovat mallissa mukana. Portfoliot, joiden osakkeet on lajiteltu itsenäisesti idiosynkraattisen riskin ja konkurssiriskin mukaan osoittavat, että korkean idiosynkraattisen riskin osakkeilla on positiiviset epänormaalit tuotot vain jos konkurssiriski on samalla matala. Korkean konkurssiriskin ja osaketuottojen välillä on puolestaan negatiivinen suhde sekä matalan että korkean idiosynkraattisen riskin portfolioissa. Tulokset osoittavat että konkurssiriski on merkittävämpi tekijä osakkeiden hinnoittelussa kuin idiosynkraattinen riski.

AVAINSANAT

Idiosynkraattinen riski, konkurssiriski, osaketuotot

Table of Contents:

List of Tables and Figures

Tables:

Figures:

1. Introduction

Idiosyncratic risk and financial distress have been under close scrutiny recently in the asset pricing literature and have been used to explain otherwise anomalous patterns in the cross section of stock returns (e.g. Fu, 2009; Campbell et al., 2008; Ang et. al., 2006). Contrary to the conventional expectation of insignificant asset pricing impact of these measures, previous empirical literature has found positive or even negative pricing impact of idiosyncratic volatility and distress risk. These concepts have also become current due the recent financial crisis, during which we have seen the level of both measures increasing substantially from historically low levels between 2003 and early 2007. My results show that the average idiosyncratic volatility has more than doubled between 2006 and 2008. Global default rates for sub investment grade bonds have meanwhile broken the post Depression record. The trailing 12 month average rose to 12.4% in October 2009. For comparison, a year ago the global default rate stood at only 3.0%[1].

The capital asset pricing model (CAPM) of Sharpe (1964), Lintner (1965a) and Black (1972) predicts that only systematic risk is priced in the stock returns. This is because investors are assumed to be able to diversify away idiosyncratic risk by holding well-diversified portfolios. However, in practice investors may fail to hold diversified portfolios for various reasons (e.g. Malkiel & Xu, 2004; Merton, 1987). This would lead in less diversified investors demanding a risk premium for bearing idiosyncratic risk. Furthermore, Barberis and Huang (2001) show that if investors are loss averse over individual stock fluctuations, expected premiums will depend on prior performance and also total risk will be positively correlated with expected returns.

The role of idiosyncratic risk on asset pricing has been under intense academic debate since an influential study by Campbell, Lettau, Malkiel, and Xu (2001). They explore the volatility of U.S. stocks at the market, industry, and firm levels over the period from 1962 to 1997. Campbell et al. (2001) find that while the market and industry level volatilities have remained quite stable, the average firm-level volatility exhibits a strong positive deterministic trend, more than doubling over the period.

[1] Moody's (2008)

Numerous papers have explored the relation between idiosyncratic risk and return both on cross-section and across time. However, the results have been inconsistent and depend heavily on the selected methodology to measure idiosyncratic risk.

Malkiel and Xu (2004) provide empirical evidence to the under-diversification hypothesis and find a positive relation between idiosyncratic risk and cross-sectional stock returns. Using exponential generalized autoregressive conditional heteroskedasticity (EGARCH) model to estimate conditional idiosyncratic volatility, Spiegel and Wang (2005) and Fu (2009) also find a significantly positive relation between idiosyncratic risk and expected returns.

On the other hand, some authors have found a puzzling negative relation between idiosyncratic risk and cross-sectional stock returns. Using daily data to estimate idiosyncratic risk, Ang et al. (2006, 2009) find that stocks with high idiosyncratic volatility have abysmally low average returns both in US and in other G7 countries. This negative cross-sectional relation contradicts the basic fundamental of finance that higher risk is compensated with higher returns. Guo and Savickas (2006) argue that idiosyncratic risk can be a proxy for dispersion in opinion among investors. Their hypothesis is that an increase in idiosyncratic risk leads the most optimistic investors to hold a particular stock, and thus we should find a negative relation between idiosyncratic risk and return.

Financial distress has also been theorized to impact stock returns. The idea is that stocks of financially distressed companies tend to move together so that their risk cannot be diversified away (Chan & Chen, 1991). Fama and French (1996) argue that financial distress is a driving factor behind the size and value effects. The covariation can exist if corporate failures are correlated with a measure not accounted in the standard CAPM, such as deteriorating investment opportunities (Merton, 1973) or declines in unmeasured components of wealth such as human capital (Fama & French, 1996) or debt securities (Ferguson & Shockley, 2003).

Several papers have studied the impact of financial distress on stock returns with contradictory results. Griffin and Lemmon (2002) find supporting evidence to Fama and French (1996) and show that the value premium is most significant among firms with high probability of financial distress. Vassalou and Xing (2004) also demonstrate that both the size and book-to-market effects are concentrated in high default risk firms. However, Dichev

(1998) and Campbell, Hilscher, and Szilagyi (2008) document that firms with high risk of financial distress have delivered anomalously low returns.

There is an intuitive reason to believe that these two puzzles are related to each other. According to the Merton's (1974) model, corporate debt is a risk-free bond less a put option on the value of the firm's assets, with strike price of the face value of the debt. Thus, a firm with more volatile equity is more likely to reach the boundary condition of default. Based on this argument, Campbell and Taksler (2003) show that idiosyncratic firm-level volatility can explain a significant part of cross-sectional variation in corporate bond yields. This suggests a possibility that the idiosyncratic volatility-return relationship may be due to a distress-return relationship or vice versa.

Only two recent working papers explore this interaction. Following Ang et al. (2006), Song (2008) estimate idiosyncratic volatility using daily data from one month period and find that while the volatility spread is -1.68% for the most distressed stocks, it is actually positive and significant at 0.61% per month for the least distressed ones. Similarly, Chen and Chollete (2006) find that after controlling for distress risk, stocks with high idiosyncratic volatility earn significantly low returns only in the highest distress risk quintile. Both conclude that distress risk has a more fundamental asset pricing impact than idiosyncratic volatility.

However, Fu (2009) argues that due to the time varying property of idiosyncratic volatility, lagged one month volatility may not be an appropriate proxy for the expected volatility this month. In order to capture the time varying property of idiosyncratic volatility, Fu suggest the use of GARCH models. Therefore, it is of interest to study the interaction of idiosyncratic volatility and financial distress using these more sophisticated models.

1.1 Objectives of the study

Purpose of this study is to empirically explore the asset pricing impact of idiosyncratic risk and financial distress on cross-sectional stock returns. I investigate whether financial distress can explain the correlation between conditional idiosyncratic volatility and return and vice versa.

This study contributes to the existing literature by relating the idiosyncratic risk to financial distress. To my best knowledge, in addition to an unpublished paper by Song (2008), this is the first paper to examine the relation of idiosyncratic volatility and distress risk using a sophisticated measure of financial distress by Campbell et al. (2008). Furthermore, this is the first study to investigate the interaction of idiosyncratic risk and financial distress by using a generalized autoregressive conditional heteroskedasticity (GARCH) models to estimate idiosyncratic risk. In addition, by employing several GARCH models, I test whether the positive relation of idiosyncratic volatility and returns found for example by Fu (2009) is model specific to EGARCH. I employ to commonly used approach to identify anomalies in my study: cross-sectional Fama-Macbeth regressions and sorts of portfolios on idiosyncratic volatility and distress risk.

1.2 Main results

By using EGARCH(1,1) model to estimate the expected conditional idiosyncratic volatility, I find a positive relation between idiosyncratic risk and expected stock returns in cross-sectional regressions. The relations is shows to be non model specific as a positive relation is also found by using GJR and GARCH(p,q) models. The relation is robust after controlling for market beta, size, book-to-market, momentum, short term return reversal and liquidity effects. The results are consistent with Spiegel and Wang (2005) and Fu (2009). However, a closer inspection of size effects by running the regressions in different size groups reveals that the relation is driven by micro and small stocks, defined by 20% and 50% percentile breakpoints of market capitalization for NYSE stocks. Due to this reason, the positive relation in portfolio sorts is found only with equally weighted portfolios. The relation between distress risk and expected stock returns is found robustly negative in both cross-sectional regressions and portfolio sorts. The results are consistent with previous empirical work by Campbell et al. (2008).

I find that both idiosyncratic volatility and financial distress maintain their explanatory power when both variables are included in the cross-sectional regression. This result is to the contrary of previous results of Song (2008) and Chen and Chollette (2006) who find that idiosyncratic volatility loses its asset pricing impact when distress risk is included in the regressions.

In the multivariate independent sort, the positive relation between idiosyncratic volatility and stock returns is shown to be conditional on low distress risk. A positive relation is found in low distress risk quintiles but in high distress risk quintiles the idiosyncratic volatility spread is insignificant. This moderating effect of distress risk on the asset pricing impact of idiosyncratic volatility, meaning that lower distress risk is associated with more positive idiosyncratic volatility spread, is consistent with findings of Song (2008) and Chen and Chollette (2006). However, contrary to Song (2008), I do not find a negative relation between idiosyncratic volatility and distress risk even in the highest distress risk quintile.

The negative effect of distress risk persists after controlling for idiosyncratic volatility across idiosyncratic volatility quintiles in multivariate independent sort. This is consistent with findings of Song (2008) and Chen and Chollette (2006) that distress risk has a more fundamental asset pricing impact than idiosyncratic volatility.

1.3 Structure of the study

The remaining of the study is structured as follows. In Section 2, I look at the existing theoretical and empirical literature on the relation between risk and expected returns and specifically effects of idiosyncratic volatility and financial distress. In Section 3, I present the hypotheses. Section 4 provides the description of the data and introduces the methodologies. In Section 5 I describe my tests and section 6 presents the empirical results and analysis. Finally, Section 7 concludes.

2. Literature review

This chapter reviews the relevant literature for my study. The first section discusses the theories of market risk and return including CAPM and intertemporal CAPM, which form the basis for subsequent discussion. In the second and third section I focus on the most relevant theories for my study, namely those concerning idiosyncratic risk and financial distress. In addition, these sections review the most important empirical evidence that has strongly promoted the theoretical development in these areas. Finally, I review the recent empirical studies exploring the link between idiosyncratic risk and financial distress effects and discuss the theoretical similarities between them.

2.1 Market risk and return

Capital Asset Pricing Model (CAPM) of Sharpe (1964), Lintner (1965a) and Black (1972) implies that a positive relation exists between the expected return on securities and their market betas and other variables should not capture the cross-sectional variation in expected returns. Early empirical cross-sectional tests of CAPM (see eg. Blume & Friend, 1973; Fama & MacBeth, 1973) seem support a positive cross-sectional relation between market risk and expected stock returns. However, many subsequent authors find that market beta alone cannot capture all the dimensions of risk, the size effect documented by Banz (1981), book-to-market effect by Rosenberg et al., 1985 and leverage effect by Bhandari (1988). Basu (1983) shows that price to earnings ratio helps to explain the cross-sectional returns. Moreover, Roll (1977) points out that it is difficult if not impossible to test CAPM empirically because market portfolio cannot be defined completely. Later, Fama and French (1992) show that in cross section, the relation between market beta and average return is flat and size and book-to-market equity alone capture the cross-sectional variation in stock return. Other cross-sectional explanatory variables of stock returns include the momentum effect of Jegadeesh and Titman (1993) and the liquidity risk documented by Pástor & Stambaugh (2003).

A static, single period CAPM has been extended to intertemporal setting (e.g., Merton, 1973; Campbell 1993, 1996). Unlike in CAPM where an investor is expected to maximize his return over a single period, in intertemporal setting an investor takes into account the current period returns and the returns that will be available in the future, i.e. future investment opportunities. Merton (1973) shows that when investment opportunities vary over time, the conditional expected excess return on the stock market should vary positively with the market's conditional variance:

$$E_t[R_{t+1}] = \mu + \gamma Var_t[R_{t+1}], \tag{1}$$

where γ is the coefficient of investor's relative risk aversion and the mean term μ should be zero. Merton's model is intuitive as it predicts that investors require larger risk premium during times when the payoff from the security is more risky.

Empirical tests on ICAPM have been inconclusive. Often the relation between risk and return has been found insignificant, and sometimes negative. Pindyck (1984) shows that increase in variance of stock returns can explain a large amount of the decline in stock prices between 1965 and 1981. French et al. (1987) find a positive relation between expected stock market return and conditional volatility using a GARCH model. Positive relation between volatility and expected returns is also found by Whitelaw (1994) and Scruggs (1998). On the other hand, Glosten et al. (1993) and Campbell (1987) find evidence to support a negative time-series relation between risk and expected returns.

Theoretical relation between market risk and return on a stock as opposed to the whole market across time is, however, not as clear as market return and risk relation. Campbell's (1993, 1996) ICAPM shows that investors care about both market risk and risk of changes in forecasts of future market returns. In Campbell's model, risk-averse investors want to hedge against changes in aggregate volatility because volatility positively affects future expected market returns as in Merton (1973). Chen (2002) extends Campbell's model to heteroskedastic environment to allow market volatility directly affect the expected returns. In Chen's model risk averse investors also want to directly hedge against changes in future market volatility. Chen shows that for a risk averse investor, an asset that has a positive covariance between its return and a variable that positively forecasts future market volatilities causes the asset to have a lower expected return. In other words, the relation between market risk and return of a stock across time can also be negative. Several studies using options on an aggregate market index or options on individual stocks as a measure of aggregate volatility have found a negative relation between sensitivity to market volatility and stock returns (eg. Coval & Shumway, 2001;Ang et al., 2006).

2.2 Idiosyncratic risk and return

The capital asset pricing model (CAPM) of Sharpe (1964), Lintner (1965a) and Black (1972) relies on the assumption that investors are well diversified. However, many authors have suggested that both systematic and idiosyncratic risk might matter to investors in practice due to poor diversification or behavioral reasons. Moreover, idiosyncratic risk is a proxy for omitted factors in the CAPM model, which may cause a relation between idiosyncratic risk and stock returns.

2.2.1 Theoretical motivation

Firstly, Levy (1978), Merton (1987) and Malkiel and Xu (2004) suggest that idiosyncratic risk is priced because many investors hold poorly diversified portfolios. This means that the remaining, “unconstrained”, investors are also unable to hold market portfolios. This is because the undiversified investors’ and unconstrained investors’ holdings together make up the whole market. An inability to hold the market portfolio will force investors to care about total risk and not simply market risk. As Malkiel and Xu (2004) note: “an idiosyncratic risk premium can be rationalized to compensate investors for the “over supply” or “unbalanced supply” of some assets”. Transaction costs are an obvious reason to prevent individual investors from holding large numbers of individual stocks though behavioral reason can be even stronger. Goetzmann and Kumar (2004) shown that more than 25% of retail investors hold only one stock in their portfolio, over half of the investor portfolios contain no more than three stocks and less than 10% of the investor portfolios contain no more than 10 stocks.

Furthermore, institutional investors too rarely hold an indexed portfolio. Approximately only 10 percent of the mutual funds held by individuals were indexed in 2003 while about one quarter of institutional funds were indexed (Malkiel and Xu, 2004). Importance of idiosyncratic risk in active portfolio management is also highlighted by Cremers and Petajisto (2009) who find that active managers who have the highest exposure to idiosyncratic risk have outperformed their benchmarks both before and after expenses.

Second, a behavioral model by Barberis and Huang (2001) predicts that idiosyncratic volatility should be positively related to expected stock returns. Key ideas behind the model include investors’ loss aversion and narrow framing. Loss aversion is a is a finding that people are more sensitive to losses than gains, first demonstrated by Kahneman and Tversky (1979). Furthermore, evidence suggests that degree of loss aversion depends on prior gains and losses. Narrow framing means that when people evaluate changes in their wealth, they often appear to pay attention to narrowly defined gains and losses such as price appreciation of a stock they own rather than the change in their total wealth. Barberis and Huang show that investors' loss aversion over individual stock fluctuations leads the expected premium to depend on prior performance. The model also predicts that total risk is positively correlated with expected returns, implying that idiosyncratic risk should also command a premium.

Third, idiosyncratic risk premium may be related to omitted assets problem in the market portfolio proxy. Eiling (2006) shows that the idiosyncratic risk premium is related to hedging demand due to investors' non-tradable human capital. When labor income is correlated with stock returns, exposure to the firm specific risk induces a hedging demand for an employee and consequently, human capital can affect the risk premium for stocks.

Fourth, idiosyncratic risk could be a determinant of equity premium due to omitted risk factors. By construction, it measures conditional variance of the risk factors of a multi-factor ICAPM model omitted from CAPM (Merton, 1973; Campbell, 1993, 1996). Hence, idiosyncratic volatility can be seen as a proxy for omitted factors such as liquidity risk or dispersion of analysts' opinion (Guo & Savickas, 2006). Brunnermeier and Pedersen (2009) generate a positive relationship between idiosyncratic risk and return within a market liquidity model where investors face margin requirements that limit their ability to maintain levered positions when stock prices turn downward. Empirical paper by Spiegel and Wang (2005) finds also an inverse relation between idiosyncratic risk and liquidity, though they find that idiosyncratic volatility itself explains cross-sectional stock returns more than liquidity.

On the other hand, idiosyncratic risk as a proxy for dispersion of opinion predicts a negative relationship between idiosyncratic risk and return. Miller (1977) shows that under short-sale constraints, increases in risk imply higher divergence of opinion, resulting in most optimist investors to hold a particular stock. Thus it is possible that expected return can be lower for riskier securities.

Ang et al. (2006) hypothesize that stocks with large idiosyncratic risk have large exposure to movements in aggregate volatility. According to Ang et al. this could imply a negative relation between idiosyncratic risk and expected returns as they find a negative relation between stock returns and sensitivity to market volatility. Idiosyncratic volatility can also be priced with a negative price of risk if it can predict changes in market volatility following Chen's (2002) model in which risk averse investors want to hedge future changes in aggregate volatility. Campbell et al. (2001) indeed find that firm level volatility can predict changes in market volatility. Ang et al. (2008) test their hypothesis but find only partial support that exposure to aggregate volatility can explain low returns of high idiosyncratic risk stocks.[2]

Finally, Boyer et al. (2007) document empirical evidence that idiosyncratic volatility is a good predictor of expected skewness. Barberis and Huang (2008) show that investors have a strong preference for positively skewed portfolios under the assumption that investors have preferences based on the cumulative prospect theory of Tversky and Kahneman (1992). Under cumulative prospects theory, investors are risk averse and use transformed rather than objective probabilities for returns, which overweigh the tails of the objective distribution. This captures the common preference for a lottery-like, or positively skewed, wealth distribution. Under these assumptions, a positively skewed portfolio can be overpriced and earn a negative average excess return.

To sum up, theories for a positive relation between idiosyncratic risk and stock returns include both long term fundamental explanations such as under-diversification and short term behavioral reasons like narrow framing of gains and losses. Negative theories focus on short term effects such as dispersion of analyst opinion and behavioral reasons such as skewness of returns, or relate to more general theories of intertemporal relation between risk and return which include also a possibility for a negative relation.

2.2.2 Empirical evidence

An influential study by Campbell et al. (2001) explores the volatility of U.S. stocks at the market, industry, and firm levels over the period from 1962 to1997. Campbell et al. find that while the market and industry level volatilities have remained quite stable, the average firm-level volatility exhibits a strong positive deterministic trend, more than doubling over the

[2] Ang et al. (2006) find that exposure to aggregate volatility partially explains the puzzling low returns to high idiosyncratic volatility stocks, but only for stocks with very negative and low past loadings to aggregate volatility innovations.

period. In addition, firm level volatility accounts for the greatest share of total average firm volatility and for the greatest share of movements over time in total firm volatility. Firm level volatility can also predict changes in market volatility though market volatility tends to lead other components of volatility. Numerous studies have since studied the asset pricing impact of idiosyncratic volatility. Table 1 presents an overview of the empirical results both on the intertemporal and cross-sectional relationship.

Table 1. Empirical evidence on idiosyncratic risk and return

The table presents an overview of the previous empirical literature on the intertemporal and cross-sectional relations between idiosyncratic risk and expected stock returns. FF-3 refers to Fama French (1993) three factor model and EGARCH to exponential GARCH introduced by Nelson (1991).

Study	Sample period	Idiosyncratic risk definition	Measure of expected volatility	Result
Panel A: Intertemporal relationship				
Goyal & Santa-Clara (2003)	1926-1999	Total variance	Lagged	Positive relation
Bali et al. (2005)	1962-2001	Total variance	Lagged	No relation
Guo & Savickas (2006)	1963-2002	Total variance	Lagged	Negative relation
Panel B: Cross-sectional relationship				
Lintner (1965b)	1954-1963	CAPM residuals	Lagged	Positive relation
Lehmann (1990)	1931-1983	CAPM residuals	Lagged	Positive relation
Malkiel & Xu (2004)	1975-2000	Total variance	Lagged	Positive relation
Spiegel & Wang (2005)	1962-2003	FF-3 residuals	EGARCH	Positive relation
Ang et al. (2006)	1963-2000	FF-3 residuals	Lagged	Negative relation
Eiling (2006)	1959-2005	CAPM residuals	EGARCH	Positive relation
Huang et al. (2007)	1963-2004	FF-3 residuals	EGARCH	Positive relation
Brockman & Schutte (2007)	1980-2007	FF-3 residuals	EGARCH	Positive relation
Bali & Cakici (2008)	1963-2004	FF-3 residuals	Lagged	No relation
Fu (2009)	1963-2006	FF-3 residuals	EGARCH	Positive relation

Studies investigating the intertemporal relationship between idiosyncratic risk and future stock market return have found contradictory results. Goyal and Santa-Clara (2003) find a positive relationship between idiosyncratic volatility[3] and future stock market returns. Bali et al. (2005) argue that Goyal and Santa-Clara results are mainly driven by small stocks and

[3] Goyal and Santa-Clara use average stock variance which is a measure of total risk as a proxy for idiosyncratic risk.

partly due to a liquidity premium. Guo and Savickas (2006) find a negative relation between the market level idiosyncratic risk and expected returns.

The most relevant papers for my study are those, which investigate the cross-sectional relationship between idiosyncratic risk and stock returns. Early studies by Lintner (1965b) and Lehmann (1990) find a positive relation between idiosyncratic volatility and cross section of stock returns. Malkiel and Xu (2004) find a positive relation between idiosyncratic risk and cross-sectional stock returns using monthly data. Switching to daily data, Ang et al. (2006, 2009) find that stocks with high idiosyncratic risk have abysmally low average returns both in US and in other G7 countries. However, Bali and Cakici (2008) show that Ang et al. (2006) results are not robust with different estimation methods. They show that results are sensitive to (i) data frequency (daily or monthly) used to estimate idiosyncratic volatility, (ii) weighting scheme (value- or equally-weighted) used to compute average portfolio returns and, (iii) breakpoints (CRSP, NYSE, equal market share) used to sort portfolios into quintiles and (iv) using a screen for size, price and liquidity. Furthermore, Huang et al. (2007) and Fu (2009) using different methods show that Ang et al. (2006) results are driven by monthly stock return reversals.

Using EGARCH method to estimate conditional idiosyncratic volatility, Spiegel and Wang (2005), Eiling (2006), Huang et al. (2007) and Fu (2009) find a significantly positive relation between idiosyncratic risk and expected returns. Brockman and Schutte (2007) find a positive relationship also in the international data. Furthermore, Brockman and Schutte show that the size of the idiosyncratic risk premium is related to the level of investor under-diversification. Baker and Wurgler (2005) find that conditional on investor sentiment idiosyncratic risk can be positively or negatively correlated with the expected return.

To summarize, majority of empirical studies support a positive relation between idiosyncratic risk and stock returns. However, with shorter term measures derived from daily return data, the relation between idiosyncratic volatility and stock returns is also found to be negative. Overall, the empirical evidence seems to support theories that idiosyncratic risk commands a risk premium due to under-diversification or omitted risk factors. The negative relation observed with daily data may indicate that in short term may be due to dispersion of analyst opinion or due to return reversals.

2.3 Risk of financial distress and return

Financial distress has been frequently invoked in the asset pricing literature to explain anomalies in the cross-section of stock returns. Value and size effects have been attributed to be proxies for financial distress (Chan & Chen, 1991; Fama & French, 1996). Chan and Chen (1991) show that the returns of financially distressed firms move together in a way that is not captured by the market return. Due to this covariation, the elevated risk of financial distress cannot be diversified away and hence investors charge a premium for bearing such risk. Similarly, Fama and French (1996) show that book-to-market equity and loadings of high-minus-low (HML) portfolio are proxy for relative distress.

2.3.1 Theoretical motivation

The premium of distress risk may not be captured by the CAPM if corporate failures are correlated either across time or an asset that is not included in the proxy for the market portfolio. Campbell et al. (2008) point out that corporate failures may not be captured by CAPM if they are correlated with deteriorating investment opportunities, which are related to expected returns in Merton's (1973) ICAPM model. In other words, one can formulate a version of ICAPM where default risk affects the investment opportunity set, and hence, investors want to hedge against this source of risk (Vassalou & Xing, 2004).

Fama and French (1996) attribute distress risk, of which they use the term "relative distress", to an unmeasured component of the market portfolio, human capital. Workers with specialized human capital are more likely to be sensitive to negative shocks to a firm's prospects if the firm is in distress. This is because as a shock is more likely to lead a contraction of employment in that firm as firm needs to reduce costs to stay afloat. Thus workers with specialized human capital have an incentive to avoid holding their firms stock. Furthermore if the variation in distress is correlated across firms, workers have an incentive to avoid the stocks of all distressed firms. This can result in distress risk to command a risk premium in the expected returns of distressed stocks.

Ferguson and Shockley (2003) argue that distress risk is priced in equity returns because it captures the missing beta risk of an equity only market proxy. Betas estimated using an equity-only proxy for the market portfolio will understate equity betas, with the error increasing with the firm's relative degree of leverage and level of financial distress. Hence, firm specific variables that correlate with leverage such as market-to-book and size will appear to explain returns after controlling for proxy beta, simply because they capture the missing beta risk. Using a three factor model incorporating the market return along with portfolios formed on variables statistically related to relative leverage and relative distress, Ferguson and Shockley (2003) find that the model outperforms the Fama and French (1993) three factor model in explaining returns on the 25 size and book-to-market sorted portfolios.

Despite the above plausible theories why distress risk might command a risk premium, low returns of distressed stocks documented for example by Dichev (1998) and Campbell et al. (2008) present a substantial puzzle as they are in violation of traditional risk-return models. Possible explanations for a negative relation of distress risk and expected returns include an in-sample phenomenon, skewed returns of distressed stocks, possible rent extraction by shareholders and valuation errors by irrational of imperfectly informed investors.

Campbell et al. (2008) note that their results may be driven by unexpected results during the sample period between 1981 and 2003. They mention the strong shift of equity ownership from individuals to institutions during this period as a possible factor driving the results.[4] Kovtunenko and Sosner (2003) and Da and Gao (2008) document that institutions prefer to hold profitable stocks and tend to sell stocks that enter financial distress. This increased selling pressure might be driving the low returns of distressed stocks during the period. An anecdotal evidence of this is provided by Campbell et al. (2008) who show that the outperformance of safe stocks over distressed ones is concentrated in periods such as late 1980s, when aggregate institutional ownership was growing rapidly. Campbell et al. (2008) also suggest that debtholders may have become more adept at forcing bankruptcy or transferring resources from equity holders to debt holders after default, which relates closely to third possible explanation, extraction of private benefits.

Second, Campbell et al. (2008) note that positive skewness may be an explanation for low returns of distressed stocks as both individual distressed stocks and their portfolios of distressed stocks have returns with strong positive skewness. As explained in connection to idiosyncratic volatility, Barberis and Huang (2008) show that investors have a strong

[4] U.S. institutional investors as a whole have increased their share of U.S. equity markets from holding 37.2% of total U.S. equities in 1980 to 51.4% of total in 2000 then to 61.2% in 2005 (The Conference Board, 2007).

preference for positively skewed portfolios, which can result overpricing and negative average excess returns.

Third, von Kalckreuth (2005) argues that extraction of private benefits by majority owners may offer a significant return component not accounted in share price return. Extraction of private benefits for example by buying company's assets at fire sale prices is more likely when a company is unlikely to survive and generate future profits for its shareholders. Furthermore, Garlappi et al. (2008) demonstrate that the possible concessions by debtholders in distressed renegotiations reduce the effective leverage of equity, leading to lower risk and hence lower expected returns for equity, as default risk increases. Garlappi et al. construct a bargaining model between equity holders and debt holders in default. In the model, the relationship between default probability and equity return is upward sloping for firms where shareholders can extract little benefit from renegotiation of debt claims but downward sloping for firms with high shareholder advantage. Garlappi et al. (2008) provide also empirical evidence based on several proxies for shareholder advantage and find results consistent with their model.

Fourth, distress anomaly may stem from investors' failure to fully evaluate the risk of failure (Campbell et al., 2008). Zhang (2007) conducts a joint study of distress risk premia in stock and bond returns and finds that higher default probabilities are associated with higher bond returns but not with higher stock returns. Furthermore, Zhang does not find evidence of rent extraction by shareholders ex ante financial distress in firms with bonds outstanding. Thus he concludes that distress anomaly is mainly driven by stock market mispricing from which arbitrageurs are unable to benefit due to high trading costs and idiosyncratic volatilities.

To sum up, theories of a positive relation between financial distress and stock returns relate to long term hedging concerns of investors. Theories of a negative relation on the other hand deal with shorter term fluctuations due to irrational investors or bargaining between different stakeholders of the firm.

2.3.1 Empirical evidence

Studies focusing explicitly on distress risk have found contradictory results. Table 2 presents an overview of studies using both accounting and market based measures of financial distress.

Griffin and Lemmon (2002) find supporting evidence to Fama and French (1996) and show that the value premium is most significant among firms with high probability of financial distress. Vassalou and Xing (2004) use a default likelihood indicator based on Merton's (1974) structural default model. They show that default risk commands a statistically significant, positive risk premium. They also demonstrate that distress effect is concentrated in small capitalization and high book to market firms.

On the other hand, Dichev (1998) documents that distressed stock have anomalously low returns using Altman's Z-score and Ohlsson's O-score as measures for financial distress. The results show that financial distress cannot fully explain the book to market effect. Similarly, Campbell, Hilscher, and Szilagyi (2008) document that firms with high risk of financial distress have delivered anomalously low returns between 1981 and 2003, using a wide range of proxies for financial distress. The returns of distressed stocks are particularly low when the implied market volatility as measured by VIX index increases, showing that these stocks are particularly vulnerable to market wide risk aversion. Campbell et al (2008) find that the distress anomaly is stronger for small firms, and for stocks with low book to market, analyst coverage, institutional ownership, price per share and liquidity.

Da and Gao (2008) explore the link between financial distress and liquidity. By using the default likelihood indicator proposed by Vassalou and Xing (2004), Da and Gao find that high returns of distressed stocks are mainly driven by compensation for liquidity shocks. Furthermore, they provide evidence that mutual funds tend to decrease their share of financially distressed companies.

Table 2. Empirical evidence on financial distress and return
The table presents an overview of previous empirical literature on the relation between financial distress and expected stock returns.

Study	Sample period	Financial distress estimation	Result
Dichev (1998)	1981-1995	Altman Z- and Ohlson O-score	Negative relation
Griffin & Lemmon (2002)	1965-1996	Ohlson O-score	Negative relation
Vassalou & Xing (2004)	1971-1999	Default Likelihood indicator	Positive relation
Garlappi et al. (2008)	1969-2003	Moody's KMV	No relation
Da & Gao (2008)	1983-1999	Default Likelihood indicator	Positive relation
Campbell et al. (2008)	1981-2003	Econometric logit model	Negative relation

Overall, studies using market based measure of financial distress whose main input is the volatility of asset returns, tend to find a positive relation between financial distress and stock returns. On the other hand, studies using econometric prediction models with purely accounting or combined accounting and market data find a negative relation. In both cases the abnormal returns are found to be driven by small, illiquid stocks. For value effect, Vassalou and Xing (2004) find that value stocks earn higher returns only if their default risk is high whereas Campbell et al. (2008) find that low returns of financially distressed firms are significantly higher for growth stocks, although the effect is somewhat extreme for stocks at either end of the growth-value spectrum.

2.4 Interaction of idiosyncratic risk and financial distress

There is an intuitive reason for idiosyncratic risk and financial distress to be related to each other. According to the Merton (1974) model, corporate debt is a risk-free bond less a put option on the value of the firm's assets, with strike price of the face value of the debt. Thus, a firm with more volatile equity is more likely to reach the boundary condition for default. Based on this argument, Campbell and Taksler (2003) show that idiosyncratic firm-level volatility can explain a significant part of cross-sectional variation in corporate bond yields. This suggests the possibility that the volatility-return relationship may be due to a distress-return relationship or vice versa.

There is no clear theory about the interaction between idiosyncratic volatility and financial distress. If financial distress is priced on the stock returns, idiosyncratic volatility should at least partly proxy it as by definition it is a proxy for omitted variables. Furthermore, the two concepts are endogenously related according to Merton's (1974) structural model as explained above. Thirdly, both idiosyncratic risk and financial distress may proxy a third factor such as skewness of the returns (Boyer, Mitton, and Vorkink, 2007; Campbell et al., 2008), liquidity (Spiegel and Wang, 2005; Da & Gao, 2008), human specific capital (Eiling, 2006 and Fama & French, 1996) or exposure to market volatility (Ang et al.,2006, Campbell et al. 2008).

Two previous studies have followed Ang et al. (2006) and used lagged idiosyncratic volatilities as a proxy for realized idiosyncratic volatility. Interestingly Song (2008) and Chen and Chollete (2006) find that after controlling for distress risk, stocks with high idiosyncratic volatility earn significantly low returns only in the highest distress risk quintile. Song also finds a positive and significant relation at 0.61% per month for the least distressed ones. Furthermore, Song finds that financial distress takes away the explanatory power of idiosyncratic volatility on cross-sectional returns in Fama-MacBeth (1973) regression.

Chen and Chollete (2006) find that after controlling for distress risk, stocks with high idiosyncratic volatility earn significantly lower returns only in the highest distress risk quintile. Furthermore Chen and Chollete (2006) follow Ferguson and Shockley (2003) framework and control missing assets in the equity only proxy for market portfolio by distress and leverage. After this they cannot reject the null hypothesis of zero abnormal returns across either idiosyncratic volatility or distress risk portfolios.

3. Hypotheses

This section presents the hypotheses that will be tested in this study. The hypotheses are divided between the univariate and multivariate tests. I first test the effect of idiosyncratic volatility and financial distress on stock returns separately. As previous studies have found contradictory results, it is of interest to study the univariate relations within my sample period. The second set of hypotheses comprises of the interaction between idiosyncratic risk and financial distress.

Based on under-diversification hypothesis of Levy (1978), Merton (1987) and Malkiel and Xu (2004) and majority of empirical evidence, I expect to find a positive relation between idiosyncratic volatility and excess returns.

> ***H1:*** *There is a positive cross-sectional relation between idiosyncratic volatility and excess returns*

Based on results by Campbell et al (2008) whose measure of financial distress I use, I expect to find a negative relation between financial distress and excess returns.

> ***H2:*** *There is a negative cross-sectional relation between distress risk and excess returns*

Due to the lack of theoretical background, hypotheses for the combined asset pricing impact of idiosyncratic volatility and financial distress are based on previous empirical results. Both Song (2008) and Chen and Chollete (2006) find that after controlling for distress risk, the relation between idiosyncratic risk and stock returns is positive (negative) given low (high) risk of financial distress. Furthermore, both studies find that financial distress seems to have more persistent effect on asset prices than idiosyncratic volatility. As my measure of idiosyncratic volatility differs from the daily lagged estimate used by Song and Chen and Chollete, it is not clear whether the same dynamics will hold. Nevertheless, as evidence and intuition suggest, financial distress should have a more fundamental impact on asset prices than idiosyncratic volatility. Thus, I expect that after controlling for financial distress, there is no relation between idiosyncratic volatility and stock returns.

H3a: *After controlling for financial distress, there is no relation between idiosyncratic volatility and excess returns*

Based on the same reasoning, I expect that controlling for idiosyncratic risk does not remove the distress risk effect.

H3b: *After controlling for idiosyncratic volatility, there is a negative relation between financial distress and excess returns*

4. Data and methodology

This chapter introduces the data and measures used to estimate idiosyncratic volatility and financial distress. Both estimates are naturally model-specific and thus using sophisticated measures for both variables is important. I first describe the data used in the study. In the second section I describe the models used to estimate expected and realized idiosyncratic volatility. Third section introduces financial distress measure and finally in section five I analyze the descriptive statistics.

4.1 Outline of the sample

The sample consists of all U.S. companies listed in NYSE, AMEX or NASDAQ between January 1971 and December 2008. The beginning of the sample period is the same as in Song (2008) and helps to avoid having too few stocks in each portfolio (discussed in more detail later). I obtain the stock return and market capitalization data from Center for Research in Security Prices (CRSP). All accounting data is collected from the COMPUSTAT database. The firms are matched between the databases using CUSIP identifiers. I use CRSP value weighted index with distributions including NYSE, AMEX and NASDAQ stocks. The Fama-French 3-factor data and momentum factor for Carhart (1997) 4-factor model are downloaded from Kenneth R. French's Web site.[5] The full sample with required accounting data and matching CRSP market data consists of 18,795 unique firms.

4.2 Measures of idiosyncratic volatility

Earlier studies have employed different methods to estimate idiosyncratic risk. Studies focusing on intertemporal relationship have tended to use total variance as a proxy for idiosyncratic risk whereas cross-sectional studies have used CAPM residuals Fama French three factor model residuals or total variance (see Table 1). Recently, Fama French residuals have been the most frequently used measure.

Attention needs to be also put on how to estimate expected idiosyncratic volatility. Ang et al. (2006) use the lagged one month volatility of excess returns relative to Fama French three

[5] http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

factor model to estimate idiosyncratic risk. The volatility is calculated as standard deviation of daily returns not explained by the three factor model. On the other hand, Fu (2009), shows that since idiosyncratic volatilities are time varying, the one month lagged estimate may not be appropriate proxy for the expected idiosyncratic volatility next month. Fu shows that during the period from July 1963 to December 2006, the average first order autocorrelation of individual stock idiosyncratic volatilities is only 0.33 and Dickey-Fuller tests show that for 9 out of 10 stocks, the idiosyncratic volatility does not follow a random walk process. Fu proposes the use of autoregressive conditional heteroskedasticity process (ARCH) to capture the time varying property of idiosyncratic risk. Furthermore, Bali and Cakici (2008) compare the conditional idiosyncratic volatility estimates GARCH (1, 1) and EGARCH (1, 1) models with different data frequencies. They show that the idiosyncratic volatility based on past monthly returns provides a more accurate prediction of conditional idiosyncratic volatility than measure based on daily return both in-sample and out-of-sample.

4.2.1 Expected idiosyncratic volatility

ARCH models introduced by Engle (1982) have proven to be useful to describe the temporal dependence of stock returns given the lack of any structural economic theory explaining the variation in higher order moments. An important contribution of ARCH models is the distinction between the conditional and unconditional second order moments. While the unconditional covariance matrix may be may be invariant in time, the conditional covariances and variances can depend on previous returns. A good overview of ARCH/GARCH models is provided by Bollerslev et al. (1994).

ARCH models enable to capture empirical regularities in asset prices including leptokurtosis, i.e. thick tails of the distribution (Mandelbrot, 1963; Fama, 1965) and volatility clustering (Mandelbrot, 1963; French et al., 1987). Furthermore, asymmetric ARCH models such as Nelson's (1991) EGARCH and Glosten, Jagannathan and Runkle’s (1993) GJR GARCH enable to model the so-called “leverage effect” first noted by Black (1976), which refers to the tendency for past stock returns to be negatively correlated with future changes in stock volatility. In other words, past positive and negative returns have an asymmetric impact on future stock volatility However, Black (1976) argues that the observed effect is too large to be explained by leverage alone and this conclusion is supported by the empirical work of Christie (1982) and Schwert (1989).

Several recent papers have used EGARCH to model conditional idiosyncratic volatility. The advantage of EGARCH models is that they do not need to impose restrictions on parameters to avoid negative variances, which may unduly restrict the dynamics of the conditional variance process. Pagan and Schwert (1990) test a number of different GARCH models on monthly U.S. stock returns and find that Nelson's EGARCH is overall the best model. Engle and Ng (1993) test multiple models with Lagrange Multiplier tests and also find that Nelson's model captures well the asymmetry of conditional volatilities.

In this study, I follow previous literature and model conditional idiosyncratic volatility with Nelson's EGARCH model. As a robustness check to test if the relation between conditional idiosyncratic volatility and stock returns depends on the choice of the volatility model, I employ GARCH model introduced by Bollerslev (1986) and GJR-GARCH introduced by Glosten et al. (1993). Idiosyncratic volatility is defined relative to Fama French three factor model, which previous papers have tended to prefer.

The first step in the estimation is to calculate a measure for the realized idiosyncratic volatility. I follow recent literature and choose FF-3 model to describe the monthly return process:

$$R_{it} - r_{ft} = \alpha_i + \beta_i \ (R_{mt} - r_{ft}) + s_i \ SMB_t + h_i \ HML_t + \epsilon_{it} \tag{2}$$
$$\epsilon_{it} \sim N(0, \sigma_{it}^2).$$

The idiosyncratic return is the residuals from the regression, which are then fitted to (E)GARCH models. The distribution of the residual $\epsilon_{i,t}$ is assumed to be normal with the mean of zero and the variance of σ_{it}^2.

The specification for EGARCH(1, 1) is as follows:

$$\ln \sigma_t^2 = \omega + \beta \ln \sigma_{i,t-1}^2 + \alpha \left\{ \Theta \left(\frac{\epsilon_{t-1}}{\sigma_{t-1}} \right) + \gamma \left[\left| \frac{\epsilon_{t-1}}{\sigma_{t-1}} \right| - \sqrt{2/\pi} \ \right] \right\} \tag{3}$$

where ω_i is long term return variance and α_i and β_i are the weights assigned to the squared return $\epsilon_{i,t-l}^2$ and period t-1variance rate $\sigma_{i,t-l}^2$, respectively. Θ is the weight of the sign effect and γ is the weight for the magnitude effect. I take the square root of conditional variance rate to get a standard deviation of the expected volatility. Later in the discussion, I refer to the EGARCH(1,1) estimate of the expected idiosyncratic volatility as E*GARCH_IV*.

The equation for GARCH(p,q) can be written as follows:

$$\sigma_t^2 = \omega + \sum_{i=1}^{p} \alpha_i \epsilon_{t-l}^2 + \sum_{i=1}^{q} \beta_i \sigma_{t-l}^2, \tag{4}$$

where ω_i is long term return variance and α_i and β_i are the weights assigned to the squared return $\epsilon_{i,t-l}^2$ and period *t*-1variance rate $\sigma_{i,t-l}^2$, respectively. The lag lengths, p and q mean that previous *t-p* observations the squared return and *t-q* observations of the conditional variance rate are used to estimate the conditional variance rate at *t*. For a stationary GARCH(1,1) process, the weights α and β in equation (3) must sum up to less than 1 so that the long-term variance rate ω_i is positive. Later in the discussion, I refer to the GARCH(1,1) estimate of the expected idiosyncratic volatility as *GARCH_IV*.

I also estimate GARCH(p,q) in which p and q are between 1 and 3. This yields nine different GARCH models: GARCH (1,1), GARCH (1,2), GARCH (1,3), GARCH (2,1), GARCH (2,2), GARCH (2,3), GARCH (3,1), GARCH (3,2), and GARCH (3,3). I follow similar procedure by Fu(2009) and select the model with the lowest Akaike Information Criterion (AIC)[6]. Later in the discussion, I refer to the GARCH(p,q) estimate of the expected idiosyncratic volatility as *GARCHpq_IV*.

The equation for GJR(1,1) can be written as follows:

$$\sigma_t^2 = \omega + \alpha \epsilon_{t-l}^2 + \gamma S^{-}{}_{i,t-1} \epsilon_{t-l}^2 + \beta \sigma_{t-l}^2, \tag{5}$$

where $S^{-}{}_{t-1}$ is a dummy that takes value 1 when ϵ_{t-l} is negative and 0 when ϵ_{t-l} is positive and γ the coefficient for asymmetric impact of negative innovations. GJR model allows an easy way to test the leverage effect by testing the significance of γ. Over the full sample, the leverage effect is statistically significant at 5% level in 32% of the firms. Later in the discussion, I refer to the GJR(1,1) estimate of the expected idiosyncratic volatility as *GJR_IV*.

The results of the GARCH models are generated using Ox console version 6.00 (Doornik, 2007) with G@RCH 4.0 package (Laurent & Peters, 2002).[7] I use maximum likelihood estimation to estimate the parameters in the equations (3) and (4). The maximum of the log likelihood function is found by using the second derivates of the of the log likelihood function.

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[6] AIC is calculated as$(-2l + 2k)/N$, where *l* is the log-likelihood of the GARCH estimation, *k* is the number of parameters estimated and *N* is the number of observations.

[7] An edited R interface code to use Ox via R and Ox code for the GARCH estimation are provided by prof. Ruey S. Tsay. Downloadable at http://www.math.stevens.edu/~ifloresc/Teaching/2007-2008/index641.html.

The GARCH model parameters for each stock are estimated using available full period data from 1959 to 2009. This implies all available monthly return data for more than 99% of the firms in my sample. This method implicitly assumes that the parameters remain stable over time and also induces a possible look-ahead bias. However, the seriousness of look-ahead bias is likely minor by judging from previous empirical research. French, Schwert, and Stambaugh (1987) use the full period data to estimate their GARCH model parameters and show that assuming time-varying parameters does not change their results. Furthermore, Fu (2009) finds the same results for the idiosyncratic volatility and stock returns relation by using the full period data and by using only prior return data.

4.2.2 Realized idiosyncratic volatility

I measure realized idiosyncratic volatility to test the accuracy of the expected idiosyncratic volatility measures against realized volatility. Furthermore, as robustness check I explore the interaction of financial distress and realized idiosyncratic volatility. This is of interest as recent studies have found a positive contemporaneous relation between realized idiosyncratic volatility and expected returns (Huang et al., 2008; Fu, 2009).

Following Ang et al. (2006) and Fu (2009), I measure realized idiosyncratic volatility by regressing daily excess returns each month to daily Fama-French factors, and calculate volatility as standard deviation of residuals, multiplied by the square root of trading days to get a monthly figure. Hence the realized idiosyncratic volatility measure, *R_IV* is defined as:

$$R(ivol)_{i,t} = \sqrt{n_{i,t}}\ \ STD(\epsilon_i), \tag{6}$$

where n is the number of trading days of firm *i* in month *t* and ϵ_i is the residual from Fama French three factor regression . Similar to Fu (2009) I require a minimum of 15 trading days per month for which CRSP reports a return.

To test the results of Ang et al. (2006) and Song (2008) within my sample, I also use a lagged measure in my robustness checks. This lagged measured of idiosyncratic volatility, which is simply *R_IV* lagged by 1 month, is referred in the later discussion as *L_IV*.

4.3 Measures of financial distress

Recent work on the distress premium has tended to use either traditional risk indices such as the Altman (1968) Z-score or Ohlson (1980) O-score, structural default model of Merton (1974) or the practitioner model Moody's KMV (Crosbie & Bohn, 2001) (see Table *2*). As using a reasonably sophisticated measure for financial distress is important for my analysis, I adopt the reduced form empirical model introduced by Campbell et al. (2008) to measure the distress risk for a given stock. Campbell et al. (2008) demonstrate that combining Moody's KMV or Merton's distance to default models to their model adds relatively little explanatory power. Furthermore, Campbell's model is driven less by volatility whereas in other models volatility is the most important variable. Thus choosing Campbell's econometric model reduces the possible endogeneity problem in the study of relation between idiosyncratic volatility and financial distress as idiosyncratic volatility is the major component of total volatility. Also Song (2008) uses Campbell's econometric model to study the interaction between financial distress and idiosyncratic volatility.

Campbell et al. (2008) construct an empirical measure of financial distress spanned by various accounting and market data. To construct the model, they use the monthly bankruptcy and failure indicators from Kamakura Risk Information Services that record the financial failures in the U.S. market between 1963 and 2003. By putting more emphasis on the market value based accounting, Campbell et al. (2008) manage to improve the Shumway (2001) bankruptcy model.

For each stock each month, I calculate the following list of prediction variables which are combined into a measure of distress (*D*). NIMTAAVG, twelve month geometrical average of net income over market-valued total assets; TLMTA, total liability over market-valued total assets; EXRETAVG, twelve month geometrical average of log excess return over S&P 500 index; SIGMA, past three months daily return volatility; RSIZE, log ratio of market cap with respect to S&P 500 total market cap; CASHMTA, ratio cash and short-term assets over the market-value total assets; MB, market-to-book ratio; and PRICE, truncated log price at \$15. The weights of the geometrical averages for NIMTAAVG and EXRETAVG are determined so that the weights are halved each quarter.

For accounting data, I align each company's quarterly data appropriately with the calendar months, i.e. I use the last month of the calendar quarter for which the quarterly report is dated, and then lag accounting data forward by 2 months. This adjustment ensures that accounting data are available at the beginning of the month over which the portfolios are sorted based on distress measure. The book value of equity is adjusted to eliminate outliers by the procedure suggested by Cohen et al. (2003). That is, I add 10% of the difference between market and book equity to the book value of total equity, thereby increasing book values that are extremely small and probably mismeasured. Furthermore, all variables are winsorized at the 5^{th} and 95^{th} percentiles of their pooled distributions across all firm-months to limit the influence of outliers. The construction of the variables is described in detail in Appendix 1.

The logit model used to obtain the estimated distress probability for each individual stock is:

$$P_{t-1}(Y_{i,t}=1)=\frac{1}{1+\exp(-D_{i,t-1})}, and \qquad (7)$$

$$D_{i,t-1}=\alpha+\beta x_{i,t-1}$$

where Y represent the incident of financial failure, $x_{i,t}$ the set of prediction variables described earlier and α and β are obtained directly from Table IV in Campbell et al. (2008)[8]. Following Campbell et al. (2008) and Song (2008) I choose the 12 months ahead default prediction regression. Variable $D_{i,t-1}$ that is a linear combination of default prediction variables is itself a measure of distress risk, and positively correlated with the forecasted probability of failure $P_{t-1}(Y_{i,t})$. To estimate the probability of bankruptcy in 12 months, I calculate $D_{i,t-1}$ as:

$$\begin{aligned}D_{i,t-1} &= -9.164-20.264\times\text{NIMTAAVG}+1.416\times\text{TLMTA}-7.129\times\text{EXRETAVG}\\ &\quad +1.411\times\text{SIGMA}-0.045\times\text{RSIZE}-2.132\times\text{CASHMTA}+0.075\times\text{MB}\\ &\quad -0.058\times\text{PRICE}\end{aligned} \qquad (8)$$

(Table IV, Campbell et al., 2008)

A point worth of mentioning here is the difference in time spans of the two studies. Campbell et al. (2008) measure the distress risk between 1963 and 2003, while my sample period from 1971 to 2008. This induces a look-ahead bias in my tests for 1971-2003, while on the other hand, the accuracy of the distress prediction model outside the original sample period may not

[8] Campbell et al. (2008) use proprietary bankruptcy and failure indicators from Kamakura Risk Information Services. Thus re-estimation of their model is not feasible in my thesis.

be as good as in the sample. However, Song (2008) employs the same methods and finds that the negative relation between distress risk and stock returns is also robust in the subsample of 1999 to 2006, with distress measure estimated using bankruptcy and failure data up to 1998.

5. Tests

This chapter introduces the test used to evaluate the asset pricing impact of idiosyncratic volatility and financial distress. I employ two commonly used approaches: cross-sectional Fama-MacBeth (1973) regression and a sort of stocks into portfolios based on the variables of interest. Both approaches have some advantages and drawbacks. Combined, they provide an useful cross check.

Sorts offer a simple non parametric and easily interpretable way to analyze stock returns across the spectrum of the variable in question while imposing no linear restrictions. A potential drawback with sorts is the choice of weighting scheme to calculate portfolio returns and the focus on hedge portfolio obtained from long-short position in extreme deciles. Equally weighted hedge portfolios may be dominated by extremely small stocks, thus giving an unrepresentative picture of the effect of the anomaly. On the other hand, using value weighted returns may lead the returns to be dominated by a few big firms. Sorts are also difficult for drawing conclusion about whether the variables contain unique information about average returns as opposed to multiple regression slopes which provide direct estimates of marginal effects. Finally, sorts are inadequate for examining the functional form of the relation between stock returns and possible pricing variable. (Fama & French, 2008)

The main advantage of the regression approach is as mentioned the direct interference of marginal effects of the variable within the whole sample by imposing an functional form on the relation between explanatory variables and returns. The assumption of linear relationship may be however incorrect. Regression can be also dominated by small companies because of their large number as regression gives equal weight to all companies. As returns of individual stocks can be extreme, influential observations problem may be present in cross-sectional regressions. In addition, high correlation of explanatory variables, i.e. multicollinearity, can invalidate the estimates for the marginal effects of individual variables. To investigate if there are high correlations between explanatory variables, I compute cross-sectional Pearson correlation in connection to the regression analysis. Correlations also provide an univariate test between an explanatory variable and stock returns.

5.1 Cross-sectional correlations and regressions

I investigate the univariate linear relationship between idiosyncratic volatility, financial distress and stock returns with cross-sectional Pearson correlations. I estimate the cross-sectional correlations for the variables each month and then calculate the time series means of the correlation coefficients. Correlation matrix is also useful in detecting correlation between regression variables, which may induce a problem of multicollinearity in the regression results.

To control for various factors known to affect the cross-sectional returns and to provide a direct comparison of the impact of financial distress and idiosyncratic volatility on stock returns, I employ the two-stage Fama-MacBeth (1973) regression analysis. For each month, I regress the excess return of all firms onto forecasted idiosyncratic volatility, distress risk in previous month and a battery of control variables know to affect the cross-sectional stock returns. These factors include market beta, size, book-to-market, momentum, liquidity and short term reversal effects.

For the financial distress, I choose the $D_{i,t-1}$ measure here instead of the probability of financial distress as does Song (2008). This is because the probabilistic measure of failure is bounded between 0 and 1, which does not expand the real line; in addition, the forecasted failure probability heavily clusters close to 0. As a result, I turn to the more spread-out alternative distress measure $D_{i,t-1}$ for the purpose of the Fama-MacBeth regression analysis.

Market beta (*BETA*) is obtained from the full period regression of equation (2) for each firm and then assigned to each month. Firm size is measured by the market value of equity (*MV*) in the previous month. For book-to-market in the previous (*BEME*), book equity is calculated as defined earlier in connection to distress risk and lagged 2 months to ensure that the information is available prior the returns. Momentum effect is controlled by calculating the cumulative return from month *t-7* to *t-2* (*RET(-2 ,-7)*). Liquidity is measured by average share turnover (TURN) in the past 36 months from *t-38* to *t-2* as in Chordia et al. (2001). I also calculate the coefficient of variation[9] (CVTURN) of the past 36 months' turnovers. Fu (2009) uses the same measures of momentum and liquidity. Furthermore, to control for possible short

[9] Coefficient of variation is defined as the ratio of the standard deviation to the mean.

term return reversal effect, a one month lagged return (RET(-1)) is added to the regression. To mitigate the impact of outliers, all explanatory variables in the regression, except D_{t-1} are winsorized at 0.5% and 99.5%. Furthermore, extreme returns of over 300% are excluded.

I use the Fama and MacBeth (1973) regression to control the cross-sectional correlation of the residuals. I run the following cross-sectional regression:

$$R_{it} = \gamma_{0t} + \sum_{k=1}^{K} \gamma_{kt} X_{kit} + \epsilon_{it}\,, \quad i = 1,2,\ldots,N_t, \quad t = 1,2,\ldots,T, \tag{9}$$

where R_{it} is the realized return on stock *i* in month *t*. X_{kit} are the explanatory variables of cross-sectional expected returns described above. N_t denotes the total number of stocks in month *t*, which can vary from month to month. T is the length of the time period and equals 456 in this study. In other words, in each month, I regress the available monthly returns of all firms to the explanatory variables and hence obtain time series for these variables.

To obtain the final estimate $\hat{\gamma}_k$, I use the time series means of $\hat{\gamma}_{kt}$ as expected values, and divide the expected value by coefficients variance to test whether these are significantly different from zero, i.e. I perform standard t-tests. Formulas for expected value and variance are:

$$\hat{\gamma}_k = \frac{1}{T}\sum\nolimits_{t=1}^{T} \hat{\gamma}_{kt} \tag{10}$$

$$Var(\hat{\gamma}_k) = \frac{\sum_{t=1}^{T}(\hat{\gamma}_{kt} - \hat{\gamma}_k)^2}{T(T-1)} \tag{11}$$

The t-test is the average slope divided by its time-series standard error, which is the square root of the variance of $\hat{\gamma}_k$divided by T ($\sqrt{Var(\hat{\gamma}_k)/T}$).

To control for the potential dominance of small stocks in the regression, the main results of the regression are repeated separately for micro, small, large and all but micro stocks as in Fama and French (2008). The breakpoints to separate these groups are 20% and 50% percentiles of market capitalization for NYSE stocks.[10] The separate regression for different size groups also enable difference of means tests on the average slopes to provide formal

[10] Breakpoint data downloaded from Professor Kenneth Frenc’s homepage: http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

inferences about whether the impact of idiosyncratic volatility and financial distress differ across size groups

5.2 Returns analysis of portfolios

I form portfolios to study the asset pricing impact of idiosyncratic and distress risk to stock returns. Portfolio strategy offers a simple non parametric and easily interpretable way to analyze stock returns, imposing no linear restrictions.

I start my analysis by exploring the effect of idiosyncratic and distress risk separately on stock returns. For the univariate portfolio analysis, I sort all stocks based on the conditional expectation of idiosyncratic volatility in month t (distress risk in month t-1). I then form 5 portfolios at the end of month t-1 and hold these portfolios for 1 month. I also report a long-short portfolio, which goes long for the highest risk portfolio and shorts the lowest risk portfolio. Because the total number of listed companies is not constant through time, the number of firms included in each portfolio can vary from month to month. I also perform a finer sort with 10 portfolios.

To study the interaction of the asset pricing impact between financial distress and idiosyncratic volatility on stock returns, I form 25 sequentially sorted portfolios. I first sort stocks into 5 quintiles based on their level of distress, and within these quintiles further sort stocks based on their idiosyncratic volatility. I also perform the sorts the other way round. As a robustness check, I perform independent sort where I first sort five idiosyncratic volatility and distress portfolios separately and then match each firm month observation to corresponding distress / idiosyncratic volatility portfolio.

To calculate abnormal returns of the formed portfolios, I regress the monthly excess returns over risk free rate of each portfolio to a simple market model, Fama-French (1993) three-factor model and Carhart (1997) four factor model.[11] The regression equations for each model are respectively:

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[11] The Fama-French and Carhart benchmark factors, SMB, HML and MOM are constructed from six size/book-to-market benchmark portfolios that do not include hold ranges and do not incur transaction costs. $R_m - R_f$, the excess return on the market, is the value-weighted return on all NYSE, AMEX, and NASDAQ stocks obtained from CRSP minus the one-month Treasury bill rate.

$$R_{jt} - r_{ft} = \alpha_j + \beta_j \ (R_{mt} - r_{ft}) + \epsilon_{jt} \tag{12}$$

$$R_{jt} - r_{ft} = \alpha_j + \beta_j \ (R_{mt} - r_{ft}) + s_j \ SMB_t + h_j \ HML_t + \epsilon_{jt} \tag{13}$$

$$R_{jt} - r_{ft} = \alpha_j + \beta_j \ \left(R_{mt} - r_{ft}\right) + s_j \ SMB_t + h_j \ HML_t + m_j \ MOM_t + \epsilon_{jt}\,, \tag{14}$$

where R_{jt} is the monthly return on portfolio j, r_{ft} is the risk-free rate, R_{mt} is market return, SMB_t is the difference between the returns on small and large firm, HML_t is the difference between the returns on low and high market-to-book firms, and MOM_t is the difference between the returns on high and low prior return firms in a period from *t-12* to *t-2*. Finally, ε_{jt} is the average monthly abnormal return of portfolio j.

In robustness checks, I additionally construct a 5 factor model including a short-term return reversal factor similar to Huang et al. (2008). Huang et al. (2008) shows that omission of previous month's stock return can lead to a negatively biased estimate of relation between idiosyncratic risk and expected stock returns especially when using volatility estimate derived from daily returns. The additional return reversal factor, "winners minus loser" (WML) is formed by taking a long position in past month's winners (the 10% best performing stocks) and short position in the past months' losers ((the 10% worst performing stocks).[12] Hence the 5 factor model is:

$$R_{jt} - r_{ft} = \alpha_j + \beta_j \ \left(R_{mt} - r_{ft}\right) + s_j \ SMB_t + h_j \ HML_t + m_j \ MOM_t + rWML_t + \epsilon_{jt}\,, \tag{15}$$

As I investigate the returns of distressed stocks, the returns of stocks that are delisted need special attention. If available, I use delisting returns reported by CRSP for the final month of the firm before it disappears from the database. I assume that the proceeds of delisted stocks are reinvested to the remaining stocks in the portfolio. Assuming that the portfolio sells distressed stocks at the end of the month inflicts an upward bias to the portfolio return as documented by Shumway and Warther (1999). However, this is unlikely to be serious as Campbell et al. (2008) results remain the same when not using CRSP delisting returns.

[12] The portfolios are downloadable from Professor Kenneth French's homepage: http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

6. Analysis and empirical results

In this section I present the main empirical findings and results of this study. In the first part I analyze the time series averages on my idiosyncratic volatility and financial distress measures. The second part includes the results of cross-sectional Pearson correlations and Fama Macbeth regressions. In third section I present the results of portfolios sorted based on idiosyncratic volatility and financial distress, including both univariate and multivariate sorts. The second part includes also various robustness checks relating to the portfolio sorts.

6.1 Time series development of idiosyncratic volatility and financial distress

This section presents the time series development of aggregated measures of idiosyncratic volatility and financial distress during the sample period. Figure 1 shows the time series of value weighted average level of expected idiosyncratic volatility *EGARCH_IV* and realized idiosyncratic volatility *R_IV*. Over the whole sample period, average idiosyncratic volatility has almost doubled, though there is no clear upward trend as observed by Campbell et al. (2001) in their study covering years from 1962 to 1997. An upward trend can be observed from 1971 to 2000, but from 2001 to 2007 the level of idiosyncratic volatility is declining until rising again steeply from fourth quarter of 2007 onwards. Both *EGARCH_IV* and *R_IV* tend to be higher during or right before NBER dated recessions, illustrating the cyclical nature of idiosyncratic volatility and the stock market reaction leading the general economic development. Equally weighted average idiosyncratic volatilities plotted in Figure 2 behave similarly. The strong spike in EGARCH_IV in both models in 1973 coincides with the stock market crash associated with devaluation of US dollar after the collapse of Bretton Woods system. The asymmetric effect of devaluation to solely domestic and international firms in NYSE, NASDAQ and AMEX combined with high overall volatility could be a likely cause for the spike in idiosyncratic volatility as measured from monthly returns.

The value weighted time series average of *EGARCH_IV* is 9.1% and for *R_IV* 5.6 %. The equally weighted time series averages are 16.3% and 12.7%, correspondingly. I use monthly returns to estimate *EGARCH_IV*, while *R_IV* is based on daily returns, which explains a part of the difference between the measures. When stocks experience small but persistent positive or negative daily returns, *R_IV* is low whereas *EGARCH_IV* should go up. Indeed, the difference between *EGARCH_IV* and *R_IV* is highest during relatively stable expansionary periods like 2003-2007 when the volatility of *R_IV* is low whereas during turbulent times such as 2008, *R_IV* is close or higher than *EGARCH_IV*. Due to the same reason, *EGARCH_IV* is more persistent than *R_IV*.

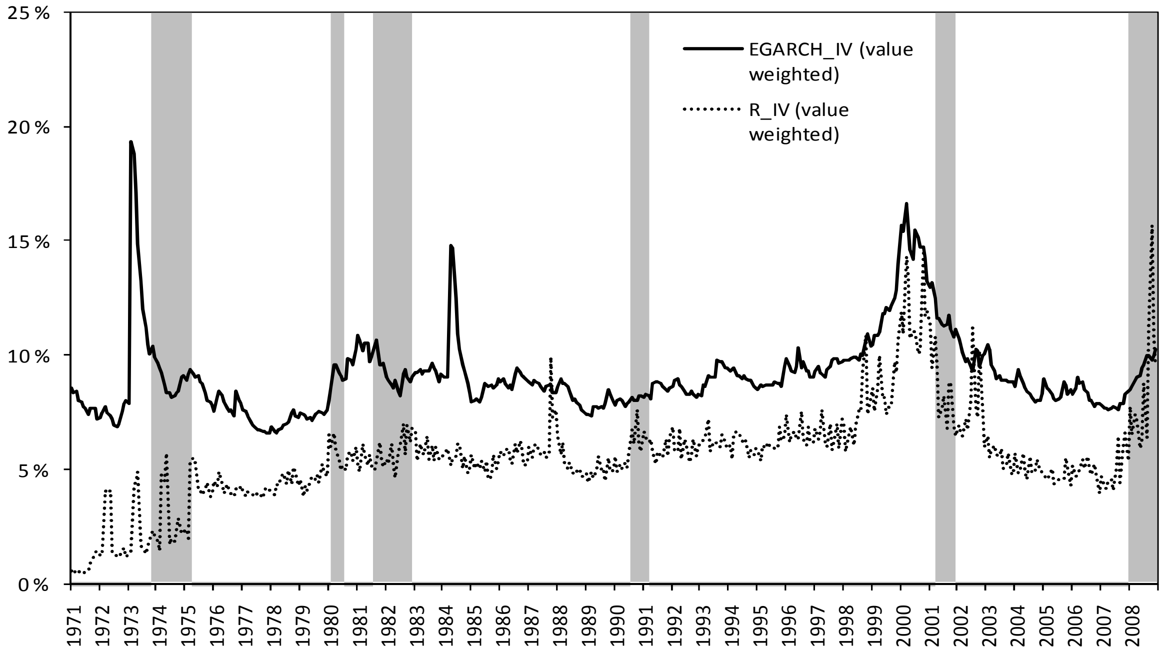

Figure 1. Expected versus realized aggregated value weighted idiosyncratic volatility. The figure shows the time-series of level of expected, *EGARCH_IV*, and realized idiosyncratic volatility, *R_IV*, from January 1971 to December 2008. Shaded areas correspond to NBER recessions.

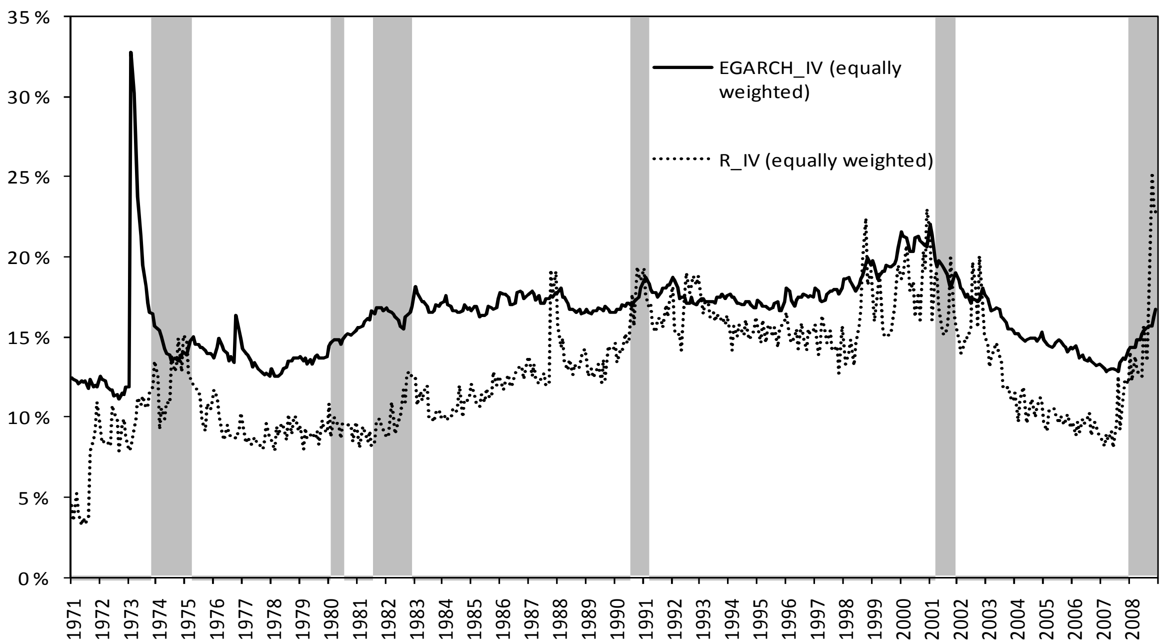

Figure 2. Expected versus realized aggregated equally weighted idiosyncratic volatility. The figure shows the time-series of level of expected, *EGARCH_IV*, and realized idiosyncratic volatility, *R_IV*, from January 1971 to December 2008. Shaded areas correspond to NBER recessions.

Figure 3 plots the value weighted average level of distress risk (*P_vw*) and equally weighted average level of distress risk (*P_ew*) during the sample period from 1971 to 2008.

The value weighted average of the predicted failure rates is 0.036% over the whole period, and the equally weighted average is 0.083%[13]. The difference reflects the predominance of small firms among the distressed stocks Both measures tend to rise during NBER recessions. Both measures are also at their highest point during at the end of the sample period in December 2008, reflecting the severity of the current recession.

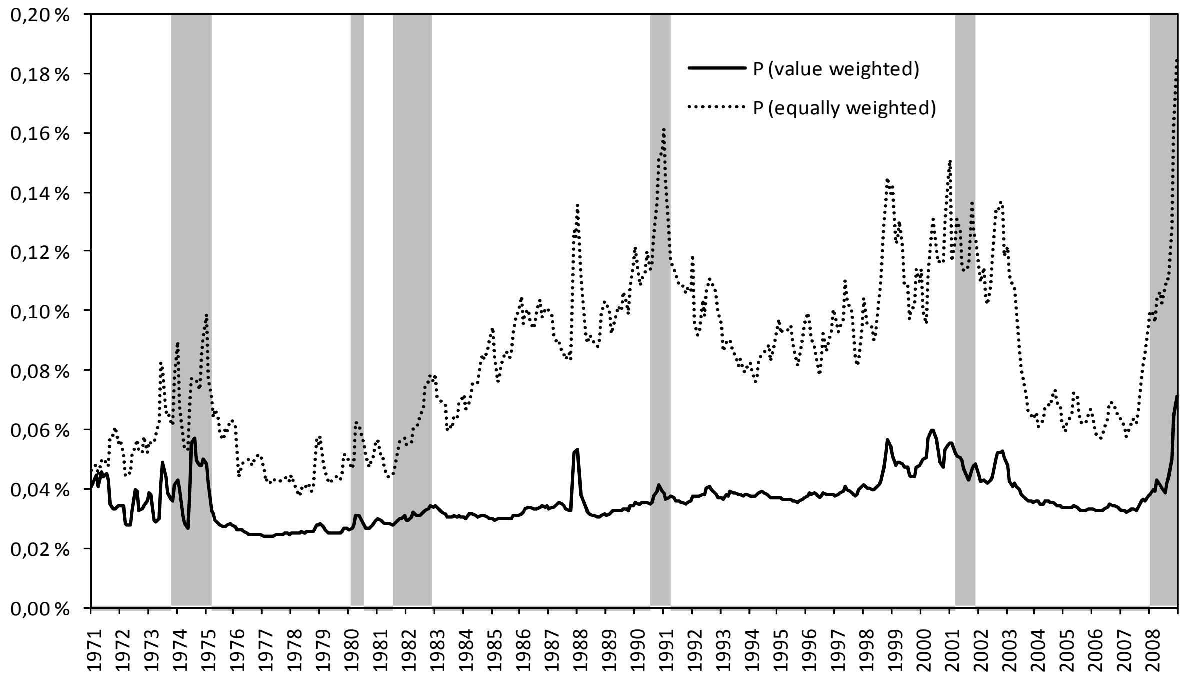

Figure 3. Value and equally weighted aggregated level of distress risk. The figure shows value and equally weighted averages of the marginal probability of bankruptcy or failure (P_{t-1}) from January 1971 to December 2008. Shaded areas correspond to NBER recessions.

6.2 Cross-sectional correlations and regressions

This section reports the results of simple Pearson correlations and cross-sectional regressions. Table 3 presents the descriptive statistics of the pooled sample. The statistics are reported for all available observations per each variable. The mean monthly return in my sample period is 1.04%. The mean expected idiosyncratic volatility (EGARCH_IV) is 14.72% and the mean

[13] Note that these probabilities are conditional probabilities of firm defaulting at a particular date, 12 months forward, and not a cumulative probability of failure in 12 months.

realized idiosyncratic volatility (R_IV) is 12.25%. The mean BETA is 1.01 and median is 0.97.

Table 3. Descriptive Statistics of regression variables

The table reports the descriptive statistics of regression variables. RET is the monthly raw return reported in percentage. BETA is the stock beta estimated from the full period regression for each firm. MV is the market value of equity in the previous month. Book-to-market equity (BEME) is the latest available quarterly book equity divided by market value of equity in the previous month. R_IV is the realized idiosyncratic volatility. GARCH_IV (EGARCH_IV) is the conditional idiosyncratic volatility estimate by GARCH(1,1) (EGARCH(1,1)) model. The measure of financial distress (D_{t-1}) is measured as in Campbell et al. (2008). RET(-2,-7) is the cumulative return from month t-7to t-2. TURN is the average turnover and CVTURN is the coefficient of variation of turnovers in the past 36 months. MV, BEME, TURN and CVTURN are as the natural logarithm due to their high skewness. All variables except RET and D_{t-1} are winsorized at 0.5% and 99.5% levels. Observations with monthly returns greater than 300% are deleted. The sample period is from 1971 to 2008.

Variable	Mean	Median	Std. Dev.	Skew	Min	Max	Observations
RET	1.04	0.00	17.35	2.19	-100.00	300.00	2,337,190
R_IV	12.25	6.52	15.43	1.28	2.08	30.01	2,338,065
GARCH	14.60	11.58	14.69	1.16	2.97	28.70	2,160,969
EGARCH_IV	14.72	11.18	15.32	1.23	5.04	30.54	2,071,079
D_{t-1}	-7.47	-7.60	0.90	0.84	-10.24	-2.80	1,921,534
BETA	1.01	0.97	0.75	0.59	-6.34	9.45	2,337,190
ln(MV)	4.49	4.35	2.13	0.29	-0.24	10.50	2,340,100
ln(BEME)	-0.50	-0.45	1.02	0.09	-3.98	3.72	1,921,534
RET(-2, -7)	4.93	2.66	31.29	0.41	-49.02	74.89	2,232,368
ln(TURN)	-2.97	-2.93	1.05	-0.13	-4.95	-1.18	2,623,217
ln(CVTURN)	-0.39	-0.38	0.41	-0.03	-1.14	0.36	2,592,383

6.2.1 Simple correlations

I start the cross-sectional regression test by investigating the correlations between the variables, which can be regarded as a univariate tests. Table 4 presents the correlation matrix. I compute cross-sectional Pearson correlations each month and report the time series means of the correlations with t-statistics.

The simple correlation between monthly stock returns and distress is risk is negative and significant at 5% level, which is consistent with Campbell et al. (2008). Correlation of *GARCH_IV* with stock returns is not significant but *EGARCH_IV* does correlate positively with stock returns and the correlation is significant at 1% level. Furthermore, realized idiosyncratic volatility, *R_IV* exhibits a significant positive correlation with *RET* but *L_IV* has a significant negative correlation, which are consistent with the results of Fu (2009) and Ang et al. (2006). The results of the Pearson correlation thus imply a positive relation between idiosyncratic risk and return. *EGARCH_IV* seems to outperform *GARCH_IV* in predicting the expected value of idiosyncratic volatility in the next month.

Consistent with the findings in the earlier literature, the returns are positively related to *BEME* and past 6 months returns but negatively correlated with previous month's returns and liquidity as measured by average share turnover *TURN*. Size correlates negatively with returns but is not statistically significant as is the case with other liquidity measure, *CVTURN*. As shown by Fama and French (1992), the relation between stock returns and market *BETA* is close to zero and statistically insignificant. Conditional idiosyncratic volatilities as measured by *EGARCH_IV* are positively related *BETA* and two liquidity variables and negatively related to size and book-to-market, which is consistent with Fu (2009). The same applies also for *R_IV*. The correlation between *EGARCH_IV* or *R_IV* and lagged returns *RET(-2, -7)* and *RET(-1)* is surprisingly negative, implying that past low returns lead to lower idiosyncratic volatility. Based on finding by Black (1976) that total volatility is negatively correlated with past stock returns, one could have expected that the "leverage-effect" would also apply for idiosyncratic volatility.

Correlation between distress measure D_{t-1} and *GARCH_IV* is quite high at 0.45, which may pose multicollinearity problem for the regression results. The high correlation also indicates that the two measures are closely related as explained in the literature review. The correlation between lagged idiosyncratic volatility and realized idiosyncratic volatility is as high as 0.79, indicating persistence in idiosyncratic volatility. This differs somewhat from the results of Fu (2009) who find that idiosyncratic volatilities do not follow a random walk process.

Table 4. Correlation matrix of regression variables

The table presents cross-sectional Pearson correlations for regression variables. RET is the monthly raw return reported in percentage. BETA is the stock beta estimated from the full period regression for each firm. MV is the market value of equity in the previous month. Book-to-market equity (BEME) is the latest available quarterly book equity divided by market value of equity in the previous month. R_IV is the realized idiosyncratic volatility and L_IV is the lagged idiosyncratic volatility by one month. GARCH_IV (EGARCH_IV) is the conditional idiosyncratic volatility estimate by GARCH(1,1) (EGARCH(1,1)) model. The measure of financial distress (Dt-1) is measured as in Campbell et al. (2008). RET(-2,-7) is the cumulative return from month t-7to t-2 and RET(-1) is return on the previous month. TURN is the average turnover and CVTURN is the coefficient of variation of turnovers in the past 36 months. MV, BEME, TURN and CVTURN are as the natural logarithm due to their high skewness. All variables except RET and Dt-1 are winsorized at 0.5% and 99.5% levels. Observations with monthly returns greater than 300% are deleted. The sample period is from 1971 to 2008. For each variable of interest. ***, **, and * indicate that the estimate is statistically different from zero at 0.1%, 1% and 5% confidence levels respectively.

	R_IV	L_IV	GARCH_IV	EGARCH_IV	D_{t-1}	BETA	ln(MV)	ln (BEME)	RET (-2, -7)	RET(-1)	ln(TURN)	ln(CVTURN)
RET	0.054***	-0.017***	-0.012	0.018**	-0.017*	-0.001	-0.006	0.032***	0.026***	-0.041***	-0.024***	-0.003
R_IV		0.794***	0.407***	0.358***	0.333***	0.084***	-0.300***	-0.003	-0.113***	-0.036***	0.081***	0.197***
L_IV			0.427***	0.361***	0.345***	0.084***	-0.297***	-0.011*	-0.117***	0.054***	0.082***	0.198***
GARCH_IV				0.789***	0.451***	0.188***	-0.511***	-0.138***	-0.083***	0.018*	0.273***	0.353***
EGARCH_IV					0.428***	0.133***	-0.455***	-0.110***	-0.132***	-0.035***	0.220***	0.294***
D_{t-1}						0.033***	-0.512***	0.172***	-0.368***	-0.199***	-0.001	0.255***
BETA							0.157***	-0.093***	0.006	-0.001	0.288***	-0.068***
ln(MV)								-0.264***	0.174***	0.06***	0.131***	-0.535***
ln(BEME)									-0.211***	-0.109***	-0.141***	0.113***
RET(-2, -7)										0.007	-0.013*	0.010*
RET(-1)											-0.023***	-0.004
ln(TURN)												-0.044***

6.2.2 Fama-MacBeth cross-sectional regressions

The results of the cross-sectional Fama-MacBeth regressions are reported in Table 5. Model 1 replicates the main results by Fama and French (1992), which is highly influential in the literature of cross-sectional return studies. Model 1 shows that size and book to market are significant determinants of cross-sectional returns whereas the relation between market beta and return is not statistically significant. Smaller firms have on average higher returns than larger firms and value firms tend to have higher returns than growth firms. Model 2 regresses the other control variables to returns. Consistent with previous literature, momentum as measured by *RET(-2, -7)* is positively related to returns but *RET(-1)* shows short term return reversal. Both liquidity measured *TURN* and *CVTURN* enter the regression with significant negative coefficients as expected.

Models 3 and 4 show that *GARCH_IV* is not significantly related to returns. However, model 5 and 6 provide evidence that conditional idiosyncratic volatility as measured by *EGARCH_IV* is positively related to stock returns. The coefficient for *EGARCH_IV* is significant at 0.1% level in both models. The average slope of in Model 6 of 0.11 means that a as the standard deviation for idiosyncratic volatility is about 15%, a stock with one standard deviation higher idiosyncratic volatility than another stock, would earn about 1.5% higher average return in a month. This implies that the effect of idiosyncratic volatility is economically significant.

The regression results of Models 3 and 4 for *GJR_IV* and *GARCHpq_IV* are reported in Appendix 2. These models for conditional idiosyncratic volatility provide evidence that the positive relation uncovered by EGARCH_IV does not depend only on specifications of the EGARCH volatility model. On univariate regressions, *GJR_IV* and *GARCHpq_IV* do not have significant slopes but after including the control variables, both have a positive relation with stock returns, which is significant at 0.1% level. In other words, the positive relation between idiosyncratic volatility and stock returns is somewhat weaker with *GJR_IV* and *GARCHpq_IV*, but they provide evidence that simple GARCH_IV model is not adequate for modeling expected idiosyncratic volatility. The results are consistent with previous literature, for example Pagan and Schwert (1990) find that EGARCH models are the most appropriate to model monthly stock returns.

In Model 7 I perform an univariate regression of return on distress risk D_{t-1}. Model 8 includes the set of control variables into regression. By itself, the distress risk is not significant determinant of returns in Model 7, but inclusion of control variables discovers a negative relation significant at 5% level. The negative relation is consistent with hypothesis and Campbell et al. (2008) who employ the same measure of distress.

Models 9 to 11 compare the relative pricing power of idiosyncratic volatility as measured by EGARCH_IV and financial distress by including both of them into regression with or without a set of control variables. In spite of high correlation between the two measures, inclusion of both variables actually increases their significance. In Model 5 I perform univariate regression of return on EGARCH_IV. The slope of EGARCH_IV is 0.07 that is significant at 0.1% level. The results is very similar although slightly weaker to Fu (2009) who uses EGARCH(p,q) model for expected idiosyncratic volatility[14]. In Model 11, which includes all control variables with idiosyncratic volatility and financial distress, a slope of EGARCH_IV is 0.14 (with t-statistic of 10.96) and D_{t-1} has a slope of -0.64 (with a t-statistic of 5.40). A word of caution in interpreting the results needs to raised here about multicollinearity problem between the variables. Models 9 and 10 show that at least control variables are not causing incorrect interference of the results as both EGARCH_IV and D_{t-1} have the same sign and are significant whether some control variables are included or not. The adjusted R squared of Model 11 is however only 5.68% whereas in Models 6 and 8, which include all control variables and either EGARCH_IV or D_{t-1}, the adjusted R squared are 7.08% and 6.70%. Inclusion of both EGARCH_IV and D_{t-1} into the regression brings thus so little new information about stock returns that penalty of including extra variables leads to a lower adjusted R squared. Nevertheless, the results are contradictory to the findings of Song (2008) and Chen and Chollete (2006) who find that the pricing power of idiosyncratic volatility is eliminated when accounting for distress risk.

Models 12-14 regres returns on lagged idiosyncratic volatility L_IV, which has been used in the earlier studies by Song (2008) and Chen and Chollete (2006) as a proxy for realized idiosyncratic volatility. Model 12 replicates the regression by Fu (2009) who also finds a negative relation between lagged idiosyncratic volatility and stock returns. The slope of the regression for L_IV in model 12 of -0.02 (with t statistic of 3.29) is the same as in Fu (2009)

[14] Fu (2009) finds the slope of expected idiosyncratic volatility in univariate regression of 0.11 with a t-statistic of 9.05.

who uses a period of 1963-2006. Model 13 includes the full set of control variables including lagged one month return. Contrary to Fu (2009) and Huang et al. (2008) who claim that the negative relation between lagged idiosyncratic volatility and stock returns is due to short term return reversal, inclusion of RET(-1) does not remove the significant negative relation between L_IV and stock returns. However, as noted by Song (2008) and Chen and Chollete (2006), controlling for distress risk eliminated the pricing power of lagged idiosyncratic volatility. This is confirmed in Model 14, which includes D_{t-1} into regression. After this, L_IV is no longer significant pricing factor.

Models 15-17 provide additional proof of a positive relation between idiosyncratic volatility and stock return by regressing returns on realized idiosyncratic volatility, R_IV. In Model 17, inclusion of distress risk does not reduce the explanatory power of R_IV. This provides additional proof that idiosyncratic volatility and distress risk are two different asset pricing factors with opposite effect. The correlation between D_{t-1} and R_IV is 0.33 meaning that multicollinearity as not as big problem in Model 17 as in Model 11 with EGARCH_IV. This can be also from adjusted R squared of 7.79% that is the highest of all the models.

Table 5. Fama-MacBeth regressions

The table presents the results of cross-sectional Fama-MacBeth regression. RET is the monthly raw return reported in percentage. BETA is the stock beta estimated from the full period regression for each firm. MV is the market value of equity in the previous month. Book-to-market equity (BEME) is the latest available quarterly book equity divided by market value of equity in the previous month. R_IV is the realized idiosyncratic volatility and L_IV is the lagged idiosyncratic volatility by one month. GARCH_IV (EGARCH_IV) is the conditional idiosyncratic volatility estimate by GARCH(1,1) (EGARCH(1,1)) model. The measure of financial distress (Dt-1) is measured as in Campbell et al. (2008). RET(-2,-7) is the cumulative return from month t-7to t-2 and RET(-1) is return on the previous month. TURN is the average turnover and CVTURN is the coefficient of variation of turnovers in the past 36 months. MV, BEME, TURN and CVTURN are as the natural logarithm due to their high skewness. All variables except RET and Dt-1 are winsorized at 0.5% and 99.5% levels. Observations with monthly returns greater than 300% are deleted.The sample period is from 1971 to 2008. For each variable of interest. ***, **, and * indicate that the estimate is statistically different from zero at 0.1%, 1% and 5% confidence levels respectively.

Model	BETA	ln(ME)	ln(BEME)	RET(-2,-7)	RET(-1)	ln(TURN)	ln(CVTURN)	GARCH_IV	EGARCH_IV	D_{t-1}	L_IV	R_IV	Adj. R^2
1	0.38	-0.14	0.34										3.97
	(1.87)	(2.65)**	(3.96)***										
2	0.42	-0.17	0.29	0.01	-0.06	-0.24	-0.38						6.31
	(2.32)*	(3.61)***	(3.41)***	(6.48)***	(10.75)***	(3.09)**	(4.76)***						
3								0.01					2.20
								(0.41)					
4	0.45	-0.14	0.27	0.01	-0.06	-0.32	-0.39	0.02					6.80
	(2.41)*	(4.1)***	(2.99)**	(6.66)***	(10.51)***	(4.89)***	(4.79)***	(1.08)					
5									0.07				1.92
									(4.09)***				
6	0.32	0.00	0.41	0.02	-0.06	-0.43	-0.48		0.11				7.08
	(1.71)	(0.10)	(5.27)***	(7.46)***	(11.03)***	(5.95)***	(6.51)***		(7.74)***				
7										-0.06			1.86
										(0.38)			
8	0.45	-0.23	0.34	0.01	-0.07	-0.21	-0.37			-0.33			6.70
	(2.41)*	(5.65)***	(4.03)***	(4.47)***	(13.19)***	(2.67)**	(4.63)***			(2.31)*			

Table 5 continued. Fama-MacBeth regressions

Model	BETA	ln(ME)	ln(BEME)	RET(-2,-7)	RET(-1)	ln(TURN)	ln(CVTURN)	GARCH_IV	EGARCH_IV	D_{t-1}	L_IV	R_IV	Adj. R^2
9									0.10	-0.34			3.15
									(6.19)***	(2.84)**			
10	0.23	-0.03	0.58						0.11	-0.50			3.15
	(1.15)	(0.78)	(7.40)***						(8.68)***	(4.29)***			
11	0.33	-0.06	0.49	0.01	-0.07	-0.42	-0.48		0.14	-0.64			5.68
	(1.74)	(1.89)	(6.49)***	(4.06)***	(13.47)***	(6.33)***	(6.56)***		(10.96)***	(5.40)***			
12		-0.18	0.40	0.02		-0.10	-0.38				-0.02		4.55
		(4.02)***	(4.00)***	(7.07)***		(1.00)	(3.8)***				(3.29)**		
13	0.41	-0.17	0.33	0.01	-0.06	-0.23	-0.40				-0.02		6.41
	(2.19)*	(3.93)***	(4.01)***	(6.29)***	(10.99)***	(3.07)**	(4.84)***				(3.35)***		
14	0.43	-0.23	0.35	0.01	-0.07	-0.21	-0.38			-0.34	-0.01		6.71
	(2.31)*	(5.81)***	(4.54)***	(4.47)***	(14.03)***	(2.71)**	(4.68)***			(2.46)*	(1.40)		
15		-0.02	0.49	0.02		-0.23	-0.49					0.14	5.55
		(0.35)	(4.39)***	(8.17)***		(2.37)*	(4.69)***					(11.93)***	
16	0.19	-0.02	0.37	0.02	-0.06	-0.33	-0.49					0.13	7.35
	(1.03)	(0.39)	(4.19)***	(7.28)***	(11.69)***	(4.47)***	(5.78)***					(11.43)***	
17	0.25	-0.11	0.43	0.01	-0.07	-0.30	-0.49			-0.64		0.14	7.79
	(1.36)	(3.06)**	(5.51)***	(4.29)***	(14.58)***	(3.94)***	(5.65)***			(4.35)***		(12.35)***	

Table 6 reports the results of regressions of Model 11 separately for micro, small, large and all but micro stocks to control for the potential dominance of small stocks in the regression. The average slopes of the regression together with t-statistics for different size groups are reported in Panel A. The differences between the average slopes are reported in Panel B in order to draw formal interference if the pricing impact of regression variables is different in different size groups.

Firstly, looking at the effect of control variables within different size groups reveals the same conclusions as in Fama and French (2008). The size effect is significant in micro and large stocks but not in small stocks. The value effect is strong within micro and small stocks but only just significant within large stocks. Momentum and liquidity effects are only significant in micro and small stocks whereas short term return reversal is significant in all size groups. The prevalence of anomalies or liquidity effects in micro and small stocks reflects the fact that smaller stocks are more difficult to arbitrage for professional investors (e.g. Campbell et al., 2008). The results are in line with Fama and French (2008) except that they find value effect to be insignificant within large stocks and the momentum effect to be pervasive among all size groups.

The regression between the size groups reveal that idiosyncratic volatility effect is concentrated in micro and small stocks whereas the pricing impact of distress risk is prevalent in all size groups. From Panel A we can see that idiosyncratic volatility effect is very strong within the smallest micro stocks. The slope of EGARCH_IV is 0.19 (t-statistic of 12.68). For small stocks, the slope is only 0.03 but still significant at 5% level. However, for large stocks or all but micro stocks, EGARCH_IV is not statistically significant. The distress risk on the other hand is also strongest within the micro stocks and weakest for large stocks. The slope of D_{t-1} is -0.95 for micro stocks, -0.64 for small stocks, and -0.39 for large stocks. However, the distress risk is still statistically significant at 0.1% level within all size groups.

Panel B confirms the conclusion drawn from inspection of regression slopes in Panel A. The differences between any size groups are significant for EGARCH_IV and D_{t-1}, so that in larger stocks the absolute effect of EGARCH_IV or D_{t-1} is smaller.

Table 6. Fama-MacBeth regressions in different size groups

The table presents the results of cross-sectional Fama-MacBeth regression within size groups. The size groups: micro, small, large and all but micro stocks are defined as in Fama and French (2008). The breakpoints to separate these groups are 20% and 50% percentiles of market capitalization for NYSE stocks. The t-statistics for the average regression slopes (or for the differences between the average slopes) use the time-series standard deviations of the monthly slopes (or the differences between the monthly slopes). The sample period is from September 1971 to December 2008. First 8 months of the original sample period are excluded as micro stocks have no firm months with all required data within that period, in September 1971 there are 56 micro stocks with all required data. For each variable of interest. ***, **, and * indicate that the estimate is statistically different from zero at 0.1%, 1% and 5% confidence levels respectively.

Size percentile	BETA	ln(ME)	ln(BEME)	RET(-2,-7)	RET(-1)	ln(TURN)	ln(CVTURN)	EGARCH_IV	D_{t-1}	Adj. R^2
Panel A: Model 11 within size groups										
All stocks	0.33	-0.06	0.49	0.01	-0.07	-0.42	-0.48	0.14	-0.64	5.68
	(1.74)	(1.89)	(6.49)***	(4.06)***	(13.47)***	(6.33)***	(6.56)***	(10.96)***	(5.40)***	
Micro	0.50	-0.25	0.60	0.01	-0.08	-0.54	-0.54	0.19	-0.95	6.08
	(2.54)*	(4.31)***	(9.oo)***	(3.54)***	(17.41)***	(7.44)***	(5.81)***	(12.68)***	(14.06)***	
Small	0.28	-0.07	0.35	0.01	-0.04	-0.16	-0.41	0.03	-0.64	8.01
	(1.45)	(0.77)	(4.82)***	(4.54)***	(6.93)***	(2.19)*	(3.94)***	(2.02)*	(6.47)***	
Large	0.03	-0.11	0.19	0.00	-0.04	-0.07	-0.16	-0.01	-0.39	11.39
	(0.15)	(2.62)**	(2.49)*	(1.13)	(6.3)***	(1.07)	(1.58)	(0.34)	(3.69)***	
All but micro	0.21	-0.10	0.27	0.01	-0.03	-0.14	-0.26	0.02	-0.53	9.35
	(1.12)	(2.8)**	(4.48)***	(3.52)***	(7.58)***	(2.3)*	(3.14)**	(1.43)	(6.48)***	
Panel B: Differences between the average slopes										
Micro- Small	0.22	-0.18	0.26	0.00	-0.04	-0.38	-0.13	0.15	-0.32	
	(1.75)	(1.68)	(3.24)**	(1.59)	(8.06)***	(5.56)***	(0.98)	(9.1)***	(3.52)***	
Micro - Large	0.46	-0.14	0.42	0.00	-0.04	-0.47	-0.39	0.19	-0.56	
	(2.52)*	(1.95)	(4.71)***	(1.13)	(8.08)***	(6.28)***	(2.91)**	(10.75)***	(4.72)***	
Micro - All but micro	0.28	-0.14	0.33	0.00	-0.05	-0.40	-0.29	0.17	-0.43	
	(2.21)*	(2.07)*	(4.48)***	(0.52)	(10.15)***	(6.55)***	(2.39)*	(11.6)***	(5.07)***	
Small - Large	0.25	0.04	0.16	0.01	0.00	-0.09	-0.25	0.04	-0.24	
	(1.61)	(0.42)	(2.07)*	(2.53)*	(0.36)	(1.32)	(2.32)*	(2.24)*	(2.00)*	

6.3 Return analysis of portfolios

This part presents the results of portfolios formed based on idiosyncratic volatility and financial distress. Based on the evidence from Fama Macbeth regression, I employ EGARCH_IV as the measure of expected idiosyncratic volatility. The first section reports univariate sort results based on idiosyncratic volatility and the second section based on financial distress. In third section I analyze the results of the distressed controlled idiosyncratic volatility sort and in the fourth section of the idiosyncratic volatility controlled distress risk sort.

6.3.1 Idiosyncratic volatility

Table 7 reports the results of trading portfolios sorted based on *EGARCH_IV*. Panel A reports the monthly value weighted simple returns in excess of Treasury bill rate, with t-statistics below in parentheses, and then alphas with respect to the CAPM, the three-factor model of Fama and French (1993), and a four-factor model proposed by Carhart (1997). Panel B reports estimated factor loadings for excess returns on the three Fama–French factors with t-statistics. Panel C reports some relevant characteristics for the portfolios: the skewness of each portfolio’s excess return, the mean market value, market-to-book, and estimated failure probability for each portfolio.

The value weighted portfolio alphas reported in Panel A do not show a robust statistically significant difference in portfolios sorted based on EGARCH_IV. The monthly Fama-French alpha for the long-short portfolio holding the highest idiosyncratic volatility stocks and shorting the safest stocks is -0.48% but statistically insignificant.

Table 7. Returns on value weighted idiosyncratic volatility sorted portfolios

The table presents value weighted monthly percentage returns of 5 portfolios sorted based level of expected idiosyncratic risk. Portfolio 1 (5) consists of stocks with the lowest (highest) volatility measure. The return spread of "5-1" refers to the difference in monthly returns between portfolio 5 and portfolio 1. In panel A, I report monthly alphas of value-weighted excess returns on a constant, market return (CAPM alpha), Fama-French 3-factor model and Carhart (1997) 4-factor model with t-statistics in parentheses. Panel B shows loadings on the three factor alphas and corresponding t-statistics. Panel C reports portfolio characteristics including skewness, mean size, market to book ratio (MB) and expected idiosyncratic volatility, EGARCH_IV, for each portfolio. The sample period is from 1971 to 2008. For each variable of interest. ***, **, and * indicate that the estimate is statistically different from zero at 0.1%, 1% and 5% confidence levels respectively.

Portfolios	1	2	3	4	5	5-1
			Panel A: Portfolio alphas			
Mean excess return	0.45	0.42	0.49	0.22	0.24	-0.21
	(2.34)*	(1.80)	(1.75)	(0.64)	(0.61)	(0.71)
CAPM alpha	0.12	0.01	0.01	-0.34	-0.36	-0.48
	(1.75)	(0.09)	(0.07)	(2.17)*	(1.68)	(1.83)
3-factor alpha	0.06	-0.04	0.02	-0.26	-0.23	-0.29
	(1.07)	(0.58)	(0.17)	(2.05)*	(1.39)	(1.51)
4-factor alpha	0.06	-0.01	0.08	-0.17	-0.22	-0.29
	(1.06)	(0.11)	(0.80)	(1.31)	(1.31)	(1.44)
			Panel B: Three-factor regression coefficients			
RM	0.93	1.07	1.14	1.23	1.25	0.32
	(69.00)***	(68.91)***	(50.57)***	(40.25)***	(31.82)***	(7.06)***
SMB	-0.20	0.03	0.25	0.54	0.85	1.05
	(11.25)***	(1.32)	(8.29)***	(13.07)***	(15.99)***	(17.02)***
HML	0.15	0.08	-0.07	-0.25	-0.43	-0.58
	(7.36)***	(3.25)**	(2.04)*	(5.39)***	(7.28)***	(8.41)***
			Panel C: Portfolio characteristics			
Skewness	-0.240	-0.556	-0.353	-0.382	-0.362	
Size ($mil)	3895	1920	1003	434	206	
MB	2.114	2.252	2.484	3.044	4.224	
EGARCH_IV (%)	6.029	8.758	11.566	15.466	30.359	
Mean $\hat{P}$ (%)	0.046	0.050	0.067	0.100	0.182	

Factor loadings reported in Panel B show that stocks with low failure idiosyncratic risk have betas less than one and negative loadings on the size factor *SMB* and positive loadings on the value factor *HML*. The high distress risk stocks have betas more than one, positive loadings on *SMB* and negative *HML* factors. High idiosyncratic volatility stocks have thus high proportion of small, growth firms as opposed to large, value firms among the safest stocks. This is consistent for example with the results of Fu (2009).

The size of the companies is monotonically decreasing with higher level of idiosyncratic volatility as reported in Panel C. Furthermore, the market-to-book value increases monotonically with higher EGARCH_IV. The strong correlation between EGARCH_IV and

D_{t-1} is apparent also in portfolios sorts. The mean failure of probability ($\hat{P}$) increases also monotonically as idiosyncratic risk increases.

Possible reasons to why sorts in Table **7** do not uncover a relation between idiosyncratic risk and return include that the relation is only visible in more extreme ends than lowest and highest quintile or that using value weighted returns leads large stocks to dominate the results. Given the evidence from regression within different size groups, which show that idiosyncratic volatility is only significant in micro and small stocks, the latter explanation is likely.

Table 8 reports a finer sort of portfolios of idiosyncratic risk portfolios into 10 portfolios, where the first portfolio consists of the 10% of the stocks with lowest E*GARCH_IV* and last portfolio with the highest level of E*GARCH_IV*. The monthly alphas of a long short portfolio that goes long the 10% of stocks with high risk and shorts the safest 10% are not statistically significant in any pricing model as in the 5 portfolio sort. However, the finer sort reveals significant negative returns in 70 to 80 and 80 to 90 percentile portfolios and positive returns in the least risk portfolio. These results would indicate a negative relation between EGARCH_IV and stock returns, contrary to the results from Fama MacBeth regressions. These puzzling results may be however explained by high correlation of idiosyncratic volatility and distress risk in EGARCH_IV sorted portfolios. The average failure probability for the lowest EGARCH_IV portfolio is 0.045%, whereas for the 70 to 80 percentile the failure probability is 0.111% and for 90 to 100 percentile 0.214%. Comparison of these values with finer sort based on distress risk that is reported in Table 11 , the 70 to 80 percentile has a statistically significant negative three factor alpha with an average failure probability of 0.093%, i.e. smaller than 70 to 80 percentile based on EGARCH_IV. Thus low returns of 70 to 80 and 80 to 90 percentiles of EGARCH_IV sort may be due to high distress risk in those portfolios. The highest EGARCH_IV portfolio however has actually positive returns though they are not statistically significant. Factor loadings reported in Panel B and portfolio characteristics reported in Panel C confirm the conclusions from the earlier sort.

Table 9 reports the equally weighted returns of finer EGARCH_IV sort. The equally weighted returns provide strong evidence of a positive relation between idiosyncratic volatility and returns. The monthly alphas of a long short portfolio reported in Panel A are statistically significant at 0.1% level for all pricing models. The monthly three factor alpha of 1.72% of the long short portfolio is also economically highly significant. The results provide further evidence that idiosyncratic risk is positively related to stock returns, but the effect is largely driven by smaller stocks.

Table 8. Finer sort of value weighted idiosyncratic volatility portfolios

The table presents value weighted monthly percentage returns of 10 portfolios sorted based level of expected idiosyncratic risk, EGARCH_IV. Portfolio 1 (10) consists of stocks with the lowest (highest) volatility measure. The return spread of "10-1" refers to the difference in monthly returns between portfolio 10 and portfolio 1. In panel A, I report monthly alphas of value-weighted excess returns on a constant, market return (CAPM alpha), Fama-French 3-factor model and Carhart (1997) 4-factor model with t-statistics in parentheses. Panel B shows loadings on the three factor alphas and corresponding t-statistics. Panel C reports portfolio characteristics including skewness, mean size, market to book ratio (MB) and expected idiosyncratic volatility, GARCH_IV, for each portfolio. The sample period is from 1971 to 2008. For each variable of interest. ***, **, and * indicate that the estimate is statistically different from zero at 0.1%, 1% and 5% confidence levels respectively.

Portfolios	1	2	3	4	5	6	7	8	9	10	10-1
Panel A: Portfolio alphas											
Mean excess	0.54	0.31	0.42	0.43	0.54	0.49	0.33	0.06	-0.11	0.71	0.17
	(2.83)**	(1.50)	(1.79)	(1.73)	(1.98)*	(1.58)	(0.98)	(0.16)	(0.29)	(1.70)	(0.50)
CAPM alpha	0.22	-0.04	0.01	0.00	0.08	-0.02	-0.22	-0.51	-0.73	0.10	-0.12
	(2.74)**	(0.54)	(0.13)	(0.01)	(0.73)	(0.16)	(1.37)	(2.75)**	(3.36)***	(0.39)	(0.39)
3-factor alpha	0.15	-0.10	-0.06	-0.04	0.09	-0.02	-0.16	-0.43	-0.62	0.27	0.12
	(2.24)*	(1.26)	(0.74)	(0.47)	(0.78)	(0.13)	(1.12)	(2.85)**	(3.69)***	(1.31)	(0.50)
4-factor alpha	0.14	-0.08	-0.03	0.01	0.15	0.06	-0.03	-0.37	-0.59	0.32	0.18
	(1.99)*	(1.00)	(0.32)	(0.09)	(1.37)	(0.50)	(0.18)	(2.39)*	(3.38)***	(1.48)	(0.73)
Panel B: Three-factor regression coefficients											
RM	0.90	0.96	1.07	1.08	1.12	1.20	1.24	1.23	1.29	1.24	0.34
	(56.31)***	(52.11)***	(59.83)***	(51.07)***	(43.14)***	(39.81)***	(36.78)***	(34.02)***	(32.06)***	(25.32)***	(6.07)***
SMB	-0.24	-0.12	-0.03	0.13	0.19	0.38	0.47	0.67	0.84	0.89	1.13
	(11.30)***	(4.95)***	(1.11)	(4.5)***	(5.42)***	(9.51)***	(10.33)***	(13.81)***	(15.48)***	(13.45)***	(15.09)***
HML	0.18	0.13	0.13	0.05	-0.05	-0.09	-0.21	-0.29	-0.37	-0.51	-0.69
	(7.45)***	(4.62)***	(4.70)***	(1.63)	(1.25)	(2.04)*	(4.16)***	(5.26)***	(6.05)***	(6.84)***	(8.17)***
Panel C: Portfolio characteristics											
Skewness	-0.001	-0.546	-0.556	-0.496	-0.165	-0.284	-0.269	-0.389	-0.433	-0.139	
Size ($mil)	4561	3229	2263	1578	1183	824	523	345	232	181	
MB	2.000	2.228	2.246	2.258	2.402	2.565	2.820	3.269	3.843	4.614	
EGARCH_IV	5.036	6.881	8.115	9.358	10.739	12.336	14.216	16.622	20.475	37.728	
Mean $\hat{P}$ (%)	0.045	0.046	0.048	0.052	0.061	0.073	0.089	0.111	0.149	0.214	

Table 9. Finer sort of equally weighted idiosyncratic volatility portfolios

The table presents equally weighted monthly percentage returns of 10 portfolios sorted based level of expected idiosyncratic risk, EGARCH_IV. Portfolio 1 (10) consists of stocks with the lowest (highest) volatility measure. The return spread of “10-1” refers to the difference in monthly returns between portfolio 10 and portfolio 1. In panel A, I report monthly alphas of value-weighted excess returns on a constant, market return (CAPM alpha), Fama-French 3-factor model and Carhart (1997) 4-factor model with t-statistics in parentheses. Panel B shows loadings on the three factor alphas and corresponding t-statistics. Panel C reports portfolio characteristics including skewness, mean size, market to book ratio (MB) and expected idiosyncratic volatility, GARCH_IV, for each portfolio. The sample period is from 1971 to 2008. For each variable of interest. ***, **, and * indicate that the estimate is statistically different from zero at 0.1%, 1% and 5% confidence levels respectively.

Portfolios	1	2	3	4	5	6	7	8	9	10	10-1
					Panel A: Portfolio alphas						
Mean excess	0.51	0.46	0.55	0.58	0.56	0.39	0.41	0.32	0.39	2.45	1.94
	(3.01)**	(2.3)*	(2.53)*	(2.49)*	(2.19)*	(1.39)	(1.32)	(0.96)	(1.02)	(5.14)***	(4.8)***
CAPM alpha	0.24	0.14	0.20	0.20	0.15	-0.05	-0.07	-0.18	-0.15	1.85	1.6
	(2.72)**	(1.41)	(1.91)	(1.82)	(1.18)	(0.32)	(0.38)	(0.92)	(0.61)	(5.3)***	(4.43)***
3-factor alpha	-0.02	-0.14	-0.10	-0.07	-0.10	-0.31	-0.32	-0.37	-0.37	1.70	1.72
	(0.29)	(1.86)	(1.41)	(0.93)	(1.33)	(3.5)***	(2.99)**	(3.07)**	(2.26)*	(6.31)***	(5.9)***
4-factor alpha	0.01	-0.09	-0.02	0.02	0.02	-0.16	-0.14	-0.19	-0.13	2.04	2.03
	(0.14)	(1.17)	(0.35)	(0.30)	(0.22)	(1.83)	(1.3)	(1.56)	(0.81)	(7.53)***	(6.87)***
					Panel B: Three-factor regression coefficients						
RM	0.76	0.89	0.95	0.96	1.00	1.04	1.09	1.10	1.14	1.22	0.46
	(46.64)***	(51.03)***	(57.26)***	(54.75)***	(54.14)***	(48.94)***	(43.07)***	(37.7)***	(29.36)***	(18.94)***	(6.59)***
SMB	0.17	0.28	0.42	0.53	0.66	0.84	0.98	1.07	1.29	1.55	1.38
	(7.94)***	(11.94)***	(18.76)***	(22.5)***	(26.68)***	(29.39)***	(28.62)***	(27.42)***	(24.54)***	(17.98)***	(14.75)***
HML	0.46	0.45	0.47	0.40	0.33	0.31	0.26	0.14	0.14	-0.06	-0.52
	(18.66)***	(17.08)***	(18.58)***	(14.86)***	(11.66)***	(9.81)***	(6.85)***	(3.1)**	(2.34)*	(0.62)	(4.94)***
					Panel C: Portfolio characteristics						
Skewness	-0.001	-0.546	-0.556	-0.496	-0.165	-0.284	-0.269	-0.389	-0.433	-0.139	
Size ($mil)	4561	3229	2263	1578	1183	824	523	345	232	181	
MB	2.000	2.228	2.246	2.258	2.402	2.565	2.820	3.269	3.843	4.614	
EGARCH_IV	5.036	6.881	8.115	9.358	10.739	12.336	14.216	16.622	20.475	37.728	
Mean $\hat{P}$ (%)	0.045	0.046	0.048	0.052	0.061	0.073	0.089	0.111	0.149	0.214	

Figure 4 plots the cumulative excess return and Fama-French 3 factor alpha of the value and equally weighted long short idiosyncratic risk portfolio (10-1) over the sample period. For comparison, the cumulative market return is also included in the figure. The value weighted long short portfolio has a strong positive performance between 1975 and 1980 followed with negative performance of equal magnitude between 1980 and 1990 after which the performance levels off. The equally weighted long short has on the other hand experience consistently positive returns throughout the sample period. The strong performance is especially concentrated on expansionary periods in 1975-1980 and 1999-2000. These two periods do not however count all of the returns of the equally weighted portfolio. Both value and equally weighted portfolios tend to experience positive returns during expansionary periods (except the strong negative performance of value weighted portfolio in 1980s) and negative returns in recessions. This likely illustrates the changes in investors risk aversion, with investors trying to earn abnormal returns via idiosyncratic risk when risk aversion is low and on the other hand flight to safer assets when risk aversion rises. Particularly strong evidence of this can be seen in 1999-2001 during the rise and fall of the IT bubble.

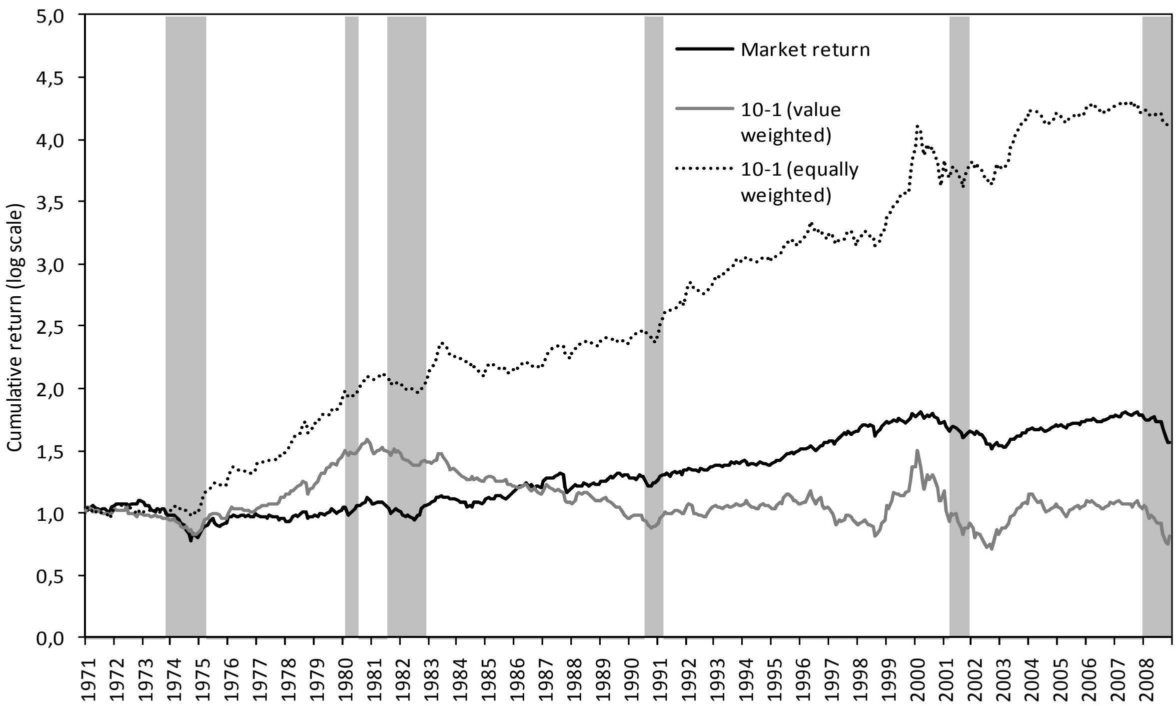

Figure 4. Returns on long short idiosyncratic risk portfolio.. The figure plots the value and equally weighted cumulative excess returns from January 1971 to December 2008 for a long short portfolio that goes long for the 10% stocks of highest idiosyncratic volatility and shorts the 10% safest stocks.. The figure plots also the cumulative market return (CRSP). Shaded areas correspond to NBER recessions.

6.3.2 Financial distress

Panel A of Table 10 shows the monthly excess returns and alphas of portfolios formed based on distress risk. Consistent with the results of Campbell et al. (2008), the results indicate a negative relation between distress risk and stock returns. A long-short portfolio holding the most distressed stocks and shorting the safest stocks has an average Fama-French 3-factor alpha of -1.49%, which is statistically significant at 0.1% level

Table 10. Returns on value weighted distress risk sorted portfolios

The table presents value weighted monthly percentage returns of 5 portfolios sorted based on the level of distress risk at the end of previous month. Portfolio 1 (5) consists of stocks with the lowest (highest) volatility measure. The return spread of "5-1" refers to the difference in monthly returns between portfolio 5 and portfolio 1. In panel A, I report monthly alphas of value-weighted excess returns on a constant, market return (CAPM alpha), Fama-French 3-factor model and Carhart (1997) 4-factor model with t-statistics in parentheses. Panel B shows loadings on the three factor alphas and corresponding t-statistics. Panel C reports portfolio characteristics including skewness, mean size, market to book ratio (MB) and probability of failure $(\widehat{P})$ for each portfolio. The sample period is from 1971 to 2008. For each variable of interest. ***, **, and * indicate that the estimate is statistically different from zero at 0.1%, 1% and 5% confidence levels respectively.

Portfolios	1	2	3	4	5	5-1
Panel A: Portfolio alphas						
Mean excess return	0.48	0.42	0.41	0.35	-0.45	-0.93
	(2.29)*	(1.88)	(1.66)	(1.17)	(1.05)	(2.85)**
CAPM alpha	0.12	0.03	-0.02	-0.14	-1.06	-1.19
	(1.58)	(0.42)	(0.20)	(0.95)	(4.13)***	(3.99)***
3-factor alpha	0.17	0.03	-0.13	-0.26	-1.33	-1.49
	(2.13)*	(0.40)	(1.55)	(1.83)	(5.82)***	(5.50)***
4-factor alpha	-0.03	0.01	0.06	0.16	-0.54	-0.51
	(0.35)	(0.12)	(0.78)	(1.26)	(2.96)**	(2.44)*
Panel B: Three-factor regression coefficients						
RM	0.90	1.01	1.13	1.25	1.48	0.58
	(48.33)***	(62.93)***	(56.85)***	(36.83)***	(27.21)***	(8.89)***
SMB	-0.02	-0.04	0.07	0.24	0.90	0.91
	(0.68)	(1.98)*	(2.47)*	(5.24)***	(12.26)***	(10.49)***
HML	-0.08	0.01	0.20	0.18	0.30	0.38
	(2.88)**	(0.44)	(6.55)***	(3.51)***	(3.66)***	(3.91)***
Panel C: Portfolio characteristics						
Skewness	-0.288	-0.328	-0.335	-0.481	0.096	
Size ($mil)	2720	2276	1400	666	120	
MB	2.682	2.859	2.788	2.894	3.332	
Mean $\widehat{P}$ (%)	0.021	0.035	0.051	0.082	0.267	
EGARCH_IV	12.040	13.648	15.306	17.381	23.245	

Panel B reports the factor loadings on Fama–French 3 factors. Stocks with low failure risk have betas less than one and negative loadings on the size factor *SMB* and the value factor

HML. The high distress risk stocks have betas more than one and positive loadings on *SMB* and *HML* factors, indicating predominance of small, growth firms among distressed stocks as opposed to large, value firms among the safest stocks. Hence when using CAPM or 3-factor model to correct for risk, the anomalously low returns of high distress risk stocks are amplified, which can be seen in Panel A. Including momentum in Carhart 4-factor model reduces the anomaly, but it remains statistically significant. The results are consistent with Campbell et al. (2008).

Panel C reports portfolio characteristics including skewness, size, MB, mean default risk and mean idiosyncratic volatility. As indicated by *HML* and *SMB* loadings, high distress risk firms are small and have high market to book values. Skewness of the excess returns is positive for the high risk portfolio, which may explain part of the anomalously low returns as noted by Campbell et al. (2008). The reported average default risk shows that default risk grows exponential when moving to high default risk companies. The mean default risk is gradually linearly increasing in portfolios from 1 to 4, on average at 0.04%, but in the highest risk quintile the value jumps to 0.27%. The idiosyncratic volatility increases also monotonically with increases in distress risk, similar to increases of distress risk when sorted based on idiosyncratic volatility.

I also perform a finer sort for value weighted distress risk portfolios from which the results are reported in Table 11. The results are consistent with the 5 portfolio sort. Low returns of distressed stocks are even more pronounced with the finer sort. The 3-factor alpha decreases almost monotonically by increase in distress risk. The monthly 3-factor alpha of a long short portfolio is -1.91%. Given the evidence from Fama MacBeth regression in different size groups that distress effect is strongest in micro and small stocks, I do not perform equally weighted sorts for distress risk as value weighted returns already provide a strong evidence of negative relation between financial distress and stock returns.

Figure 5 plots the value weighted cumulative excess return and Fama-French 3 factor alpha of the long short distress risk portfolio (10-1) that goes long the 10% of most distressed stocks and shorts the 10% safest stocks over the sample period.. From 1980 to 2000, both the excess return and three factor alpha of the portfolio are persistently negative, i.e. distressed stocks have unperformed safe stocks. A notable sharp rise in the portfolio’s excess return and alpha can be seen from third quarter of 2002 to the end of 2003. This rise coincides exactly with the start of the stock market rebound after the long bear market since the burst of the IT bubble in 2000. In other words, distressed stocks have produced very high returns during this period. On the other hand, opposite returns of similar magnitude are observed during the financial crisis in 2003. The high returns of distressed stocks during the expansionary period and low returns during riskier periods are consistent with the view that investors "flee to quality" and sell distressed stocks when risk aversion increases and vice versa. Campbell et al. (2008) document similar finding by showing that the return of the long short portfolio of distressed stocks correlates with the implied volatility (VIX) of S&P 500 index.

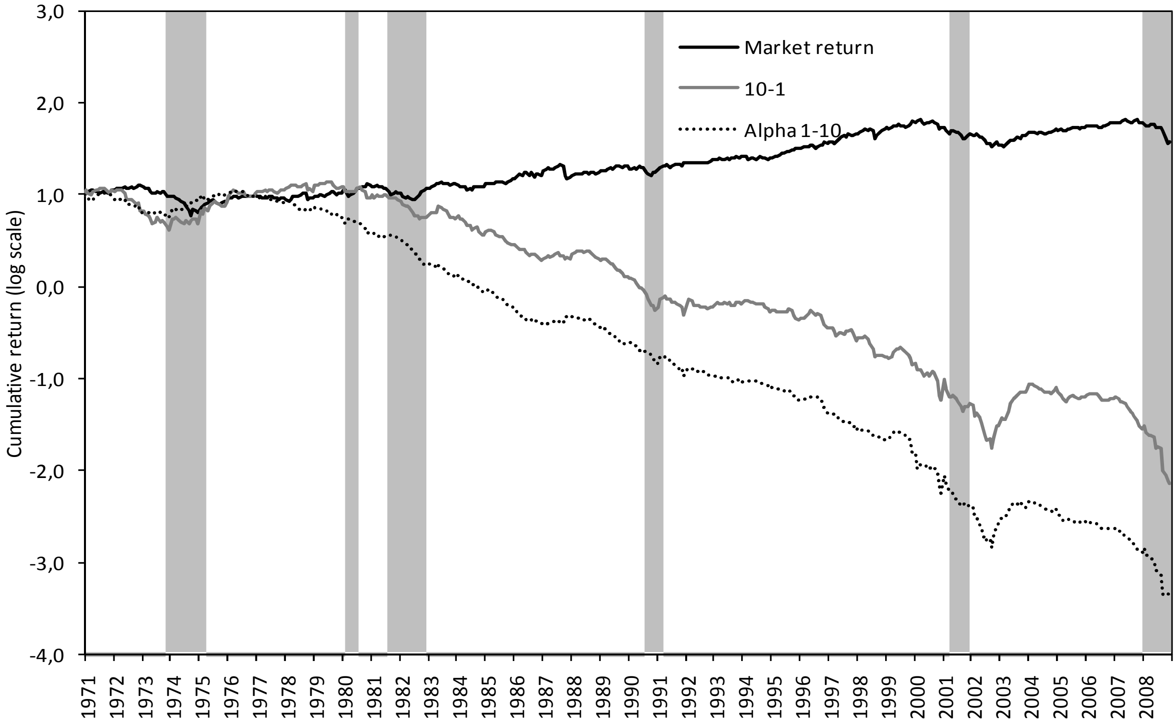

Figure 5. Returns on long short distressed risk portfolio. The figure plots the value weighted cumulative excess return and Fama-French three factor alpha from January 1971 to December 2008 for a long short portfolio that goes long the 10% most distressed stocks and short for the 10% safest stocks. The figure plots also the cumulative market return (CRSP). Shaded areas correspond to NBER recessions.

Table 11. Finer sort of value weighted distress risk portfolios

The table presents monthly percentage returns of 10 portfolios sorted based on the level of distress risk at the end of previous month. Portfolio 1 (10) consists of stocks with the lowest (highest) volatility measure. The return spread of "10-1" refers to the difference in monthly returns between portfolio 10 and portfolio 1. In panel A, I report monthly alphas of value-weighted excess returns on a constant, market return (CAPM alpha), Fama-French 3-factor model and Carhart (1997) 4-factor model with t-statistics in parentheses. Panel B shows loadings on the three factor alphas and corresponding t-statistics. Panel C reports portfolio characteristics including skewness, mean size, market to book ratio (MB) and probability of failure $(\widehat{P})$ for each portfolio. The sample period is from 1971 to 2008. For each variable of interest. ***, **, and * indicate that the estimate is statistically different from zero at 0.1%, 1% and 5% confidence levels respectively.

Portfolios	1	2	3	4	5	6	7	8	9	10	10-1
					Panel A: Portfolio alphas						
Mean excess	0.58	0.43	0.43	0.42	0.49	0.31	0.38	0.21	-0.42	-0.60	-1.19
	(2.55)*	(2.02)*	(1.87)	(1.80)	(2.03)*	(1.18)	(1.32)	(0.6)	(1.03)	(1.22)	(2.84)**
CAPM alpha	0.22	0.07	0.03	0.02	0.07	-0.13	-0.09	-0.33	-1.02	-1.26	-1.48
	(1.90)	(0.82)	(0.42)	(0.22)	(0.86)	(1.15)	(0.64)	(1.72)	(4.12)***	(3.66)***	(3.8)***
3-factor alpha	0.31	0.08	0.05	-0.02	-0.03	-0.27	-0.22	-0.46	-1.26	-1.60	-1.91
	(2.68)**	(0.97)	(0.63)	(0.19)	(0.31)	(2.44)*	(1.67)	(2.42)*	(5.59)***	(5.25)***	(5.34)***
4-factor alpha	0.03	-0.06	-0.01	0.01	0.09	0.00	0.12	0.07	-0.50	-0.76	-0.79
	(0.30)	(0.72)	(0.06)	(0.13)	(1.09)	(0.00)	(0.98)	(0.44)	(2.75)**	(2.78)**	(2.61)**
					Panel B: Three-factor regression coefficients						
RM	0.87	0.93	0.99	1.04	1.10	1.17	1.21	1.33	1.45	1.54	0.67
	(31.98)***	(46.27)***	(48.47)***	(52.74)***	(53.85)***	(44.13)***	(37.52)***	(29.75)***	(26.96)***	(21.19)***	(7.86)***
SMB	0.04	-0.03	-0.03	-0.04	0.06	0.11	0.20	0.36	0.80	1.18	1.15
	(1.02)	(1.06)	(1.09)	(1.37)	(2.04)*	(3.22)**	(4.60)***	(6.03)***	(11.02)***	(12.07)***	(9.98)***
HML	-0.18	-0.02	-0.03	0.07	0.18	0.24	0.22	0.16	0.27	0.39	0.57
	(4.24)***	(0.67)	(0.93)	(2.39)*	(5.79)***	(5.99)***	(4.42)***	(2.35)*	(3.34)***	(3.57)***	(4.4)***
					Panel C: Portfolio characteristics						
Skewness	-0.147	-0.104	-0.240	-0.430	-0.297	-0.370	-0.458	-0.547	-0.100	0.517	
Size ($mil)	2330	3111	2591	1962	1513	1287	925	407	176	64	
MB	2.418	2.946	2.911	2.807	2.798	2.778	2.838	2.951	3.178	3.497	
Mean $\hat{P}$ (%)	0.017	0.025	0.031	0.038	0.046	0.056	0.070	0.093	0.142	0.392	
EGARCH_IV	11.701	12.371	13.221	14.061	14.979	15.626	16.503	18.218	20.746	25.498	

6.3.3 Distress risk controlled idiosyncratic volatility

Multivariate portfolios sorts enable a closer examination of how idiosyncratic risk and distress risk effects vary along the full spectrum of other variable. Table 12 reports the results of sequential sort of distress controlled idiosyncratic risk portfolios. Panel A shows value weighted excess returns and Panel B the Fama-French three factor alphas and corresponding t-statistics. Panels C to E report the average failure probability, idiosyncratic volatility and size of each portfolio.

Panels A and B show that after controlling for distress risk, idiosyncratic risk spread seems to be negative for the least distressed stocks and insignificant for more distressed stocks. However, an inspection of average failure probabilities and idiosyncratic volatilities of portfolios shows that sequential sort fails to achieve considerable spread between low and high idiosyncratic volatility portfolios within distress quintiles. In fact, within the distress quintiles which are reported in rows, EGARCH_IV is on average only 17% higher in highest EGARCH_IV portfolio than in lowest EGARCH_IV portfolio. Distress risk on the other hand increases on average 126% along the low – high idiosyncratic volatility sort. Thus the negative spread of -0.37% (with t-statistic of 2.30) of long short idiosyncratic risk portfolio in lowest distress quintile tells more about the negative relation between distress risk and return than about the relation between idiosyncratic volatility and return. From Panel E, which reports the average sizes of the portfolios, we can see that within distress quintiles, stocks

The results differ from Song (2008) who find a positive (negative) relation between idiosyncratic risk and stock returns given low (high) distress risk. As the sequential sort fails to give a sufficient spread for idiosyncratic volatility portfolios within distress quintiles due to high correlation of the two measures, an independent sort of idiosyncratic volatility and distress risk should be performed before drawing conclusions. I perform this robustness check in 6.3.5 after examining idiosyncratic volatility controlled distress risk portfolios.

Table 12. Distress controlled idiosyncratic volatility portfolios

The table presents the Fama-French 3 Factor alphas of the 25 distress controlled, value weighted idiosyncratic volatility portfolios.. A sequential sort is performed to control for the level of distress: I first sort stocks into 5 quintiles based on their level of distress, and then within each distress quintile, further sort stocks into 5 portfolios based on their level of idiosyncratic volatility (EGARCH_IV). The return spread of "5-1" refers to the difference in monthly returns between idiosyncratic risk portfolio 5 and portfolio 1 within each distress quintile. T-statistics are reported in brackets. The sample period is from September 1971 to December 2008. First 8 months of the original sample period are excluded in order to have sufficient number of stocks in each portfolio. For each variable of interest. ***, **, and * indicate that the estimate is statistically different from zero at 0.1%, 1% and 5% confidence levels respectively.

	Ranking on Idiosyncratic Volatility					
	1 Low	2	3	4	5 High	5-1
Panel A: Excess returns						
1 Low	0.74	0.64	0.46	0.48	0.36	-0.37
Distress risk	(2.98)**	(2.64)**	(2.03)*	(2.15)*	(1.60)	(2.30)*
2	0.52	0.52	0.45	0.48	0.35	-0.17
	(2.18)*	(2.16)*	(1.85)	(2.01)*	(1.45)	(1.23)
3	0.55	0.49	0.37	0.33	0.40	-0.15
	(2.22)*	(1.84)	(1.49)	(1.16)	(1.39)	(0.99)
4	0.33	0.34	0.54	0.12	0.25	-0.08
	(1.13)	(1.10)	(1.70)	(0.34)	(0.64)	(0.35)
5 High	-0.02	-0.62	-0.34	-0.45	-0.32	-0.30
Distress risk	(0.04)	(1.37)	(0.72)	(0.86)	(0.53)	(0.75)
Panel B: Three factor alphas						
1 Low	0.38	0.40	0.18	0.11	-0.02	-0.40
Distress risk	(2.75)**	(2.90)**	(1.44)	(1.05)	(0.19)	(2.47)*
2	0.12	0.17	0.01	0.04	-0.09	-0.22
	(1.11)	(1.59)	(0.08)	(0.37)	(1.03)	(1.55)
3	0.04	-0.02	-0.18	-0.27	-0.22	-0.26
	(0.37)	(0.13)	(1.63)	(2.03)*	(1.51)	(1.7)
4	-0.26	-0.30	-0.08	-0.52	-0.42	-0.16
	(1.86)	(1.88)	(0.47)	(2.44)*	(1.87)	(0.75)
5 High	-0.83	-1.50	-1.33	-1.41	-1.48	-0.64
Distress risk	(3.55)***	(5.37)***	(4.58)***	(4.08)***	(3.42)***	(1.64)
Panel C: Average failure probability						
1 Low	0.014	0.019	0.022	0.024	0.027	
2	0.029	0.031	0.034	0.037	0.040	
3	0.043	0.046	0.050	0.054	0.059	
4	0.064	0.070	0.077	0.087	0.099	
5 High	0.116	0.142	0.183	0.262	0.591	
Panel D: Average idiosyncratic volatility						
1 Low	11.51	11.80	12.01	12.26	12.59	
2	12.85	13.39	13.59	13.97	14.38	
3	14.78	15.03	15.27	15.59	15.83	
4	16.02	16.67	17.21	17.99	18.87	
5 High	19.89	21.00	22.34	24.22	27.91	
Panel E: Average size (MUSD)						
1 Low	1473	2871	3262	3215	3068	
2	2911	2620	2297	2103	1912	
3	1705	1520	1411	1374	1327	
4	1132	930	729	478	320	
5 High	234	174	119	81	35	

6.3.4 Idiosyncratic volatility controlled distress risk

Table 13 shows the results of the multivariate effect between idiosyncratic volatility and financial distress when distress risk is controlled by idiosyncratic volatility. Panels A and B show that after controlling for idiosyncratic volatility, distress risk spread seems to be negative for low idiosyncratic volatility stocks and positive for high idiosyncratic volatility stocks. However, Panels C and D show that the idiosyncratic volatility controlled sort suffers from the same problem as distress controlled sort. In the lowest idiosyncratic volatility quintile, there is almost no spread in distress risk. On average, distress risk increases 33% within idiosyncratic volatility quintiles, whereas EGARCH_IV increases 63% within the quintiles. Hence no definitive conclusions can be drawn from idiosyncratic controlled sequential sort.

Table 13. Idiosyncratic volatility controlled distress risk portfolios

The table presents the Fama-French 3 Factor alphas of the 25 idiosyncratic risk controlled, value weighted distress portfolios.. A sequential sort is performed to control for the level of idiosyncratic volatility: I first sort stocks into 5 quintiles based on their level of idiosyncratic volatility, and then within each quintile, further sort stocks into 5 portfolios based on their level of distress. The return spread of "5-1" refers to the difference in monthly returns between distress risk portfolio 5 and portfolio 1 within each idiosyncratic risk quintile. T-statistics are reported in brackets. The sample period is from September 1971 to December 2008. First 8 months of the original sample period are excluded in order to have sufficient number of stocks in each portfolio. For each variable of interest. ***, **, and * indicate that the estimate is statistically different from zero at 0.1%, 1% and 5% confidence levels respectively.

	Ranking on Financial Distress					
	1 Low	2	3	4	5 High	5-1
Panel A: Excess returns						
1 Low	0.63	0.54	0.49	0.33	0.35	-0.28
Idiosyncratic risk	(3.22)**	(2.63)**	(2.30)*	(1.48)	(1.60)	(1.92)
2	0.51	0.46	0.31	0.59	0.46	-0.05
	(2.15)*	(1.82)	(1.20)	(2.22)*	(1.72)	(0.28)
3	0.32	0.65	0.73	0.44	0.29	-0.03
	(1.21)	(2.15)*	(2.37)*	(1.30)	(0.85)	(0.15)
4	0.34	0.33	0.48	0.12	-0.13	-0.47
	(0.97)	(0.91)	(1.32)	(0.32)	(0.33)	(1.99)*
5 High	0.06	-0.22	0.12	0.58	1.20	1.14
Idiosyncratic risk	(0.15)	(0.54)	(0.26)	(1.23)	(2.63)**	(3.78)***
Panel B: Three factor alphas						
1 Low	0.26	0.15	0.04	-0.15	-0.04	-0.30
Idiosyncratic risk	(2.81)**	(1.76)	(0.44)	(1.76)	(0.39)	(2.07)*
2	0.00	-0.05	-0.13	0.08	0.02	0.02
	(0.04)	(0.40)	(1.17)	(0.70)	(0.19)	(0.13)
3	-0.17	0.22	0.23	-0.08	-0.17	0.00
	(1.37)	(1.42)	(1.62)	(0.54)	(0.99)	(0.00)
4	-0.15	-0.17	0.02	-0.36	-0.61	-0.46
	(0.85)	(1.02)	(0.12)	(1.87)	(3.07)**	(1.96)
5 High	-0.42	-0.75	-0.40	0.17	0.77	1.18
Idiosyncratic risk	(1.93)	(3.67)***	(1.62)	(0.60)	(2.79)**	(3.86)***
Panel C: Average default probability						
1 Low	0.045	0.045	0.045	0.045	0.046	
2	0.047	0.048	0.050	0.052	0.054	
3	0.057	0.061	0.066	0.071	0.077	
4	0.083	0.090	0.098	0.108	0.120	
5 High	0.134	0.153	0.178	0.211	0.233	
Panel D: Average idiosyncratic volatility						
1 Low	4.04	5.39	6.17	6.75	7.26	
2	7.74	8.23	8.72	9.22	9.74	
3	10.29	10.87	11.49	12.15	12.84	
4	13.59	14.40	15.28	16.28	17.47	
5 High	18.93	20.82	23.52	28.36	49.53	
Panel E: Average size (MUSD)						
1 Low	4938	4539	3741	3298	2962	
2	2527	2193	1822	1618	1443	
3	1304	1143	1010	859	700	
4	605	484	411	367	302	
5 High	256	225	195	166	190	

6.3.5 Multivariate independent sort

To control for the drawbacks of sequential sorts of not generating large enough spreads, I perform independent sort with idiosyncratic volatility and financial distress. Table 14 presents the results of the sort. Panel A reports the value weighted excess returns and Panel B the Fama-French three factor alphas and corresponding t-statistics. Panels C to F report the average failure probability, idiosyncratic volatility, size and number of companies of each portfolio.

In Panels A and B, the long short idiosyncratic volatility spread reported in column “5-1” shows that high idiosyncratic volatility stocks exhibit significantly positive returns only in the least distressed quintiles. The three factor alpha of long short idiosyncratic volatility portfolio is 1.24% and is significant at 0.1% level. The inspection of average failure probabilities and idiosyncratic volatilities show that positive returns of the long short portfolio can be attributed to idiosyncratic volatility. The average failure probability of the least distressed quintile reported in Panel C is constant at 0.021% while the average idiosyncratic volatility increases from 6.20% to 27.82% within the least distressed quintile. Distress risk remains relatively constant across the idiosyncratic risk quintiles except in the highest idiosyncratic volatility quintile where distress risk increased from 0.131% to 0.314%. Idiosyncratic volatility increases quite uniformly in each distress quintile from around 6% to 30%. The results of idiosyncratic volatility spread are qualitatively similar to Song (2008) who finds a negative spread of lagged idiosyncratic volatility portfolios only in high distress risk quintiles whereas in the lowest distress risk quintile the idiosyncratic volatility spread is positive albeit insignificant. My results do not show a negative relation between idiosyncratic volatility and returns even in the highest distress risk quintile, but the positive relation between idiosyncratic volatility and stock returns in only significant in the lowest distress risk quintile.

The returns of the long short distress risk are reported in row “5-1” in Panels A and B. Three factor alphas are significantly negative for all idiosyncratic risk quintiles, except the second quintile. With the exception of second idiosyncratic volatility quintile, the return spread of long short distress portfolio decreases as idiosyncratic risk increases. This is mainly explained by simultaneous increase in distress risk in the highest distress risk quintile as idiosyncratic risk increased. In the fourth distress quintile where distress risk remains constant across idiosyncratic risk quintiles, the three factor alpha is significantly negative only in the highest idiosyncratic risk portfolio. The results suggest that the asset pricing impact of distress risk is not depended on idiosyncratic volatility though it is somewhat amplified by idiosyncratic volatility.

The size of the companies decreases almost monotonically across each distress (idiosyncratic volatility) quintile as idiosyncratic volatility (distress risk) increases. Due to high correlation of the measures, a drawback of independent sort is that number of companies in each portfolio can differ greatly. Panel F reports than in lowest (highest) D_{t-1}, highest (lowest) *EGARCH_IV* portfolio there is on average 48 (31) stocks. Campbell et al. (2001) suggest that the number of stocks needed to achieve complete portfolio diversification has been about 20 between 1963 and 1985and about 50 during 1986-1997 as the level of idiosyncratic volatility has increased. Thus on average there is quite well enough stocks also in these extreme portfolios to achieve sufficient portfolio diversification even after taking into account that there fewer stocks in these portfolios than on average in the first years of the sample period.

Table 14. Multivariate independent sort of idiosyncratic risk and distress risk portfolios

The table presents the results of independent sort on idiosyncratic volatility and level of financial distress. I sort stocks into 5 quintiles based on their idiosyncratic volatility and level of financial distress independently and then form 25 portfolios by matching both criteria. Panel A and B report the value weighted excess return and Fama-French three factor alphas of the value weighted portfolios respectively. The spread of long-short volatility trading strategy is reported in column “5-1”. The spread of long-short distress trading strategy is reported in row “5-1”. T-statistics are reported in brackets. Panels C to F report the average default probability, idiosyncratic volatility, size and number of companies in each portfolio respectively. The sample period is from September 1971 to December 2008. First 8 months of the original sample period are excluded in order to have sufficient number of stocks in each portfolio. For each variable of interest. ***, **, and * indicate that the estimate is statistically different from zero at 0.1%, 1% and 5% confidence levels respectively.

	Ranking on Idiosyncratic Volatility					
	1 Low	2	3	4	5 High	5-1
Panel A: Excess returns						
1 Low	0.48	0.38	0.71	0.77	1.73	1.26
Distress risk	(2.44)*	(1.60)	(2.45)*	(2.16)*	(4.08)***	(3.54)***
2	0.48	0.47	0.52	0.31	1.17	0.68
	(2.27)*	(1.91)	(1.80)	(0.87)	(2.68)**	(1.93)
3	0.45	0.54	0.27	0.04	0.10	-0.34
	(1.95)	(2.01)*	(0.82)	(0.11)	(0.25)	(1.04)
4	0.52	0.58	0.33	0.19	-0.12	-0.64
	(1.96)	(1.82)	(0.95)	(0.50)	(0.27)	(1.76)
5 High	-0.24	0.39	-0.09	-0.75	-0.37	-0.13
Distress risk	(0.71)	(0.96)	(0.22)	(1.59)	(0.72)	(0.32)
5-1	-0.72	0.01	-0.80	-1.52	-2.11	
	(2.56)*	(0.03)	(2.26)*	(4.19)***	(4.56)***	
Panel B: Three factor alphas						
1 Low	0.19	0.01	0.37	0.37	1.45	1.26
Distress risk	(2.33)*	(0.08)	(2.46)*	(1.79)	(4.93)***	(4.19)***
2	0.04	0.02	0.11	-0.05	0.79	0.75
	(0.54)	(0.17)	(0.85)	(0.27)	(3.11)**	(2.72)**
3	-0.11	-0.05	-0.26	-0.54	-0.29	-0.19
	(1.07)	(0.41)	(1.54)	(3.08)**	(1.31)	(0.75)
4	-0.12	-0.14	-0.40	-0.34	-0.61	-0.49
	(0.79)	(0.79)	(2.13)*	(1.71)	(2.63)**	(1.79)
5 High	-0.97	-0.51	-1.04	-1.69	-1.21	-0.25
Distress risk	(4.00)***	(1.84)	(3.82)***	(6.52)***	(3.95)***	(0.71)
5-1	-1.16	-0.52	-1.41	-2.06	-2.66	
	(4.31)***	(1.56)	(4.15)***	(5.89)***	(5.91)***	
Panel C: Average failure probability						
1 Low	0.021	0.021	0.021	0.021	0.021	
2	0.034	0.034	0.034	0.034	0.035	
3	0.050	0.050	0.050	0.050	0.051	
4	0.073	0.078	0.081	0.082	0.083	
5 High	0.131	0.160	0.199	0.236	0.314	

Table 14 continued. Independent sort

	Ranking on Idiosyncratic Volatility					
	1 Low	2	3	4	5 High	5-1
Panel D: Average idiosyncratic volatility						
1 Low	6.20	8.75	11.42	15.01	27.82	
2	6.03	8.74	11.47	15.23	30.32	
3	5.95	8.76	11.55	15.36	31.18	
4	5.91	8.76	11.67	15.62	30.52	
5 High	5.85	8.81	11.82	15.80	30.38	
Panel E: Average size						
1 Low	5409	2630	1714	844	479	
2	4937	2464	1334	705	481	
3	3262	1620	854	469	351	
4	1795	992	533	301	201	
5 High	239	309	201	123	77	
Panel F: Average number of companies in portfolio						
1 Low	205	215	173	110	48	
2	196	189	165	128	73	
3	185	161	157	143	105	
4	134	135	152	169	161	
5 High	31	51	104	201	365	

For an additional robustness check, I divide the entire sample into 4 subsamples, 1971-1980, 1981-1990, 1991-2000 and 2001-2006 and perform independent sorts for each subsample. The results of these sorts are presented in Table 15. Panel A (Panel B) reports the value weighted three factor alpha of long short idiosyncratic (distress) risk portfolio across distress (idiosyncratic) risk quintiles.

Panel A shows that the return spread of long short idiosyncratic volatility portfolio is higher in low distress risk quintile than in high distress risk quintile in all subsamples. The spread is however statistically significant only in 1971-1980 and 2001-2008 periods. The results are of similar direction as in Song (2008) who finds that the idiosyncratic volatility spread is most positive in 1971-1980 and 2001-2006.

Panel B shows that the negative distress spread across idiosyncratic volatility quintiles comes mostly from 1981-1990, which is the only subsample where distress spread is significantly negative in all idiosyncratic volatility quintiles. In other subsamples, the return spread is significantly negative in some third, fourth or fifth idiosyncratic quintiles. As seen in Table

14, the difference in distress risk is higher in high idiosyncratic volatility quintiles, which may explain this pattern.

Table 15. Multivariate independent sorts in different time periods

The table presents the value weighted three factor alpha of a long short portfolio idiosyncratic (distress) risk portfolios"5-1" across distress (idiosyncratic) risk quintiles from an independent sort. For each variable of interest. ***, **, and * indicate that the estimate is statistically different from zero at 0.1%, 1% and 5% confidence levels respectively.

	5-1 idiosyncratic risk portfolio				
	1 Low distress / idiosyncratic risk	2	3	4	5 High distress / idiosyncratic risk
Panel A: 5-1 idiosyncratic risk portfolio					
1971-1980	1.70	1.02	0.21	0.71	0.62
	(2.77)**	(2.02)*	(0.41)	(1.55)	(1.07)
1981-1990	0.47	0.52	-0.82	-1.16	-0.98
	(0.95)	(0.97)	(1.85)	(2.92)**	(1.78)
1991-2000	1.05	1.04	-0.52	-0.75	-1.08
	(1.57)	(2.16)*	(1.08)	(1.34)	(1.63)
2001-2008	1.49	0.18	0.48	-0.57	0.51
	(2.89)**	(0.29)	(1.01)	(0.85)	(0.54)
Panel B: 5-1 distress risk portfolio					
1971-1980	-0.89	0.20	-1.17	-0.53	-1.97
	(1.88)	(0.34)	(1.87)	(0.88)	(2.60)*
1981-1990	-1.44	-1.19	-0.98	-3.13	-2.88
	(2.84)**	(2.21)*	(2.37)*	(6.51)***	(4.86)***
1991-2000	-0.44	0.02	-2.13	-2.40	-2.57
	(0.95)	(0.03)	(3.88)***	(3.4)***	(2.55)*
2000-2008	-1.02	-0.56	-0.64	-1.84	-2.00
	(1.80)	(0.66)	(0.68)	(2.00)*	(1.71)

7. Conclusion

This study examines the asset pricing impact of idiosyncratic risk and financial distress on cross-sectional stock returns. Specifically, I investigate whether financial distress can explain the observed positive or negative correlation between idiosyncratic risk and return. Idiosyncratic volatility is defined as standard deviation of the firm return that cannot be explained by the Fama French (1993) three factor model. The conditional expected volatility is then measured by exponential generalized autoregressive conditional heteroskedasticity (EGARCH) model whereas financial distress is measured by employing both market and accounting data with Campbell et al. (2008) econometric model. This study is the first to study the interaction between idiosyncratic risk and financial distress by means of GARCH models and in addition to unpublished working paper by Song (2008), first to employ Campbell et al. (2008) measure of financial distress. I employ the cross-sectional Fama MacBeth regression and portfolio sorts in order to form a comprehensive picture of the asset pricing impacts of idiosyncratic volatility and financial distress.

The summary of result is presented in Table 16. Consistent with the under-diversification hypothesis of Malkiel and Xu (2002) and narrow framing hypothesis of Barberis and Huang (2001), I find a positive relation between idiosyncratic volatility and expected stock returns. The results are also consistent with previous empirical literature employing EGARCH models for conditional idiosyncratic volatility (Eiling, 2006; Huang et al., 2007; Brockman & Schutte, 2007; Fu, 2009). The relation is robust after controlling for market beta, size, book-to-market, momentum, short term return reversal and liquidity effects. The relation is however driven by micro and small stocks, defined by 20% and 50% percentile breakpoints of market capitalization for NYSE stocks. Due to this reason, the positive relation in portfolio sorts is found only with equally weighted portfolios. I contribute to the existing literature by providing evidence that the positive relation between idiosyncratic volatility and stock returns is not model specific to EGARCH models. The positive relation between idiosyncratic volatility and returns is also found by using GJR and GARCH(p,q) models.

The relation between distress risk and expected stock returns is found robustly negative in both cross-sectional regressions and portfolio sorts. The results are consistent with the theory that the returns of distressed stocks are correlated in a way that is not captured by the market return due to deteriorating investment opportunities (Merton, 1973), decline in unmeasured components of wealth such as human capital (Fama & French, 1996), or incomplete market proxy that excludes debt securities (Ferguson & Shockley, 2003). The results are also consistent with previous empirical work by Campbell et al. (2008) who find a significant negative relation.

The main contributions to the literature of this study are the results relating to the interaction of idiosyncratic volatility and financial distress. In cross-sectional Fama-MacBeth regressions, I find that both idiosyncratic volatility and financial distress maintain their explanatory power when both variables are included in the regression. This result is to the contrary of previous results of Song (2008) and Chen and Chollette (2006) who find that a negative effect of idiosyncratic risk exists conditional on high distress risk. Furthermore, I show that the negative relation between lagged idiosyncratic volatility and stock returns is not fully explained by short term return reversal as suggested by Huang et al. (2007) and Fu (2009), but an inclusion of distress risk does explain the negative relation as suggested by Song (2008) and Chen and Chollette (2006).

Another main contribution of this study is the finding that the positive relation between idiosyncratic volatility and stock returns is conditional on low distress risk. This moderating effect of distress risk on the asset pricing impact of idiosyncratic volatility, meaning that lower distress risk is associated with more positive idiosyncratic volatility spread, is consistent with findings of Song (2008) and Chen and Chollette (2006). However, contrary to Song (2008), I do not find a negative relation between idiosyncratic volatility and distress risk even in the highest distress risk quintile. Furthermore, I provide additional evidence that the negative effect of distress risk persists across idiosyncratic volatility quintiles in multivariate independent sort.

Table 16. Summary of results

	Hypothesis	Expected relation Formulation of hypothesis	Empirical evidence Summary of key findings
Univariate relation	H1	Positive cross-sectional relation between idiosyncratic volatility and excess returns	**Partial support.** The positive relation exists only in micro and small stocks and in equally weighted portfolios. The relation is not EGARCH model specific.
	H2	Negative cross-sectional relation between distress risk and excess returns	**Strong support.** The negative relation exists in all size groups and in value weighted portfolios.
Multivariate relation	H3a	Controlling for financial distress, there is no relation between idiosyncratic volatility and excess returns	**Rejected.** Positive relation between idiosyncratic volatility and stock returns remains after inclusion of distress risk in regression. In independent sorts, the relation exists only in the low distress risk stocks.
	H3b	Controlling for idiosyncratic volatility, there is a negative relation between financial distress and excess returns	**Strong support.** Distress risk effect remains after inclusion of idiosyncratic volatility in cross-sectional regressions. The negative relation persists in all idiosyncratic risk quintiles in independent sort.

In the interpretation and generalization of the results of this study, a few of important limitations need to be taken into account. Both idiosyncratic volatility and distress risk are estimated using full period data, imposing a look-ahead bias into the results. While the severity of the bias is likely to be minor (French et al., 1987; Song, 2008; Fu, 2009), the results do not suggest directly a useable trading strategy. Secondly, a strong correlation between idiosyncratic volatility and distress risk measures imposes a multicollinearity problem in uncovering the true relation between the two variables and stock returns. I have employed various robustness checks, most notably independent multivariate sort to alleviate this problem in the study. The results from the independent sort suggest that the conclusions draw from cross-sectional regressions and univariate sorts are robust.

In future research, it would be interesting to see a decomposition of idiosyncratic volatility that includes a distress risk component. Idiosyncratic risk could be defined relative to an asset pricing model that includes distress risk and relative leverage as outlined by Ferguson and Shockley (2003) and then further modeled with GARCH models. Another interesting topic would be investigate the relation between change in idiosyncratic volatility and financial distress on stock returns. If the volatility of the firm's asset value unexpectedly increases, the option value (equity price) will increase in Merton's (1974) model. Hence the change in idiosyncratic volatility should also be positively related to stock returns. The option effect also implies that the observed relationship be stronger for firms with higher financial leverage, since the equity of these firms are more option-like. Thus it would be interesting to see if financial distress moderates the effect of change in idiosyncratic volatility differently than the asset pricing impact of the level of idiosyncratic volatility.

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Appendix 1 – Construction of the distress risk measure

In this appendix, I describe in detail the construction of measure for financial distress as outlined in Campbell et al. (2008).All variables are constructed using COMPUSTAT and CRSP data. Relative size, excess return, and accounting ratios are defined as follows:

$$RSIZE_{i,t} = \log\left(\frac{Firm\ Market\ Equity_{i,t}}{Total\ S\&P\ 500\ Market\ Value_{\ i,t}}\right)$$

$$EXRET_{i,t} = \log\left(1 + R_{i,t}\right) - \log\left(1 + R_{S\&P\ 500,t}\right)$$

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

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

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

$$MB_{i,t} = \frac{Firm\ Market\ Equity_{i,t}}{Firm\ Book\ Equity_{i,t}}$$

The COMPUSTAT quarterly data items used are ATQ for total assets, NIQ for net income, LTQ for total liabilities, and CHEQ for cash and short term investments.

To deal with outliers in the data that are very small and probably mismeasured, adjust I market to book ratio by adding 10% of the difference between market equity (ME) and book equity (BE) to book equity. After this adjustment, each of the six explanatory variables is winsorized using a 5/95 percentile interval in order to eliminate outliers.

Book equity is as defined in Davis, Fama, and French (2000) and outlined in detail in Cohen, Polk, and Vuolteenaho (2003). Book equity is the stockholders' equity (data item SEQQ, plus balance sheet deferred taxes and investment tax credit (data item TXDITCQ; if available), plus postretirement benefit liabilities adjustment (PRCAQ; if available), minus the book value of preferred stock (data item PSTKQ). If stockholder's equity is not available I use common equity (data item CEQQ) plus book value of preferred stock instead.

To measure the volatility of a firm's stock returns, I use an annualized 3-month rolling sample standard deviation:

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

To eliminate cases in which few observations are available, SIGMA is coded as missing if there are fewer than five nonzero observations over the 3 months used in the rolling window computation. In calculating summary statistics and estimating regressions, I replace missing SIGMA observations with the cross- sectional mean of SIGMA; to avoid losing some failure observations for infrequently traded companies. I use a similar procedure for missing lags of NIMTA and EXRET in constructing the moving average variables NIMTAAVG and EXRETAVG.

The twelve month moving average variables NIMTAAVG and EXRETAVG are constructed by imposing geometrically declining weights:

$$NIMTAAVG_{i,t-1,t-12} = \frac{1-\phi}{1-\phi^{12}} (NIMTA_{t-1} + \cdots + \phi^{11} NIMTA_{t-12})$$

$$EXRETAVG_{i,t-1,t-12} = \frac{1-\phi}{1-\phi^{12}} (EXRET_{t-1} + \cdots + \phi^{11} EXRET_{t-12}),$$

where $\phi = 2^{-\frac{1}{3}}$, implying that the weight is halved each quarter. Note that while the same quarterly data of Net Income and Total Liabilities is used for two preceding months, Firm Market Equity is measured monthly and thus adjusts each monthly NIMTA.

Appendix 2 – GJR and GARCH(p,q) Fama-Macbeth regressions

The table presents the results of cross-sectional Fama-MacBeth regression. The sample period is from 1971 to 2008. For each variable of interest. ***, **, and * indicate that the estimate is statistically different from zero at 0.1%, 1% and 5% confidence levels respectively.

Model	BETA	ln(ME)	ln(BEME)	RET(-2,-7)	RET(-1)	ln(TURN)	ln(CVTURN)	GJR_IV	GARCHpq_IV	Adj. R^2
1								0.04		2.31
								(1.82)		
2	0.39	-0.07	0.31	0.01	-0.07	-0.40	-0.41	0.06		6.89
	(2.09)*	(1.95)	(3.53)***	(7.02)***	(10.38)***	(6.1)***	(4.55)***	(3.78)***		
3									0.02	2.21
									(1.21)	
4	0.38	-0.09	0.31	0.01	-0.06	-0.38	-0.44		0.05	6.87
	(2.02)*	(2.63)**	(3.45)***	(6.82)***	(10.9)***	(5.85)***	(5.82)***		(3.31)***	