# Option-Implied Systematic Disaster Concern[*]

Fang Liu[†]

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## Abstract

The covariation of option-implied disaster concern of the market index and individual stocks allows me to estimate the conditional and systematic disaster concern of stocks with respect to the market. The estimated conditional and systematic disaster concern variables can be interpreted in terms of the risk-neutral conditional disaster probabilities, and they strongly predict future realizations of stock-level disasters and stock returns in different market states. This suggests that the comovement of option prices between stocks and the market index carries forward-looking information on their joint tail distributions.

# 1 Introduction

Rare disasters occur with very small probabilities, but they can cause extremely negative outcomes conditional upon occurrence. Given the low frequency and severe impact of rare disasters, researchers have spent considerable efforts in quantifying disaster risk. A recent strand of literature proposes using option prices to estimate investors' perception of the future disaster risk, namely, the "disaster concern" (e.g., Bollerslev and Todorov (2011, 2014), Bollerslev, Todorov, and Xu (2015), Gao, Lu, and Song (2017), and Gao, Gao, and Song (2017)). Compared to estimating disaster risk from realized equity returns, inferring disaster concern from option prices has two advantages. First, it gives rise to forward-looking measures of disaster risk, reflecting investors' expectations on the future likelihood of rare disasters. Second, the availability of option prices at a broad range of strike prices allows for the estimation of disaster concern without the actual realization of disastrous events. Despite these advantages, the investigation of option-implied disaster concern is mostly restricted to the aggregate market. Little attention is paid to the disaster concern of individual assets and the systematic variations of individual asset disaster concern with that of the market.

This paper studies the joint behavior of the option-implied disaster concern of individual stocks and the market index. I exploit the covariation of stock and market disaster concern to estimate the conditional and systematic disaster concern of stocks with respect to the market, which can be intuitively interpreted in terms of the risk-neutral conditional disaster probabilities. The estimated conditional and systematic disaster concern variables exhibit substantial fluctuations both in the time series and in the cross section. They strongly predict the future realization of stock-level disasters and stock returns in different states of the market and can be used to construct profitable trading strategies. These findings support that the comovement of option prices between stocks and the market index contains forward-looking information on their joint tail distributions.

I consider an individual asset and a market index in a one-period setting. Both the market and the asset can fall in either of two states, disaster or non-disaster, depending on their returns over the period. For both the market and the asset, I define disaster concern as the ex-ante risk-neutral probability that the corresponding return falls in the

disaster state. Measuring disaster concern as the risk-neutral disaster probability implies that it increases with both the physical probability of disasters and investors' risk aversion. I next define the conditional disaster concern of the asset given disaster and non-disaster markets as the ex-ante risk-neutral conditional disaster probability of the asset given that the market index will fall in the disaster and non-disaster states, respectively. Then, I define the asset's systematic disaster concern as the difference in its conditional disaster concern given disaster versus non-disaster markets. Intuitively, the systematic disaster concern measure describes how much more likely an asset is expected to experience a disaster if a market-wide disaster occurs over the coming period relative to if the market performs normally. Using the total probability formula, I show that my systematic disaster concern measure captures the sensitivity of the asset disaster concern to the market disaster concern.

The empirical estimation of the conditional and systematic disaster concern variables requires that both the individual asset and the market index have traded options. The estimation consists of two steps. In the first step, I estimate the market disaster concern and the asset disaster concern from prices of options written on the market index and the asset, respectively, using the method of Ross (1976) and Breeden and Litzenberger (1978). In the second step, motivated by the total probability formula I conduct a time-series linear regression to estimate the conditional and systematic disaster concern of the asset using the market and asset disaster concern obtained from the first step. In particular, I impose as constraints on the regression that the conditional disaster concern variables must lie between zero and one to ensure that the resulting estimates can be interpreted as risk-neutral conditional probabilities.

Existing papers often measure the systematic disaster risk of an individual asset as the sensitivity of the realized asset return to the market disaster risk (e.g., Kelly and Jiang (2014) and Gao, Lu, and Song (2017)). This approach in essence focuses only on the market disaster risk. In contrast, my approach emphasizes the joint disaster risk of the asset and the market. By using option prices, my measures are able to answer "what if" questions that depend on hypothetical future states of the market. For example, what would be the perceived disaster risk of an asset if the market performs well in the coming period. What would be the expected incremental likelihood of an asset disaster if the market switches

from the non-disaster state to the disaster state. These questions are difficult to answer by looking at realize returns, but the comovement of option prices between the asset and the market index allows me to conveniently address them.

I next turn to estimating the conditional and systematic disaster concern for a large set of stocks. I choose the S&P 500 index as the proxy for the market index, which has actively traded options at a broad range of strike prices. I use all common stocks with active option trading as candidates for the individual asset. For both the market and the stocks, I define the disaster and non-disaster states based on monthly equity returns, and hence the corresponding disaster concern variables can be estimated using prices of options maturing in one month. In particular, I define that the market index is in the disaster or non-disaster state if its monthly return is below or above -10%, respectively. Similarly, a stock is defined to be in the disaster or non-disaster state if its monthly return is below or above -25%, respectively. These disaster thresholds are chosen based on historical equity return distributions.

The estimated conditional disaster concern is on average much higher given disaster markets than given non-disaster markets, resulting in positive systematic disaster concern estimates. This reflects that investors expect higher stock-level disaster risk if the market overall will experience a disaster than if it will not. The conditional and systematic disaster concern variables exhibit wide fluctuations both in the time series and in the cross section. For example, the systematic disaster concern of Microsoft peaks around the Internet Bubble, whereas that of Bank of America (BOA) peaks around the financial crisis. This is consistent with economic intuitions. In addition, the systematic disaster concern variable has a weak correlation with the market disaster concern beta (sensitivity of stock returns to the market disaster concern, which is the common approach in the literature to measure the systematic disaster risk of individual assets). This suggests that these two approaches capture different aspects of individual assets' exposure to systematic disaster risk.

I then ask whether the estimated conditional and systematic disaster concern variables are informative on the future realization of stock-level disasters and stock returns. My results show that the conditional disaster concern strongly predicts the occurrence of stock disasters in the corresponding market state. In particular, increasing the conditional disaster concern given disaster (non-disaster) markets from zero to one increases the future

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probability of stock disasters by 31% (58%) in the realized disaster (non-disaster) state of the market. The relation between systematic disaster concern and future stock returns also depends on the market performance. Specifically, stocks with higher systematic disaster concern on average earn higher (lower) future returns if the future market return is positive (negative), and these results cannot be explained by the CAPM beta or the market disaster concern beta. Unconditionally, there is a hump-shaped relation between systematic disaster concern and future stock returns, and hence profitable trading strategies can be constructed by going long in stocks with middle levels of systematic disaster concern and shorting a combination of stocks with the lowest and the highest systematic disaster concern. All of these findings provide evidence that the comovement of option-implied disaster concern between the stocks and the market index indeed carries forward-looking information on their joint return distributions, especially at the tails.

Finally, I examine the relation between systematic disaster concern and a variety of stock and firm characteristics. In general, systematic disaster concern is higher for stocks with larger CAPM betas, more negative market disaster concern betas, higher idiosyncratic volatility and illiquidity, smaller market capitalization, lower returns on equity and leverage, and higher book-to-market ratios and investment. However, stocks with the lowest systematic disaster concern tend to be very illiquid with small market capitalization and below-average CAPM betas.

This paper is related to the growing literature on disaster risk. A large body of research has shown that the economy is subject to rare disasters and that disaster risk has important implications on asset prices and the equity and variance risk premia (e.g., Rietz (1988), Barro (2006, 2009), Barro and Ursúa (2008), Gabaix (2008, 2012), Chen, Joslin, and Tran (2012), Gourio (2012), Nakamura et al. (2013), Wachter (2013), and Seo and Wachter (2017)). Various measures of disaster risk have been proposed to examine its relation with equity returns both in the time series and in the cross section (e.g., Bollerslev and Todorov (2011, 2014), Bali, Cakici, and Whitelaw (2014), Kelly and Jiang (2014), Bollerslev, Todorov, and Xu (2015), van Oordt and Zhou (2016), Chabi-Yo, Ruenzi, and Weigert (2017), Gao, Gao, and Song (2017), and Gao, Lu, and Song (2017)). In particular, Bollerslev and Todorov (2011, 2014), Bollerslev, Todorov, and Xu (2015), Gao, Gao, and Song (2017), and Gao, Lu, and Song (2017) focus on the option-implied disaster concern of

the market index that capture investors' perception of the future disaster risk of the overall economy. To the best of my knowledge, my paper is the first to explore individual assets' option-implied disaster concern and its systematic variations with respect to the market.

The paper also contributes to the extensive research on the comovement of individual assets with the market. It is widely acknowledged that individual asset returns comove with the market return. Plenty of empirical evidence suggests that this return comovement increases during market downturns (e.g., Roll (1988), Jorion (2000), and Longin and Solnik (2001)), and various methods have been developed to test this asymmetric return comovement (e.g., Ang and Chen (2002), Hong, Tu, and Zhou (2007), and Jiang, Wu, and Zhou (2017)). Another strand of research documents liquidity commonality of individual stocks with the market (e.g., Chordia, Roll and Subrahmanyam (2000), Hasbrouck and Seppi (2001), and Huberman and Halka (2001)), and many papers examine both supply-side and demand-side explanations for this liquidity commonality (e.g., Chordia, Roll, and Subrahmanyam (2000), Hasbrouck and Seppi (2001), Coughenour and Saad (2004), Hameed, Kang, and Viswanathan (2010), and Karolyi, Lee, and van Dijk (2012)). Recently, Christoffersen, Fournier, and Jacobs (2017) shows that the market is a common factor driving the variations in equity option prices. My paper provides further evidence that the option prices of individual stocks comove with those of the market index and that this comovement is informative on the joint tail distributions of stock and market returns.

My paper also adds to the literature on estimating the risk-neutral return distributions from option prices. Ross (1976) and Breeden and Litzenberger (1978) first show that one can extract the risk-neutral probability distribution of security returns from prices of European options written on the security of interest. Since then, many parametric and nonparametric methods have been proposed to refine the estimation. (See Jackwerth (1999) for a review.) Overall, the literature has restricted attention to estimating the risk-neutral marginal return distributions. My paper extends this literature by providing an approach of estimating the risk-neutral conditional return distribution of an individual asset given the market return.

The rest of the paper proceeds as follows. Section 2 defines the conditional and systematic disaster concern measures. Section 3 explains how to estimate these measures from option prices. Section 4 empirically estimates the conditional and systematic disas-

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ter concern variables and investigates their performance in predicting stock-level disasters and stock returns in different states of the market. Section 5 concludes. Some technical discussions are delegated to the Appendix.

## 2    A Measure of Systematic Disaster Concern

Consider a market index $M$ and an individual asset $i$ in a one-period setting. Suppose that the return of the market over the period can fall in either a disaster state $(D^M)$ or a non-disaster state $(N^M)$. Similarly, the return of asset $i$ can also be in a disaster state $(D^i)$ or a non-disaster state $(N^i)$.

For both the market index and the individual asset, define the disaster concern as the risk-neutral probability evaluated at the beginning of the period that the corresponding return will fall in the disaster state, i.e.,

$$Dis^M = Q\left(r^M \in D^M\right),$$
$$Dis^i = Q\left(r^i \in D^i\right),$$

where $Dis^M$ and $Dis^i$ represent the market disaster concern and the asset disaster concern, $r^M$ and $r^i$ are the market return and the asset return over the period, and $Q$ stands for the risk-neutral probability. Intuitively, the risk-neutral probability is equal to the associated physical probability adjusted for risk aversion. The idea of defining disaster concern as the risk-neutral disaster probability is that it depends on both the physical probability of disaster and investors' aversion towards risk. Given the same level of risk aversion, disaster concern increases with the physical probability of disaster. Given the same physical disaster probability, the more risk averse investors are, the higher disaster concern they have.

I define the conditional disaster concern of the asset given disaster and non-disaster markets, $ConDis^i\left(D^M\right)$ and $ConDis^i\left(N^M\right)$, as the risk-neutral conditional disaster probability of the asset return given that the market return will be in the disaster and non-disaster states, respectively, i.e.,

$$ConDis^i\left(D^M\right) = Q\left(r^i \in D^i | r^M \in D^M\right),$$
$$ConDis^i\left(N^M\right) = Q\left(r^i \in D^i | r^M \in N^M\right).$$

I further define the systematic disaster concern of the asset, $SysDis^i$, as the difference in its conditional disaster concern given disaster versus non-disaster markets, i.e.,

$$SysDis^i = ConDis^i \left( D^M \right) - ConDis^i \left( N^M \right). \tag{1}$$

Intuitively, the systematic disaster concern describes by how much an asset is perceived to be more likely to experience a disaster if the market overall will have a disaster relative to if the market performs normally.

To better understand the economic meaning of the systematic disaster concern measure, it is useful to consider the total probability formula under the risk-neutral measure. According to the total probability formula, the disaster probability of an asset is equal to the weighted average of its conditional disaster probabilities given the market state, with the associated weights being the probabilities of the corresponding market states, i.e.,

$$Q \left( r^i \in D^i \right) = Q \left( r^M \in D^M \right) Q \left( r^i \in D^i | r^M \in D^M \right) + Q \left( r^M \in N^M \right) Q \left( r^i \in D^i | r^M \in N^M \right).$$

Equivalently, this can be rewritten as

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\begin{aligned}
Dis^i &= Dis^M \cdot ConDis^i \left( D^M \right) + \left( 1 - Dis^M \right) ConDis^i \left( N^M \right) & (2) \\
&= ConDis^i \left( N^M \right) + \left[ ConDis^i \left( D^M \right) - ConDis^i \left( N^M \right) \right] Dis^M & (3) \\
&= ConDis^i \left( N^M \right) + SysDis^i \cdot Dis^M. & (4)
\end{aligned}
$$

This implies that $Dis^i$ is linearly related to $Dis^M$, with $SysDis^i$ being the slope and $ConDis^i \left( N^M \right)$ being the intercept. Hence, the systematic disaster concern of an asset measures the sensitivity of the asset disaster concern to the market disaster concern. This is comparable to the CAPM beta, which captures the sensitivity of the asset return to the market return and is used as the standard measure of systematic risk.

Since $ConDis^i \left( D^M \right)$ and $ConDis^i \left( N^M \right)$ are risk-neutral conditional probabilities which take values from 0 to 1, $SysDis^i$ ranges from -1 to 1. In particular, a positive value of $SysDis^i$ means that the asset disaster concern becomes higher when the market disaster concern rises. In other words, the asset is perceived to be more prone to disasters if the market will be in the disaster state relative to the non-disaster state. In contrast, a negative value of $SysDis^i$ indicates that the asset disaster concern decreases when the market

disaster concern rises, or equivalently, the asset is considered less likely to experience a disaster if the market will be in the disaster state relative to the non-disaster state. While theoretically $SysDis^i$ can be either positive or negative, in practice I expect it to be positive more often, reflecting that investors tend to become more concerned about asset disasters when the market disaster concern is higher.

Notice that the systematic disaster concern measure defined here is different from the existing approach used in the literature to gauge the disaster risk of individual assets with respect to the market. A number of papers, including Kelly and Jiang (2014) and Gao, Lu, and Song (2017), use the sensitivity of individual asset returns to the market disaster risk to measure the systematic disaster risk of an asset. By doing this, they still focus on the disaster risk of the market index. My systematic disaster concern measure, in comparison, focuses on the joint behavior of the asset disaster concern and the market disaster concern. I will show in Section 4 that these two approaches lead to different measures that are likely to capture different aspects of individual assets' exposure to systematic disaster risk.

## 3    Estimation Methodology

Ross (1976) and Breeden and Litzenberger (1978) show that the risk-neutral return distribution of any asset with traded options can be estimated from prices of European options written on that asset. The conditional and systematic disaster concern measures introduced above are defined in terms of the risk-neutral conditional distribution of the asset return given the state of the market. Intuitively, estimation of these measures would require options written on the joint values of both the asset and the market index. This poses an empirical challenge, since such options are not traded in the market.

This section shows that one can actually estimate the conditional and systematic disaster concern measures from prices of options written on the individual asset together with prices of options written on the market index. The covariations in the prices of these options allow one to estimate the required risk-neutral conditional probabilities without the need for options written on the joint values of the asset and the market.

The estimation procedure consists of two steps. The first step estimates the asset disaster concern and the market disaster concern from the asset and market option prices,

respectively, based on Ross (1976) and Breeden and Litzenberger (1978). In the second step, I then estimate the conditional disaster concern of the asset given different market states using the asset and market disaster concern estimates obtained in the first step by a constrained linear regression over time. Below I discuss each of these two steps in turn.

## 3.1  Estimating Disaster Concern

I start with the estimation of the asset disaster concern $Dis$ and the market disaster concern $Dis^M$ from option prices based on Ross (1976) and Breeden and Litzenberger (1978), assuming that both the asset and the market index are traded in the options market. Since the asset and market disaster concern can be estimated in the same manner, below I drop the superscript for brevity.

Ross (1976) and Breeden and Litzenberger (1978) show that given the prices of European options with a continuous range of strike prices covering all possible values of the underlying asset at maturity, the risk-neutral probability distribution of the asset's value at maturity can be estimated in a model-free manner. At any time $t$, consider a European put option that matures at time $T$. Let $S_t$ represent the current price of the underlying asset, and let $S_T$ be the price of the asset at maturity. Denote the strike price of the option by $K$ and the risk-free rate by $r_f$. The price of the put option can then be expressed as a function of the strike price:

$$Put\,(K) \;\; = \;\; e^{-r_f(T-t)} \int_{S_T=0}^{\infty} (K-S_T)^+\, dF\,(S_T) \tag{5}$$

$$= \;\; e^{-r_f(T-t)} \int_{S_T=0}^{K} (K-S_T)\, dF\,(S_T), \tag{6}$$

where $F\,(\cdot)$ is the risk-neutral cumulative distribution function (CDF) of $S_T$ evaluated at time $t$. Differentiating (6) with respect to the strike price obtains

$$\frac{\partial Put\,(K)}{\partial K} = e^{-r_f(T-t)} F\,(K)\,.$$

Solving for $F\,(K)$ leads to

$$F\,(K) = e^{r_f(T-t)} \frac{\partial Put\,(K)}{\partial K}\,.$$

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Evaluating $F(K)$ at all possible values of $K$ thus yields the risk-neutral distribution of the asset price at maturity.[1]

Assume that an asset is in the disaster state whenever its return over a period of length $T - t$ falls below some disaster threshold $\bar{r}$. Then, the disaster concern of the asset is given by

$$Dis = Q\left(r \leq \bar{r}\right). \tag{7}$$

Fixing the current price of the asset $S_t$ and assuming that the expected dividend yield paid by the asset from $t$ to $T$ is equal to $d$, there is a one-to-one mapping between the asset return and the asset price at maturity through

$$S_T = S_t\left(1 + r - d\right).$$

As a result, (7) is equivalent to

$$Dis = Q\left(S_T \leq \bar{S}_T\right) = F\left(\bar{S}_T\right), \tag{8}$$

where

$$\bar{S}_T = S_t\left(1 + \bar{r} - d\right). \tag{9}$$

Evaluating (8) then yields the disaster concern of the asset.

Two technical issues entail further discussions. First, evaluating (8) requires differentiating the option price with respect to the strike price at the disaster threshold. Given the difficulty of obtaining a closed-form expression for this derivative, I estimate it by linear approximation as

$$F\left(\bar{S}_T\right) \approx e^{r_f(T-t)}\frac{Put\left(\bar{S}_T^+\right) - Put\left(\bar{S}_T^-\right)}{\bar{S}_T^+ - \bar{S}_T^-},$$

where $\bar{S}_T^- = \bar{S}_T - \$0.01$ and $\bar{S}_T^+ = \bar{S}_T + \$0.01$.

The second issue has to do with obtaining European option prices with the required time to maturity $T - t$ and strike prices around the disaster threshold. In practice, option prices are available only at discrete maturities and strikes. Additionally, while most indices are

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[1]One could alternatively estimate $F(\cdot)$ based on European call option prices. By the put-call parity, theoretically the estimation results based on call and put options should be identical. Empirically, however, out-of-the-money options are more liquid than in-the-money options and hence have more accurate prices. To estimate disaster concern, I need to focus on options with very low strike prices. I thus rely on put options for my estimation, which are out of the money around the disaster thresholds.

represented by European options, individual stock options are generally American options. To obtain the European option prices with the required time to maturity and strike prices, I adopt a simple and commonly used approach of first fitting the implied volatility surface by kernel smoothing and then recovering the European option prices based on the BS model (Black and Scholes (1973) and Merton (1973)) using fitted implied volatilities. (See the Appendix for detailed discussions.)

It is important to note that using the BS model here does not rely on the BS model being the correct option pricing model. The OptionMetrics database provides the BS implied volatility for all European options. For American options, OptionMetrics computes the implied volatility based on the Cox-Ross-Rubinstein (CRR) model (Cox, Ross, and Rubinstein (1979)), which converges to the BS implied volatility in the absence of early exercise. For the deep-out-of-the-money put options examined in this paper, early exercise is very unlikely, and hence the European prices should be very close to the American prices. Because of these reasons, recovering European prices using the BS model simply inverts the calculation of the BS implied volatility from observed option prices and hence does not relying on the validity of the BS model. I choose to conduct kernel smoothing in the implied volatility space rather than in the option price space, since it is more robust this way and hence has become standard in the literature.

## 3.2 Estimating Conditional and Systematic Disaster Concern

I then proceed to estimate the conditional and systematic disaster concern of an asset with respect to the market index. The essence here is to estimate the risk-neutral conditional disaster probabilities of the asset given the disaster and non-disaster states of the market. This might seem impossible without options written on the joint values of the asset and market index. I now show that the time variations of the asset disaster concern and the market disaster concern together make the estimation possible.

The key of this estimation lies with the total probability formula (2). Rearranging (2) yields (4), which shows that the systematic disaster concern $SysDis^i$ measures the sensitivity of the asset disaster concern $Dis^i$ to the market disaster concern $Dis^M$. Thus, a natural idea is to estimate $SysDis^i$ using a time-series regression. Specifically, if the time series of $Dis^i$ and $Dis^M$ are available, one could estimate $SysDis^i$ as the slope

coefficient from regressing $Dis^i$ on $Dis^M$ over time. While this idea might be simple, an implicit restriction is that $SysDis^i$ is a bounded variable. In fact, the boundedness of $SysDis^i$ stems from the boundedness of $ConDis^i\left(D^M\right)$ and $ConDis^i\left(N^M\right)$, which are by definition risk-neutral conditional probabilities and hence must take values between zero and one. Unfortunately, running an unconstrained regression of $Dis^i$ on $Dis^M$ cannot guarantee that this boundedness condition is satisfied.

To fix this problem, I use a constrained linear regression. Since the boundedness constraint is on $ConDis^i\left(D^M\right)$ and $ConDis^i\left(N^M\right)$, I need to estimate $ConDis^i\left(D^M\right)$ and $ConDis^i\left(N^M\right)$ first instead of estimating $SysDis^i$ directly. By (2), $Dis^i$ is linear in $Dis^M$ and $1-Dis^M$ through coefficients $ConDis^i\left(D^M\right)$ and $ConDis^i\left(N^M\right)$. Therefore, if I run a time-series regression of $Dis^i$ on $Dis^M$ and $1-Dis^M$ without the constant term, the resulting slope coefficients would be estimates of $ConDis^i\left(D^M\right)$ and $ConDis^i\left(N^M\right)$. To make sure that these estimates are valid risk-neutral conditional probabilities, I require that they must be bounded between zero and one. Formally, I conduct the following constrained linear regression over time:

$$Dis_t^i = b_1^i Dis_t^M + b_2^i \left(1 - Dis_t^M\right) + \varepsilon_t^i, \qquad (10)$$
$$s.t.$$
$$0 \le b_1^i, b_2^i \le 1.$$

The estimated $b_1^i$ and $b_2^i$ will be the conditional disaster concern variables $ConDis^i\left(D^M\right)$ and $ConDis^i\left(N^M\right)$, respectively, and their difference immediately gives the systematic disaster concern $SysDis^i$.

It is worth mentioning that an implicit assumption needed in the above estimation is that the conditional and systematic disaster concern measures stay fixed throughout the estimation period. This assumption is indeed not as restrictive as it appears. In practice, one can always allow time variations in these measures using a rolling-window approach, which is similar to how the CAPM beta is estimated in the literature. I will discuss this in greater detail in the following section.

# 4 Empirical Estimation and Results

In this section, I estimate the conditional and systematic disaster concern variables for a large set of stocks and explore their empirical properties. I investigate their performance in predicting stock-level disasters and stock returns in different market states. I then construct a trading strategy based on the systematic disaster concern measure and explore the source of the trading profit. I also examine the relation between systematic disaster concern and a variety of stock and firm characteristics.

Since most variables in this paper are stock-specific, below I will often drop the asset superscript $i$ when no confusion is caused, but I will keep the market superscript for clarity. For example, $Dis$ without a superscript represents the disaster concern of a stock, and $Dis^M$ represents the market disaster concern.

## 4.1 Data and Estimation

The sample period is from January 1996 to December 2015. My main source of data is the OptionMetrics database, which contains option prices along with information on prices and dividend payments of the underlying securities. I choose the S&P 500 index as the proxy for the market index. This index has actively traded options covering a wide range of moneyness and time to maturity levels. I take all common stocks in OptionMetrics as candidates for the individual asset with further filtering criteria to be described below. In addition, I also collect stock return data from CRSP and firm fundamentals information from Compustat.

In order to estimate the disaster concern variables, I need to define appropriate disaster thresholds for the market index and individual stocks. I focus on monthly returns of the S&P 500 index and all stocks, and thus the associated disaster concern variables can be inferred from prices of options maturing in one month (30 days). I define the disaster threshold as a monthly return of -0.1 for the S&P 500 index and -0.25 for all individual stocks. In other words, the market is considered to be in the disaster state if it loses more than 10% of its value within one month, and an individual stock is considered to be in the disaster state if it loses more than 25% of its value within one month. Given these disaster thresholds, the correspondingly defined disaster events occurred with historical frequencies

around 2% for both the S&P 500 index and the group of sample stocks. The fact that the market index has a higher (less negative) disaster threshold than the stocks reflects that the market is less volatile than individual assets.

For the S&P 500 index and the stocks, I estimate their disaster concern on a daily basis according to (8). To maintain the accuracy of my estimation, I focus on stocks actively traded on the option market using the following filtering criteria. For each date, I compute the disaster concern of a stock only if (1) there are at least twenty different option contracts written on the stock with implied volatility available, (2) the lowest moneyness level (ratio of strike price to current stock price) of available option contracts written on the stock is no higher than 0.9, and (3) the shortest (longest) time to maturity of available option contracts written on the stock is no longer (shorter) than one month.

When estimating the disaster concern, I also need the expected dividend yield over the upcoming one-month period (see (9)). The expected dividend yield paid by the S&P 500 index is directly provided in OptionMetrics. For the individual stocks, I assume that investors accurately predict future regular dividend payments and thus estimate the expected dividend yield as the ratio of the total regular dividends paid by the stock over the next month to the current stock price.

Having the disaster concern of the S&P 500 index and all stocks, I then estimate the conditional and systematic disaster concern of each stock by the constrained linear regression (10). At the end of each month, I perform estimation for each stock based on daily disaster concern estimates from the most recent twelve-month window (250 trading days), provided that the disaster concern estimate is available for the stock on at least 200 days during the estimation window. This allows for considerable time variations in the conditional and systematic disaster concern variables, as will be shown below. Since twelve months are needed for each estimation, I obtain monthly estimates of the conditional and systematic disaster concern variables from December 1996 through December 2015. The number of stocks left in my sample in each month ranges from 287 to 2770, with nearly 70% of all months having more than 1000 stocks.

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## 4.2  Descriptive Statistics

Figure 1 plots the market disaster concern along with the cross-sectional average stock disaster concern. The two variables tend to move in tandem with each other, and both exhibit wide fluctuations over time. In particular, there are two periods of substantial increase in the disaster concern of both the market index and individual stocks. The first one is the 1998–2002 period, corresponding to the Internet bubble and the subsequent bubble bursting, and the second one is the 2008–2011 period, corresponding to the recent financial crisis and the subsequent recession.

Figure 2 plots the cross-section average conditional disaster concern of stocks given the disaster and non-disaster market states, respectively. The average conditional disaster concern is always higher given disaster markets relative to non-disaster markets, meaning that investors are on average more concerned about future stock disasters if the market will have a disaster in the future than if not. Furthermore, while the average conditional disaster concern given non-disaster markets does not vary much over time, the average conditional disaster concern given disaster markets exhibits significant time variations, with peaks around the crisis periods.

Table 1 reports summary statistics for the disaster concern variables. Panel A shows that the market disaster concern ($Dis^M$), estimated based on option prices of the S&P 500 index, has a mean value of 0.0509, indicating that investors expect a market-wide disaster to happen with a risk-neutral probability of 5% on average. The median of $Dis^M$ is 0.0389, and the standard deviation is 0.0444. The minimum and maximum are 0.0008 and 0.3025, respectively, meaning that the market disaster concern is considered close to zero during the safest time but as high as 30% during the riskiest time.

Panel B reports summary statistics for stock-level variables. For each of these variables, I first compute the average value for each stock over time, and then report the cross-sectional summary statistics of these stock averages. The cross-sectional mean of the stock disaster concern ($Dis$) is 0.0873, indicating that an average firm is expected to experience a disaster with a risk-neutral probability of around 9%. The median is 0.0661, and the standard deviation is 0.0678. The minimum and maximum are 0 and 0.7583, respectively, highlighting the wide cross-sectional variations in the disaster concern of different stocks.

The conditional disaster concern variables have very different statistics depending on the state of the market. Given disaster markets, the conditional disaster concern $(ConDis\left(D^M\right))$ has a mean value of 0.3718, implying that if the market will be in the disaster state, an average firm is expected to experience a disaster with a risk-neutral probability of 37%. The median is 0.3251, and the standard deviation is 0.2419. The minimum and maximum are 0 and 1, respectively. This means that some firms are considered to have a zero probability of disaster even if the market itself will experience a disaster, whereas some other firms are expected to have a disaster for sure if a market-wide occurs.

In comparison, given non-disaster markets, the conditional disaster concern $ConDis\left(N^M\right)$ has a much lower cross-sectional mean of 0.0519. This implies that firms are considered much less likely to have a disaster if the market will not have a disaster than if it will. The median value is 0.0358. The standard deviation is 0.0488, also much lower than that of $ConDis\left(D^M\right)$, meaning that conditional on future non-disaster markets, firms are considered less heterogeneous in terms of how likely a disaster would happen. The minimum of $ConDis\left(N^M\right)$ is 0, and the maximum is 0.3476.

The systematic disaster concern $(SysDis)$ has a mean of 0.3200, indicating that an average firm is considered more likely to experience a disaster in disaster markets than in non-disaster markets by a risk-neutral probability of 32%. The standard deviation is 0.2295, which is mostly driven by the cross-sectional heterogeneity in $ConDis\left(D^M\right)$. Over 90% of all stocks have positive $SysDis$ estimates on average, as suggested by a 10th quantile of 0.0626. The cross-sectional minimum of $SysDis$ is a negative value of -0.3438, meaning that some firms are considered more likely to experience a disaster if the market will perform normally relative to if the market will have a disaster. The cross-sectional maximum of $SysDis$ is 1, which can only happen when the conditional disaster concern is 1 given disaster markets and 0 given non-disaster markets.

Panel B of Table 1 also reports summary statistics for the CAPM beta $(Beta)$ of the stocks. At the end of each month, I estimate $Beta$ for each stock by regressing daily excess stock returns on daily excess market returns over the preceding twelve-month window. For consistency, I continue to use the S&P 500 as the market index for the estimation of $Beta$. Across my sample stocks, $Beta$ has a mean of 1.1210, a median of 1.0713, and a standard deviation of 0.4258. All stocks have positive betas on average, with a cross-

sectional minimum of 0.0248 and a cross-sectional maximum of 4.4703.

At the end of each month, I also estimate the market disaster concern beta ($DisBeta$) for each stock, which is obtained by regressing daily stock returns on daily estimates of $Dis^M$ over the preceding twelve-month window. Intuitively, $DisBeta$ measures the sensitivity of the stock return to the market disaster concern, which is similar to the approach commonly used in the literature to gauge the systematic disaster risk of individual stocks. Panel B of Table 1 shows that most stocks have negative $DisBeta$ on average, suggesting that stocks tend to have lower returns as the market disaster concern rises. In fact, a more negative value of $DisBeta$ indicates a larger decrease in the stock return when the market disaster concern rises, representing higher systematic disaster risk. The cross-sectional mean and median of $DisBeta$ are -0.1509 and -0.1301, respectively, and the cross-sectional standard deviation is 0.1129.

Table 2 reports the pairwise correlations across the stock-level variables. It shows that $ConDis\left(D^M\right)$ and $ConDis\left(N^M\right)$ have a mild positive correlation of 0.1308. Also, $SysDis$ has a very high correlation of 0.9943 with $ConDis\left(D^M\right)$ and only a weak correlation of 0.0242 with $ConDis\left(N^M\right)$. This suggests that the variations in $SysDis$ are mostly driven by $ConDis\left(D^M\right)$. In addition, $SysDis$ is positively correlated with $Beta$ with a correlation coefficient of 0.4003. Somewhat surprisingly, $SysDis$ and $DisBeta$ have a very small negative correlation of -0.0693. This suggests that these two measures are likely to capture different aspects of individual stocks' exposure to systematic disaster risk. Furthermore, $DisBeta$ is negatively correlated with $Beta$ with a correlation coefficient of -0.3707.

The constrained regression estimation approach introduced in Section 3.2 implies that the market disaster concern is a factor driving the time variations in the disaster concern of individual stocks. It is then curious to ask what proportions of the time variations in individual stock disaster concern can be explained by variations in the market disaster concern. To answer this question, I compute the R-squared from the constrained linear regression (10) as

$$R^2 = 1 - \frac{Var\left(\varepsilon\right)}{Var\left(Dis\right)},$$

where $Var\left(Dis\right)$ is the variance of the disaster concern of a stock over the estimation window, and $Var\left(\varepsilon\right)$ is the variance of the regression residuals. Intuitively, $R^2$ measures

the proportion of the total time variations in the stock disaster concern that is attributable to changes in the market disaster concern.

Figure 3 plots the cross-sectional average R-squared over time. The figure shows that the average R-squared varies dramatically over the sample period. It tends to increase during crises. In particular, during the 2008–2009 financial crisis, the average R-squared rises sharply above 0.5, indicating that more than half of the time variations in individual stock disaster concern over this period is driven by changes in the market disaster concern.

## 4.3 Two Examples: Microsoft and Bank of America

To provide more intuitions about the systematic disaster concern of different stocks, I examine Microsoft and BOA as two examples. We have seen in Figure 1 that there are two periods of substantial increases in the market disaster concern throughout my sample, with the 1998–2002 period driven by the Internet bubble and the 2008–2011 period corresponding to the financial crisis. Since Microsoft is a technology firm and BOA is a financial firm, one would wonder if these two firms respond differently over these two periods.

To address this question, I first plot the disaster concern of Microsoft and BOA over time in Figure 4. Both stocks exhibit dramatic increases in the disaster concern during both the 1998–2002 and the 2008–2011 periods, reflecting that the disaster concern of both stocks responds positively to increases in the market disaster concern. Interestingly, in the top figure the increase in the disaster concern of Microsoft is more pronounced during the first period. In contrast, the bottom figure shows that the increase in the disaster concern of BOA is more pronounced during the second period. This suggests that the disaster concern of Microsoft appears to be more sensitive to the increase in the market disaster concern driven by the Internet bubble, whereas the disaster concern of BOA appears to be more sensitive to the increase in the market disaster concern driven by the financial crisis.

I further plot the systematic disaster concern of these two stocks over time in Figure 5, which directly measures the sensitivity of individual stock disaster concern to the market disaster concern. As expected, in the top figure the systematic disaster concern of Microsoft rises sharply to around 0.8 during the Internet bubble, compared to a much milder rise during the financial crisis. In contrast, the bottom figure shows that the systematic disaster concern of BOA shoots up to 1 during the financial crisis, much higher than its peak level

during the Internet bubble. These findings are consistent with intuitions and serve as supportive evidence for the validity of my estimation.

## 4.4 Condition Disaster Concern and Future Stock Disasters

The conditional disaster concern reflects investors' expectation on how likely a stock-level disaster is to happen in different market states. It is interesting to ask whether the estimated conditional disaster concern variables provide information on the future occurrence of stock disasters in the corresponding state of the market.

At any time $t$, two conditional disaster concern variables, $ConDis_t^i\left(D^M\right)$ and $ConDis_t^i\left(N^M\right)$, can be estimated for each stock $i$ corresponding to future disaster and non-disaster markets, respectively. Eventually, only one of these two market states realizes, and the conditional disaster concern given the subsequently realized market state should be more relevant to the prediction of future stock disasters. Based on this idea, I denote by $ConDis_t^i\left(r_{t+1}^M\right)$ the conditional disaster concern of stock $i$ estimated at the end of month $t$ given the realized state of the market in month $t+1$, i.e.,

$$ConDis_t^i\left(r_{t+1}^M\right) = \left\{ \begin{array}{l} ConDis_t^i\left(D^M\right), \text{ if } r_{t+1}^M \leq -0.1 \\ ConDis_t^i\left(N^M\right), \text{ if } r_{t+1}^M > -0.1 \end{array} \right. .$$

I further define a dummy variable $DisD_t^i$ for a realized disaster of stock $i$ in month $t$, i.e.,

$$DisD_t^i = \left\{ \begin{array}{l} 1, \text{ if } r_t^i \leq -0.25 \\ 0, \text{ if } r_t^i > -0.25 \end{array} \right. .$$

If my conditional disaster concern estimates are informative, $ConDis_t^i\left(r_{t+1}^M\right)$ should positively predicts $DisD_{t+1}^i$.

Table 3 compares $ConDis_t^i\left(r_{t+1}^M\right)$ with $DisD_{t+1}^i$. The average value of $ConDis_t^i\left(r_{t+1}^M\right)$ across all stocks over the entire sample is 0.0328, meaning that on average investors expect a stock-level disaster to occur with a risk-neutral probability of 3% conditional on the subsequently realized state of the market. The average value of $DisD_{t+1}^i$ is 0.0229, indicating that the frequency of a realized stock disaster is about 2% in my sample. The table also reports results for subsamples with realized disaster and non-disaster markets separately. For the 224 months without market disasters $(r_{t+1}^M > -0.1)$, the average value of $ConDis_t^i\left(r_{t+1}^M\right)$ is 0.0272, and the average value of $DisD_{t+1}^i$ is 0.0195. For the remaining

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4 months with realized market disasters ($r_{t+1}^M \leq -0.1$), the average of $ConDis_t^i \left( r_{t+1}^M \right)$ is 0.3391, and the average of $DisD_{t+1}^i$ is 0.2470. This indicates that both the conditional disaster concern and the realized disaster frequency of stocks are higher given disaster markets relative to non-disaster markets. Notice that since $ConDis_t^i \left( r_{t+1}^M \right)$ is defined under the risk-neutral measure and $DisD_{t+1}^i$ reflects the frequency of stock disasters under the physical measure, the difference in the average value between these two variables may result from both biased expectation and risk aversion of investors.

To see if stocks with higher $ConDis_t^i \left( r_{t+1}^M \right)$ are more likely to experience disasters, for each month $t$, I run a cross-sectional regression of $DisD_{t+1}^i$ on $ConDis_t^i \left( r_{t+1}^M \right)$, i.e.,

$$DisD_{t+1}^i = \gamma_{0,t+1} + \gamma_{1,t+1} ConDis_t \left( r_{t+1}^M \right) + \eta_{t+1}.$$

If $ConDis_t^i \left( r_{t+1}^M \right)$ contains information on the realization of stock disasters, $\gamma_{1,t+1}$ should be positive.

The last column of Table 3 reports the time average of the estimated $\gamma_{1,t+1}$. For the entire sample, $\gamma_{1,t+1}$ has a positive mean value of 0.5781, which is significant at the 1% level based on the Newey-West standard error.[2] This means that on average, if $ConDis_t^i \left( r_{t+1}^M \right)$ increases from 0 to 1, the probability of a stock disaster increases by 58%. For the sub-samples with realized disaster and non-disaster markets, the average values of $\gamma_{1,t+1}$ are 0.3066 and 0.5830, respectively, both strongly significant. This implies that increasing $ConDis_t^i \left( r_{t+1}^M \right)$ from 0 to 1 raises the probability of a stock disaster by 31% and 58% given realized disaster and non-disaster markets, respectively.

It is worth taking a closer look at each of the 4 months with realized market disasters. These 4 months are August 1998, September 2002, October 2008 and February 2009, with the monthly market return being -0.1431, -0.1090, -0.1670, and -0.1036, respectively. The lower panel of Table 3 shows that the estimated $\gamma_{1,t+1}$ is significantly positive in each of these months, with values ranging from 0.2050 to 0.4271.

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[2] The Newey-West standard error is used to account for potential autocorrelation of the error term. Following Stock and Watson (2011) page 599, I choose the number of lags using the rule of thumb:

$$L = 0.75 T^{1/3},$$

where $L$ is the number of lags and $T$ is the number of observations in the time series. There are 228 months in my sample, which leads to the use of 5 lags.

Overall, these results show that my estimated conditional disaster concern variables indeed provide useful information on the future occurrence of stock disasters in the corresponding state of the market.

## 4.5 Systematic Disaster Concern and Expected Stock Returns

I now explore the relation between systematic disaster concern and the expected stock return. I start with a portfolio sorting approach. At the end of each month, I sort all stocks into five quintile portfolios by their systematic disaster concern estimates, and then calculate the equal-weighted return of each portfolio over the next month. Table 4 reports the average returns of the five $SysDis$-sorted portfolios over time. From the lowest-$SysDis$ portfolio to the highest-$SysDis$ portfolio, the average returns of the five portfolios over the entire sample are 0.0078, 0.0096, 0.0104, 0.0085 and 0.0072, respectively, which exhibit a hump shape. Portfolios with the lowest and highest systematic disaster concern tend to have lower returns on average than portfolios in the middle. The return difference between the bottom and top portfolios is not significantly different from zero.

To find out what drives the hump-shaped relation, I then calculate the average returns of the five $SysDis$-sorted portfolios over months with positive and negative market returns separately. For the 140 months with positive market returns, the average returns of the five portfolios from the lowest $SysDis$ to the highest $SysDis$ are 0.0330, 0.0359, 0.0413, 0.0460, and 0.0531, respectively, which are monotonically increasing. The average return difference between the bottom and the top portfolios is -0.0201, and this difference is significant at the 1% level. This suggests that stocks with high systematic disaster concern outperform stocks with low systematic disaster concern on average when the market overall performs well. In particular, going long in stocks with the highest $SysDis$ and shorting stocks with the lowest $SysDis$ results in an average monthly return of 2.01% conditional on the market delivering positive returns.

I then repeat the analysis for the 88 months with negative market returns. The average returns of the five portfolios from the lowest $SysDis$ to the highest $SysDis$ are -0.0323, -0.0324, -0.0387, -0.0511, and -0.0657, respectively, which are monotonically decreasing. The average return difference between the bottom and the top portfolios is 0.0334, also significant at the 1% level. This shows that stocks with high systematic disaster concern

underperform stocks with low systematic disaster concern on average when the market overall performs poorly. In particular, going long in stocks with the lowest $SysDis$ and shorting stocks with the highest $SysDis$ results in an average monthly return of 3.34% conditional on the market return being negative.

The opposite relations between the systematic disaster concern and the expected portfolio return in good and bad markets are intuitive. The systematic disaster concern describes investors' expectations on the incremental likelihood of future stock disasters if there will be a market-wide disaster relative to if there will not. It has been shown in Section 4.4 that these expectations are indeed informative on the future occurrence of stock disasters in different states of the market. Given this, if a market-wide disaster happens in the future, one would expect stocks with high systematic disaster concern to be more heavily affected and hence deliver lower returns than other stocks. In addition, given the continuous nature of equity returns, negative market returns above the disaster threshold, despite being defined as in the non-disaster state, also represent poor performance of the market. As a result, stocks with high systematic disaster concern may underperform in this situation as well. In contrast, when the market performs well, stocks with high systematic disaster concern should outperform other stocks. Otherwise, they would be dominated by stocks with low systematic disaster concern in all market states, and thus no investors would be willing to hold them. This explains the positive relation between systematic disaster concern and the expected portfolio return conditional on the future market return being positive. Overall, the opposite patterns in good and bad markets together give rise to the hump-shaped relation between systematic disaster concern and expected portfolio returns in the full sample.

The analysis so far is at the portfolio level. To further examine the relation between systematic disaster concern and the expected stock return in different market states, I use a regression approach at the stock level. In each month, I cross-sectionally regress the monthly stock return on the systematic disaster concern estimated as of the end of the previous month, controlling for lagged values of the CAPM beta ($Beta$) and the market disaster concern beta ($DisBeta$), i.e.,

$$r_{t+1}^i = \delta_{0,t+1} + \delta_{1,t+1} SysDis_t^i + \delta_{2,t+1} Beta_t^i + \delta_{3,t+1} DisBeta_t^i + \psi_{t+1}^i.$$

The reason for including *Beta* in the regression is because it is positively correlated with *SysDis*. Stocks with large *Beta* are cyclical in the sense that they tend to outperform other stocks in good markets and underperform other stocks in bad markets. I thus wonder if the relation between the systematic disaster concern and the expected stock return in different market states is driven by *Beta*. I also control for *DisBeta* in the regression to disentangle the effects of *SysDis* and *DisBeta* on the expected stock return.

Table 5 shows the average values of the regression coefficients over time. I start by running the regression without controlling for *Beta* and *DisBeta*. Over the full sample, the average slope coefficient on *SysDis* is not significantly different from zero, which is expected given the hump-shaped relation found with the portfolio sorting approach. I then split the full sample into subsamples with positive and negative monthly market returns. For the months with positive market returns, the average coefficient on *SysDis* is significant positive at the 1% level, implying that stocks with higher systematic disaster concern tend to deliver higher returns in good markets. On the other hand, for the months with negative market returns, the average coefficient on *SysDis* is negative and significant at the 1% level, implying that stocks with higher systematic disaster concern tend to deliver lower returns in bad markets. These finding are consistent with the results from portfolios sorting

I then include *Beta* and *DisBeta* in the regression. For the full sample, including the controls does not change the result much. The average coefficient on *SysDis* remains insignificant. In fact, neither *Beta* nor *DisBeta* seems to have a significant effect on the expected stock return over the entire sample. For the months with positive market returns, *Beta* has a positive coefficient and *DisBeta* has a negative coefficient, and both variables are statistically significant. This means that stocks with higher *Beta* and lower *DisBeta* tend to deliver higher returns if the market performs well. With these variables being controlled for, *SysDis* is still positive and significant at the 10% level. This indicates that the positive relation between *SysDis* and the expected stock return in good markets is not fully driven by *Beta* and *DisBeta*. When I focus on months with negative market returns, I now find a negative coefficient on *Beta* and a positive coefficient on *DisBeta*, meaning that stocks with lower *Beta* and higher *DisBeta* tend to perform better in bad markets. Interestingly, the coefficient on *SysDis* remain negative and significant at the

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1% level. This shows that the negative relation between $SysDis$ and the expected stock return remains strong even when $Beta$ and $DisBeta$ are controlled for.

Overall, my results show that the relation between systematic disaster concern and the expected stock return depends on the market state. Higher systematic disaster concern predicts higher stock returns in good markets and lower stock returns in bad markets. These effects are not driven by the CAPM beta or the market disaster concern beta.

## 4.6   A Trading Strategy

Section 4.5 shows that stocks with the lowest and the highest systematic disaster concern have lower expected returns than stocks in the middle. This allows me to construct a trading strategy by going long in stocks with middle levels of systematic disaster concern and shorting a combination of stocks with the lowest and the highest systematic disaster concern.

Let $r_{t+1}^{p_j}$ represent the equal-weighted return of the $j$th quintile portfolio sorted by $SysDis_t$ over month $t+1$, where $j = 1, 2, \ldots 5$. The trading return from going long in the middle quintile and shorting a combination of $x$ in the bottom quintile and $1-x$ in the top quintile is

$$r_{t+1}^{Trade} = r_{t+1}^{p_3} - x r_{t+1}^{p_1} - (1-x) r_{t+1}^{p_5}, \tag{11}$$

where $x$ takes values from 0 to 1.[3] In particular, $x = 0$ corresponds to going long in the mid-$SysDis$ portfolio and shorting the highest-$SysDis$ portfolio, and $x = 1$ corresponds to going long in the mid-$SysDis$ portfolio and shorting the lowest-$SysDis$ portfolio. A larger $x$ represents shorting a larger proportion of stocks with the lowest systematic disaster concern.

Table 6 reports the average returns from the trading strategy with $x$ varying from 0 to 1. The average monthly trading return is positive for all values of $x$. It slowly decreases from 0.32% when $x = 0$ to 0.26% when $x = 1$, which is a result of the fact that the lowest-$SysDis$ portfolio has a slightly higher average return than the highest-$SysDis$ portfolio during the sample period. Statistically, $x = 0.7$ gives rise to the most significant average

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[3]The trading strategy proposed here is a long-short strategy that requires zero net investment. The trading return (11) represents the profit earned for each one dollar engaged in the long-short strategy. One can easily scale up or down the trading profit while maintaining zero net investment.

trading return of 0.28%, corresponding to a long position in the mid-$SysDis$ portfolio and a short position consisting of 70% in the lowest-$SysDis$ portfolio and 30% in the highest-$SysDis$ portfolio. The statistical significance results from reduced trading volatility from shorting a non-zero proportion of both the lowest-$SysDis$ and the highest-$SysDis$ stocks, since these two groups of stocks tend to have offsetting returns.

To understand the source of the positive average trading returns, I calculate the abnormal returns (i.e., risk-adjusted alphas) with respect to a number of popular factor models. I start with the CAPM model, in which the market factor is the only source of systematic risk. The CAPM alpha ranges from 0.65% when $x = 0$ to 0.15% when $x = 1$, and it is significantly positive at the 5% level for values of $x$ between 0 and 0.7. This indicates that the positive average trading returns are not attributable to the exposure of my trading strategy to the market risk. I next estimate the alpha using the Fama and French (1993) three factors (market, size, and value) plus a fourth momentum factor (Carhart (1997)). The four-factor alpha ranges from 0.41% when $x = 0$ to 0.25% when $x = 1$. Indeed, for almost all values of $x$, the four-factor alpha is weakly higher than the corresponding average trading return and statistically significant. Again, my trading strategy generates positive abnormal returns that cannot be explained by the market, size, value, and momentum factors. Finally, I estimate the risk-adjusted alpha using the Fama and French (2016) five factors (market, size, value, profitability, and investment) plus the momentum factor. Now the abnormal return disappears for all values of $x$. This suggests that the positive average trading returns are mostly driven by the profitability and investment factors.[4]

Finally, Table 7 reports the slope coefficients and the adjusted R-squared from regressing the trading returns on the Fama-French five factors and the momentum factor for different values of $x$. Each factor has a significant coefficient for at least some values of $x$. The adjusted R-squared ranges from 0.6991 when $x = 0$ to 0.3309 when $x = 1$. Hence, the six factors together explain 33%–70% of the variations in the returns from the $SysDis$-based trading strategy.

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[4]Including the Pástor and Stambaugh (2003) liquidity factor does not change the results. I thus omit it for brevity.

## 4.7 Systematic Disaster Concern and Firm Characteristics

This section examines the relation between systematic disaster concern and various stock and firm characteristics. I focus on the following characteristics:

- CAPM beta ($Beta$): the sensitivity of the stock return to the market return (proxied by the S&P 500 return);

- Market disaster concern beta ($DisBeta$): the sensitivity of the stock return to the market disaster concern ($Dis^M$);

- Idiosyncratic volatility ($Idio$): the annualized standard deviation of the residuals from the CAPM regression;

- Illiquidity ($Illiq$): the average of daily ratios of the absolute stock return to the dollar trading volume, scaled by the cross-sectional mean (following Amihud (2002));

- Firm size ($Size$): the log market capitalization;

- Book-to-market ratio ($B2M$): the ratio of the book value of equity to the market value of equity;

- Return on equity ($ROE$): the ratio of income before extraordinary items to the book value of equity;

- Investment ($Inv$): the proportional quarterly change in total assets;

- Leverage ($Lever$): the ratio of total liabilities to total assets.

At the end of each month, I estimate $Beta$, $DisBeta$, $Idio$ and $Illiq$ using stock returns and other information at the daily frequency from the most recent twelve-month window. This is consistent with the window period used to estimate the systematic disaster concern $SysDis$. For $Size$, $B2M$, $ROE$, $Inv$ and $Lever$, I use the most recent values of these variables available as of the end of each month. To examine the relation between systematic disaster concern and the characteristics, in each month I again sort stocks into five quintile portfolios based on $SysDis$, and I compute the equal-weighted average value of

each characteristic for the five portfolios. I use values of $SysDis$ and the characteristics in the same month instead of looking at the lead-lag relation, since the focus here is not about prediction.

Table 8 reports the time averages of $SysDis$ and the characteristics for the $SysDis$-sorted portfolios. The average values of $SysDis$ for the five portfolios are -0.0103, 0.0917, 0.2121, 0.4016 and 0.7433, respectively. The average portfolio characteristics exhibit some nonlinearity with respect to $SysDis$, and a closer look reveals that the nonlinearity comes solely from the lowest-$SysDis$ portfolio. Ignoring the lowest-$SysDis$ portfolio, I find that portfolios with higher $SysDis$ are associated with larger CAPM betas, more negative market disaster concern betas, higher idiosyncratic volatility and illiquidity, smaller market capitalization, lower returns on equity and leverage, and higher book-to-market ratios and investment. On the other hand, the lowest-$SysDis$ portfolio has the highest level of illiquidity of all five portfolios, and it also tends to contain stocks with small market capitalization and below-average CAPM betas. Such stocks may be less likely to draw attention from investors and hence less actively traded. This in turn may cause the stock disaster concern to be less sensitive to the market disaster concern, thus giving rise to very low levels of systematic disaster concern.

## 5 Conclusion

The existing literature on the option-implied disaster concern is restricted to the aggregate market. This paper extends the literature by studying individual assets' disaster concern and its systematic variations with the market. I propose new measures of the conditional and systematic disaster concern of an asset with respect to the market index, which can be estimated based on the comovement of the option-implied disaster concern between the asset and the market index. These measures have intuitive interpretations in terms of the risk-neutral conditional disaster probabilities, reflecting investors' expectations on the asset disaster risk given different future states of the market. Using the S&P 500 index as the proxy for the market index, I empirically estimate the conditional and systematic disaster concern measures for a large set of common stocks. I show that the estimated conditional and systematic disaster concern variables vary widely both in the time series

and in the cross section and that they strongly predict stock-level disasters and stock returns in different market states. These findings indicate that the comovement of option prices between stocks and the market index contains forward-looking information on their joint tail distributions.

The idea of using the covariations in the option prices of different securities to infer their joint return behavior extends far beyond the study of disaster risk. By defining richer state spaces, one could potentially estimate the entire risk-neutral joint return distributions of different securities from option prices. In addition, the constrained regression approach motivated by the total probability formula is nonparametric and does not rely on an assumed functional form of the generating process of asset returns. Hence, it may help uncover potential nonlinearity in the structure of asset returns with respect to systematic factors. All of these could have important implications on theoretical and empirical work in asset pricing, which I leave for future research.

## Appendix: Estimating European Option Prices

As discussed in Section 3.1, in order to estimate the disaster concern of an asset, one needs European put option prices for some specific time to maturity and strike prices around the disaster threshold, which are usually not directly observed in the market. To obtain these option prices, I adopt the following approach from the literature (e.g., Shimko (1993), Malz (1997), and Figlewski (2010)). On any given date, I start with the implied volatilities provided in OptionMetrics of all traded options written on the asset of interest, and fit the implied volatility surface across different strike prices and maturities. Then, I plug the fitted implied volatilities at the required maturity and strike prices into the BS pricing formula to estimate the corresponding European option prices.

I fit the implied volatility surface by kernel smoothing, following the procedure used by OptionMetrics. For each date, I index all traded option contracts written on the asset by $h = 1, 2, \ldots, H$. For each option contract $h$, let $\sigma^h$ represent the implied volatility, and let $V^h$ be the option vega (which measures the sensitivity of the option price to the volatility). Denote by $mn^h = X^h/S_t$ the moneyness of the option, by $mt^h$ the time to maturity in years, and by $cp^h$ a dummy variable that equals 0 for call options and 1 for

put options. Then, for any arbitrary moneyness $mn^*$ (within the range of moneyness for traded options), time to maturity $mt^*$ (within the range of maturity for traded options), and call-put indicator $cp^*$ ($cp^* = 1$ for all my analyses since I use put option prices for disaster concern estimation), the fitted volatility can be computed as

$$\hat{\sigma}\left(mn^*, mt^*, cp^*\right) = \frac{\sum_{h=1}^{H} V^h \sigma^h \Psi\left(mn^* - mn^h, mt^* - mt^h, cp^* - cp^h\right)}{\sum_{h=1}^{H} V^h \Psi\left(mn^* - mn^h, mt^* - mt^h, cp^* - cp^h\right)}, \qquad (12)$$

where the kernel function $\Psi$ is given by

$$\Psi\left(x, y, z\right) = \frac{1}{\sqrt{2\pi}} \exp\left[-\frac{x^2}{2c_1} - \frac{y^2}{2c_2} - \frac{z^2}{2c_3}\right].$$

I naively choose $c_1 = c_2 = c_3 = 0.001$. I check to make sure that these parameter values yield reasonable fitting.

The idea of the kernel smoothing procedure is intuitive. For any $(mn^*, mt^*, cp^*)$, I estimate the associated implied volatility as the weighted average of the implied volatilities of all traded options, where those with moneyness, time to maturity, and call-put indicator close to $(mn^*, mt^*, cp^*)$ are assigned higher weights than those far away. In addition, since I eventually need to compute the European option prices from the fitted implied volatilities, I also assign higher weights to traded options whose prices have higher sensitivity to the volatility (higher vega).

It is worth mentioning that the kernel smoothing formula (12) applies only for values of $mn^*$ and $mt^*$ within the observed ranges of the corresponding parameters for traded options. In order to estimate the disaster concern, I need European put option prices (and hence the volatilities) around the disaster thresholds, and thus $mn^*$ may lie below the observed moneyness range of traded options. In this case, I assume that the implied volatility outside the observed range is flat and hence set $mn^*$ equal to the lowest observed moneyness of traded options.

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## Figure 1: Market and Stock Disaster Concern

This figure plots the market disaster concern and the cross-sectional average stock disaster concern over time.
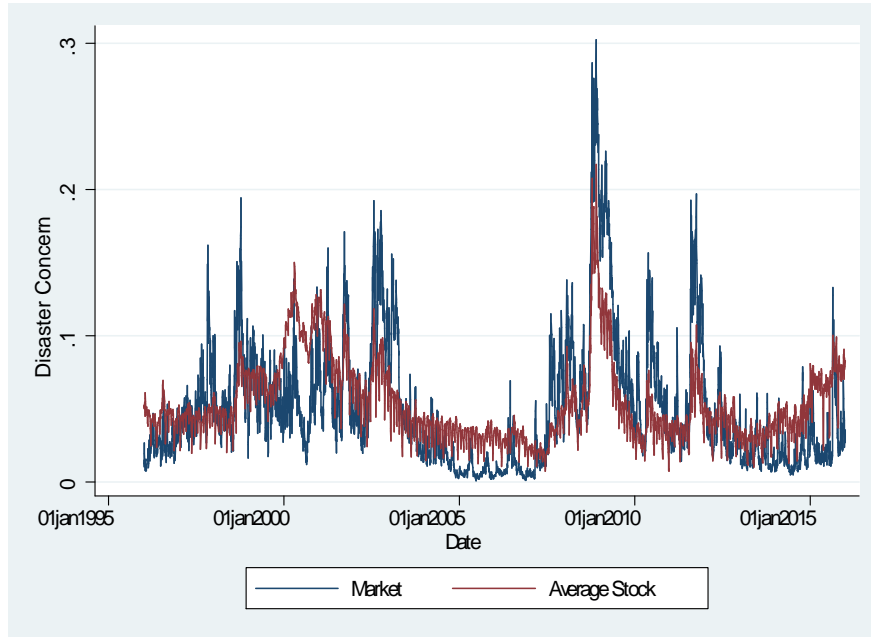
## Figure 2: Conditional Disaster Concern

This figure plots the cross-sectional average conditional disaster concern of stocks given disaster and non-disaster markets over time.
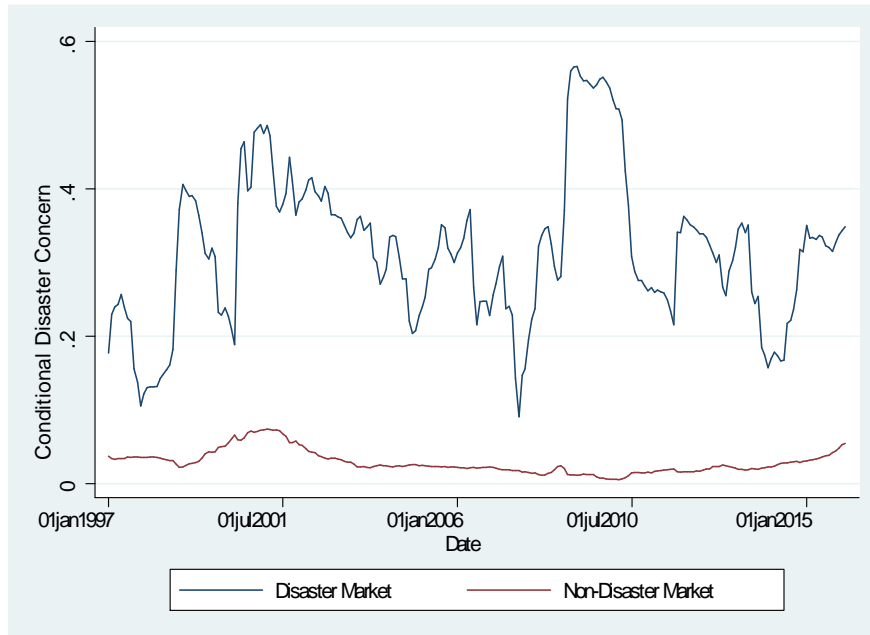
Figure 3: Estimation R-Squared

This figure plots the cross-sectional average R-squared from the conditional disaster concern estimation over time.

Figure 4: Disaster Concern of Microsoft and Bank of America

The top and bottom figures plot the disaster concern of Microsoft and Bank of America over time, respectively.

Figure 5: Systematic Disaster Concern of Microsoft and Bank of America

The top and bottom figures plot the systematic disaster concern of Microsoft and Bank of America over time, respectively.
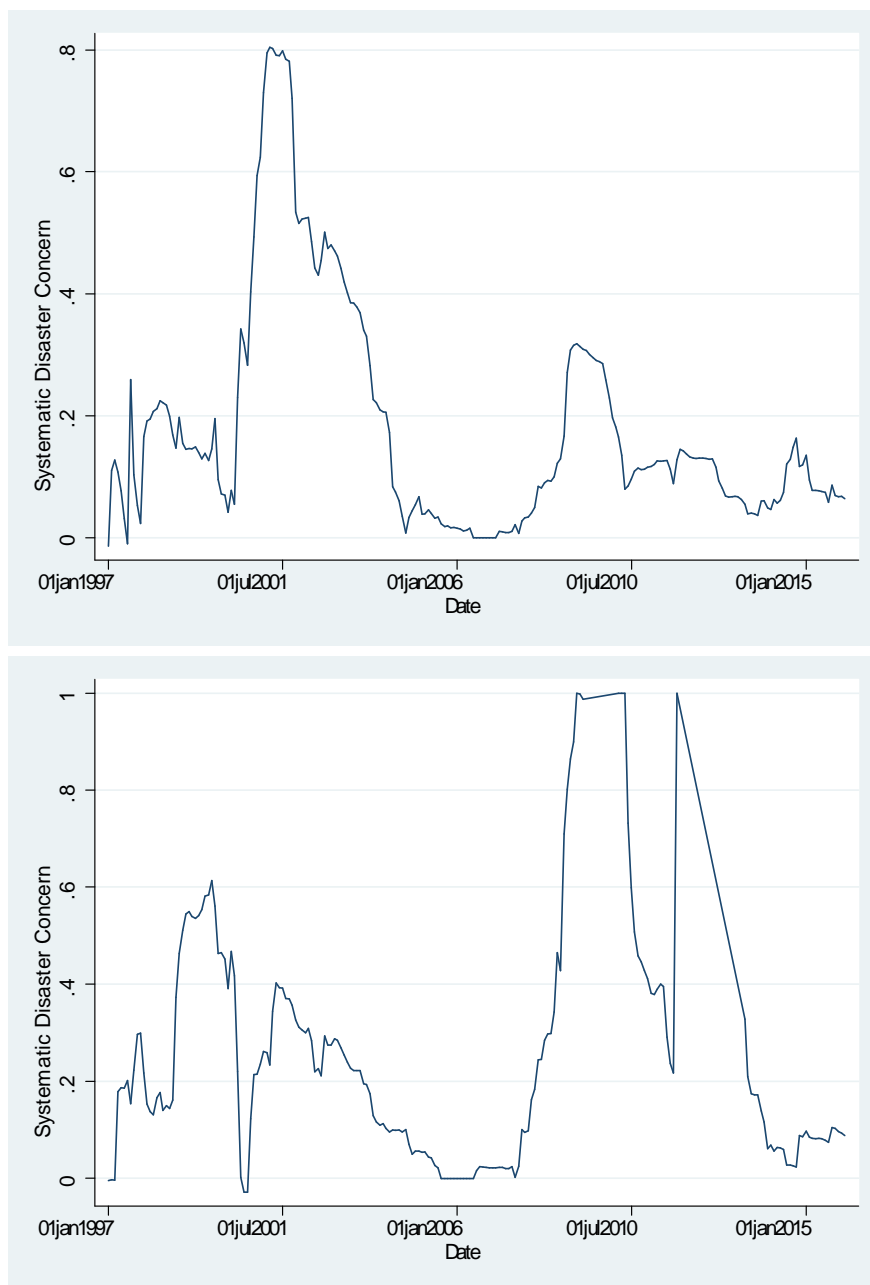
## Table 1: Summary Statistics

Panel A shows summary statistics for the market disaster concern ($Dis^M$). Panel B shows summary statistics for stock-level variables including the disaster concern ($Dis$), conditiona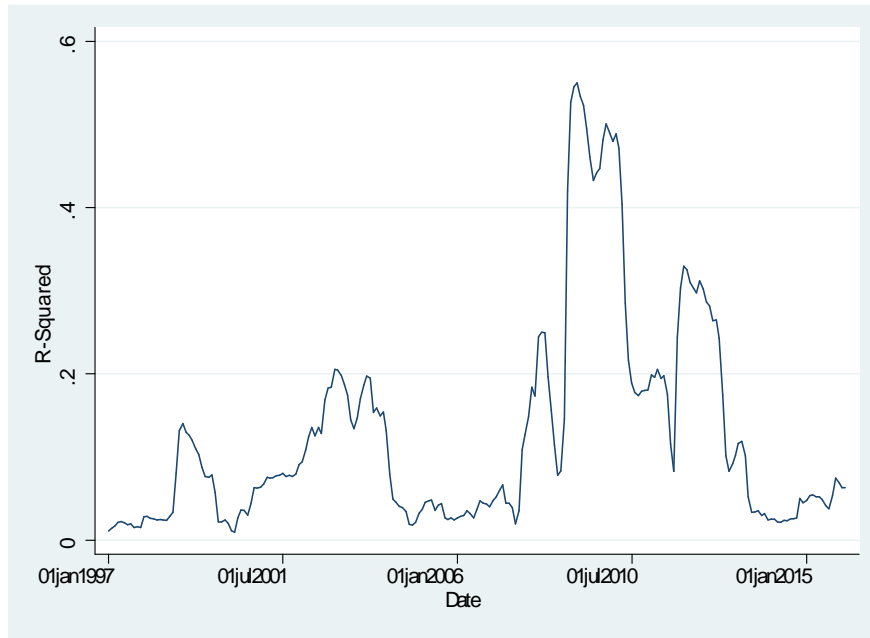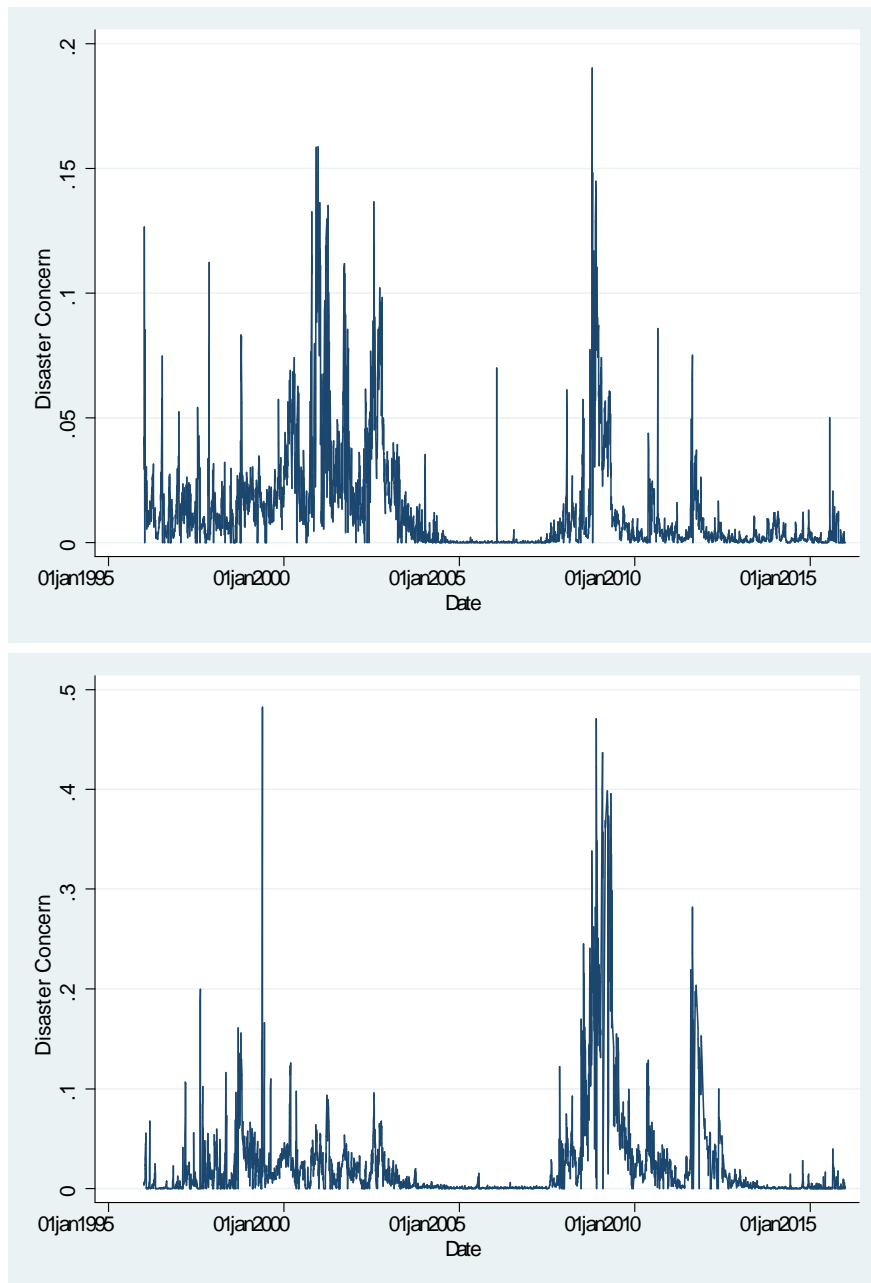l disaster concern given disaster and non-disaster markets ($ConDis(D^M)$ and $ConDis(N^M)$), systematic disaster concern ($SysDis$), CAPM beta ($Beta$), and market disaster concern beta ($DisBeta$). For each of the stock-level variables, I compute the average value for each stock over time and report the cross-sectional summary statistics of these stock averages.

| | Mean | S.D. | Min | Q10 | Median | Q90 | Max |
|---|---|---|---|---|---|---|---|
| Panel A: Market Variables | | | | | | | |
| $Dis^M$ | 0.0509 | 0.0444 | 0.0008 | 0.0092 | 0.0389 | 0.1088 | 0.3025 |
| Panel B: Stock Variables | | | | | | | |
| $Dis$ | 0.0873 | 0.0678 | 0 | 0.0266 | 0.0661 | 0.1827 | 0.7583 |
| $ConDis(D^M)$ | 0.3718 | 0.2419 | 0 | 0.1027 | 0.3251 | 0.7217 | 1 |
| $ConDis(N^M)$ | 0.0519 | 0.0488 | 0 | 0.0104 | 0.0358 | 0.1187 | 0.3476 |
| $SysDis$ | 0.3200 | 0.2295 | -0.3438 | 0.0626 | 0.2872 | 0.6384 | 1 |
| $Beta$ | 1.1210 | 0.4258 | 0.0248 | 0.6445 | 1.0713 | 1.6277 | 4.4703 |
| $DisBeta$ | -0.1509 | 0.1129 | -0.9744 | -0.2653 | -0.1301 | -0.0543 | 0.4804 |

## Table 2: Pairwise Correlations

This table reports pairwise correlations of stock-level variables including the disaster concern ($Dis$), conditional disaster concern given disaster and non-disaster markets ($ConDis\left(D^M\right)$ and $ConDis\left(N^M\right)$), systematic disaster concern ($SysDis$), CAPM beta ($Beta$), the market disaster concern beta ($DisBeta$).

|  | $ConDis\left(D^M\right)$ | $ConDis\left(N^M\right)$ | $SysDis$ | $Beta$ | $DisBeta$ |
|---|---|---|---|---|---|
| $ConDis\left(D^M\right)$ | 1 | 0.1308 | 0.9943 | 0.4220 | -0.0877 |
| $ConDis\left(N^M\right)$ | 0.1308 | 1 | 0.0242 | 0.2340 | -0.1782 |
| $SysDis$ | 0.9943 | 0.0242 | 1 | 0.4003 | -0.0693 |
| $Beta$ | 0.4220 | 0.2340 | 0.4003 | 1 | -0.3707 |
| $DisBeta$ | -0.0877 | -0.1782 | -0.0693 | -0.3707 | 1 |

## Table 3: Conditional Disaster Concern and Realized Stock Disasters

This table reports the average values of the estimated conditional disaster concern given the subsequently realized state of the market ($ConDis_t\left(r_{t+1}^M\right)$) and the realized stock disaster dummy ($DisD_{t+1}$) for the full sample as well as for subsamples with realized disaster and non-disaster markets separately. The table also reports the time average of the slope coefficient ($\gamma_{1,t+1}$) from cross-sectionally regressing $DisD_{t+1}$ on $ConDis_t\left(r_{t+1}^M\right)$ for each month. Also shown in the table are results for each of the 4 months with realized market disasters The standard errors are displayed in the parentheses below the corresponding estimates. For the full-sample $t$-test, I use the Newey-West standard error with 5 lags to account for potential autocorrelation. Asterisks denote statistical significance at the 1% (***), 5% (**) and 10% (*) levels.

| | $r_{t+1}^M$ | $ConDis_t\left(r_{t+1}^M\right)$ | $DisD_{t+1}$ | $\gamma_{1,t+1}$ |
|---|---|---|---|---|
| Full Sample | | 0.0328 | 0.0229 | 0.5781 |
| (228 Months) | | | | (0.0728)*** |
| Non-Disaster Markets | $> -0.1$ | 0.0272 | 0.0195 | 0.5830 |
| (224 Months) | | | | (0.0475)*** |
| Disaster Markets | $\leq -0.1$ | 0.3991 | 0.2470 | 0.3066 |
| (4 Months) | | | | (0.0471)*** |
| Aug 1998 | -0.1431 | 0.1591 | 0.3055 | 0.2050 |
| | | | | (0.0943)** |
| Sep 2002 | -0.1090 | 0.3936 | 0.0846 | 0.2685 |
| | | | | (0.0400)*** |
| Oct 2008 | -0.1670 | 0.3694 | 0.4278 | 0.4271 |
| | | | | (0.0484)*** |
| Feb 2009 | -0.1036 | 0.5653 | 0.1216 | 0.3260 |
| | | | | (0.0433)*** |

## Table 4: Systematic Disaster Concern and Expected Portfolio Returns

This table reports the average monthly returns of portfolios sorted by the lagged value of systematic disaster concern ($SysDis$) for the full sample as well as for subsamples with positive and negative market returns separately. Also reported are the average return differences between portfolios with the lowest and the highest $SysDis$. The standard errors are displayed in the parentheses below the corresponding estimates. For the full-sample test, I use the Newey-West standard error with 5 lags to account for potential autocorrelation. Asterisks denote statistical significance at the 1% (***), 5% (**) and 10% (*) levels.

| Portfolio by $SysDis$ | Low | 2 | 3 | 4 | High | Low–High |
|---|---|---|---|---|---|---|
| Full Sample | 0.0078 | 0.0096 | 0.0104 | 0.0085 | 0.0072 | 0.0006 |
| (228 Months) | | | | | | (0.0038) |
| Positive Market Return | 0.0330 | 0.0359 | 0.0413 | 0.0460 | 0.0531 | -0.0201 |
| (140 Months) | | | | | | (0.0042)*** |
| Negative Market Return | -0.0323 | -0.0324 | -0.0387 | -0.0511 | -0.0657 | 0.0334 |
| (88 Months) | | | | | | (0.0058)*** |

## Table 5: Systematic Disaster Concern and Expected Stock Returns

This table reports the average slope coefficients from cross-sectionally regressing monthly stock returns on the lagged values of the systematic disaster concern ($SysDis$), the CAPM beta ($Beta$), and the market disaster concern beta ($DisBeta$) for the full sample (Panel A) as well as for subsamples with positive and negative market returns separately (Panels B and C). The standard errors are displayed in the parentheses below the corresponding estimates. For the full-sample tests, I use the Newey-West standard errors with 5 lags to account for potential autocorrelation. Asterisks denote statistical significance at the 1% (***), 5% (**) and 10% (*) levels.

| Panel A: Full Sample | | |
|---|---|---|
| $SysDis$ | -0.0017 | -0.0014 |
| | (0.0054) | (0.0031) |
| $Beta$ | | -0.0007 |
| | | (0.0032) |
| $DisBeta$ | | -0.0204 |
| | | (0.0207) |
| Constant | 0.0088 | 0.0081 |
| | (0.0029)*** | (0.0029)*** |
| Panel B: Positive Market Return | | |
| $SysDis$ | 0.0261 | 0.0055 |
| | (0.0059)*** | (0.0031)* |
| $Beta$ | | 0.0168 |
| | | (0.0037)*** |
| $DisBeta$ | | -0.0611 |
| | | (0.0239)** |
| Constant | 0.0317 | 0.0152 |
| | (0.0022)*** | (0.0031)*** |
| Panel C: Negative Market Return | | |
| $SysDis$ | -0.0459 | -0.0125 |
| | (0.0076)*** | (0.0039)*** |
| $Beta$ | | -0.0285 |
| | | (0.0045)*** |
| $DisBeta$ | | 0.0444 |
| | | (0.0241)* |
| Constant | -0.0277 | -0.0031 |
| | (0.0039)*** | (0.0042) |

## Table 6: Average Trading Returns and Risk-Adjusted Alphas

This table reports the average monthly returns from a trading strategy constructed based on the systematic disaster concern ($SysDis$). The trading strategy involves going long in stocks in the mid-$SysDis$ quintile and shorting a combination of stocks with a proportion of $x$ in the lowest-$SysDis$ quintile and $1-x$ in the highest-$SysDis$ quintile. Also reported are the risk-adjusted alphas based on the CAPM model, the Fama-French three-factor model plus the momentum factor, and the Fama-French five-factor model plus the momentum factor. The Newey-West standard errors with 5 lags are displayed in the parentheses below the corresponding estimates. Asterisks denote statistical significance at the 1% (***), 5% (**) and 10% (*) levels.

|  | $x=0$ | $x=0.1$ | $x=0.2$ | $x=0.3$ | $x=0.4$ | $x=0.5$ |
|---|---|---|---|---|---|---|
| Average Return | 0.0032 | 0.0031 | 0.0031 | 0.0030 | 0.0030 | 0.0029 |
|  | (0.0031) | (0.0028) | (0.0025) | (0.0022) | (0.0019) | (0.0017)* |
| Alpha (CAPM) | 0.0065 | 0.0060 | 0.0055 | 0.0050 | 0.0045 | 0.0040 |
|  | (0.0027)** | (0.0024)** | (0.0022)** | (0.0020)** | (0.0018)** | (0.0017)** |
| Alpha (FF3F+UMD) | 0.0041 | 0.0039 | 0.0038 | 0.0036 | 0.0035 | 0.0033 |
|  | (0.0019)** | (0.0018)** | (0.0016)** | (0.0014)** | (0.0013)*** | (0.0012)*** |
| Alpha (FF5F+UMD) | 0.0007 | 0.0008 | 0.0010 | 0.0011 | 0.0013 | 0.0014 |
|  | (0.0019) | (0.0017) | (0.0015) | (0.0014) | (0.0013) | (0.0012) |
|  | $x=0.6$ | $x=0.7$ | $x=0.8$ | $x=0.9$ | $x=1$ |  |
| Average Return | 0.0029 | 0.0028 | 0.0028 | 0.0027 | 0.0026 |  |
|  | (0.0015)* | (0.0014)** | (0.0015)* | (0.0016)* | (0.0018) |  |
| Alpha (CAPM) | 0.0035 | 0.0030 | 0.0025 | 0.0020 | 0.0015 |  |
|  | (0.0016)** | (0.0015)** | (0.0015)* | (0.0015) | (0.0016) |  |
| Alpha (FF3F+UMD) | 0.0032 | 0.0030 | 0.0028 | 0.0027 | 0.0025 |  |
|  | (0.0011)*** | (0.0012)*** | (0.0012)** | (0.0013)** | (0.0015)* |  |
| Alpha (FF5F+UMD) | 0.0016 | 0.0017 | 0.0019 | 0.0020 | 0.0022 |  |
|  | (0.0012) | (0.0012) | (0.0013) | (0.0014) | (0.0016) |  |

## Table 7: Coefficients from Regressing Trading Returns on Factors

This table reports the slope coefficients and the adjusted R-squared from regressing the returns from a trading strategy constructed based on the systematic disaster concern ($SysDis$) on the Fama-French five factors and the momentum factor. The trading strategy involves going long in stocks in the mid-$SysDis$ quintile and shorting a combination of stocks with a proportion of $x$ in the lowest-$SysDis$ quintile and $1-x$ in the highest-$SysDis$ quintile. The Newey-West standard errors with 5 lags are displayed in the parentheses below the corresponding estimates. Asterisks denote statistical significance at the 1% (***), 5% (**) and 10% (*) levels.

| | $x=0$ | $x=0.1$ | $x=0.2$ | $x=0.3$ | $x=0.4$ | $x=0.5$ |
|---|---|---|---|---|---|---|
| MKTRF | -0.2152 | -0.1715 | -0.1277 | -0.0839 | -0.0402 | 0.0036 |
| | (0.0777)*** | (0.0700)** | (0.0627)** | (0.0560) | (0.0500) | (0.0450) |
| SMB | -0.2661 | -0.2582 | -0.2504 | -0.2426 | -0.2348 | -0.2270 |
| | (0.0789)*** | (0.0711)*** | (0.0648)*** | (0.0602)*** | (0.0580)*** | (0.0583)*** |
| HML | 0.2060 | 0.1897 | 0.1734 | 0.1572 | 0.1409 | 0.1246 |
| | (0.0924)** | (0.0821)** | (0.0727)** | (0.0646)** | (0.0582)** | (0.0542)** |
| UMD | 0.2350 | 0.1981 | 0.1612 | 0.1243 | 0.0874 | 0.0505 |
| | (0.0622)*** | (0.0545)*** | (0.0473)*** | (0.0407)*** | (0.0352)** | (0.0313) |
| RMW | 0.6145 | 0.5617 | 0.5088 | 0.4560 | 0.4031 | 0.3503 |
| | (0.0823)*** | (0.0730)*** | (0.0648)*** | (0.0580)*** | (0.0531)*** | (0.0509)*** |
| CMA | 0.3041 | 0.2741 | 0.2441 | 0.2141 | 0.1841 | 0.1541 |
| | (0.1188)** | (0.1052)*** | (0.0923)*** | (0.0804)*** | (0.0701)*** | (0.0622)** |
| Adj $R^2$ | 0.6991 | 0.6969 | 0.6903 | 0.6759 | 0.6478 | 0.5976 |
| | $x=0.6$ | $x=0.7$ | $x=0.8$ | $x=0.9$ | $x=1$ | |
| MKTRF | 0.0473 | 0.0911 | 0.1349 | 0.1786 | 0.2224 | |
| | (0.0415) | (0.0398)** | (0.0402)*** | (0.0426)*** | (0.0466)*** | |
| SMB | -0.2192 | -0.2114 | -0.2035 | -0.1957 | -0.1879 | |
| | (0.0611)*** | (0.0661)*** | (0.0729)*** | (0.0809)** | (0.0899)** | |
| HML | 0.1084 | 0.0921 | 0.0758 | 0.0595 | 0.0433 | |
| | (0.0531)** | (0.0551)* | (0.0599) | (0.0669) | (0.0754) | |
| UMD | 0.0135 | -0.0234 | -0.0603 | -0.0972 | -0.1341 | |
| | (0.0297) | (0.0306) | (0.0339)* | (0.0391)** | (0.0454)*** | |
| RMW | 0.2975 | 0.2446 | 0.1918 | 0.1389 | 0.0861 | |
| | (0.0516)*** | (0.0551)*** | (0.0609)*** | (0.0684)** | (0.0772) | |
| CMA | 0.1241 | 0.0942 | 0.0642 | 0.0342 | 0.0042 | |
| | (0.0578)** | (0.0575) | (0.0615) | (0.0690) | (0.0790) | |
| Adj $R^2$ | 0.5187 | 0.4217 | 0.3438 | 0.3160 | 0.3309 | |

## Table 8: Systematic Disaster Concern and Firm Characteristics

This table shows the average values of firm characteristics for portfolios of stocks sorted by the systematic disaster concern (*SysDis*). For each portfolio, I compute the equal-weighted average value of each characteristic in each month, and the table reports the averages of the portfolio characteristics over time. The characteristics examined include the CAPM beta (*Beta*), market disaster concern beta (*DisBeta*), annualized idiosyncratic volatility (*Idio*), illiquidity (*Illiq*), firm size (*Size*), book-to-market ratio (*B2M*), return on equity (*ROE*), investment (*Inv*), and leverage (*Lever*).

| Portfolio by *SysDis* | Low | 2 | 3 | 4 | High |
|---|---|---|---|---|---|
| *SysDis* | -0.0103 | 0.0917 | 0.2121 | 0.4016 | 0.7433 |
| *Beta* | 0.9099 | 0.8857 | 1.0149 | 1.1871 | 1.4332 |
| *DisBeta* | -0.1332 | -0.1145 | -0.1313 | -0.1569 | -0.1898 |
| *Idio* | 0.3357 | 0.2898 | 0.3220 | 0.3825 | 0.4753 |
| *Illiq* | 1.3872 | 0.6759 | 0.7562 | 0.9502 | 1.2309 |
| *Size* | 14.6615 | 15.4948 | 15.4275 | 14.9994 | 14.5786 |
| *B2M* | 0.4465 | 0.4229 | 0.4311 | 0.4440 | 0.4908 |
| *ROE* | 0.0325 | 0.0410 | 0.0376 | 0.0302 | 0.0164 |
| *Inv* | 0.0345 | 0.0294 | 0.0317 | 0.0365 | 0.0390 |
| *Lever* | 0.5347 | 0.5673 | 0.5496 | 0.5158 | 0.4920 |