Option-Implied Systematic Disaster Concern*

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Abstract

The covariation of option-implied disaster concern of a stock and the market index allows me to estimate the conditional and systematic disaster concern of the stock with respect to the market. The estimated variables can be interpreted as the stock's risk-neutral conditional disaster probabilities given possible future market states. Theoretically, these risk-neutral conditional probabilities are equal to the corresponding physical conditional probabilities if the market state is the only priced factor—a sufficient but not necessary condition. Empirically, the conditional and systematic disaster concern variables strongly predict future realizations of stock disasters and 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.

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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 future disaster risk, namely, the "disaster concern" (e.g., Bollerslev and Todorov (2011, 2014), Bollerslev, Todorov, and Xu (2015), Gao, Lu, and Song (2018), and Gao, Gao, and Song (2018)). 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' expectation 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 study of option-implied disaster concern is mostly restricted to the aggregate market. While some papers look at the pricing effect of rare disaster concern in the cross section, they typically measure individual assets' exposure to disaster concern as the sensitivity of individual asset returns to the market disaster concern. Essentially, their focus is still on the market-wide disasters. Indeed, little attention is paid to the disaster concern of individual assets themselves, and perhaps more importantly in a diversifying investor's point of view, the systematic variation of individual asset disaster concern with that of the market.

This paper studies the option-implied systematic disaster concern of individual assets with respect to the market index. In particular, I ask the following questions. What is investors' expected probability of a future asset disaster if the overall market is to experience a disaster in the coming period? What is investors' expected probability of a future asset disaster if the market is to perform normally in the coming period? How does the expected asset disaster probability depend on the future market state? Answering these questions requires knowing the conditional disaster probabilities of the asset given hypothetical future states of the market. Realized equity returns, unfortunately, do not provide such information. Instead, option prices on the asset and the market index together allow me to obtain measures of the conditional and systematic disaster concern of the asset with respect to the market, which are well suited to answering these questions. Using a 20-year sample period and a large group of stocks, I show that the estimated conditional and systematic disaster concern variables strongly predict future realization of stock-level disasters and stock returns in different market states 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 a market index and an individual asset 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 probability that the corresponding return falls in the disaster state. I next define the conditional disaster concern of the asset given disaster and non-disaster markets as the ex-ante conditional disaster probability of the asset given that the market index is to fall in the disaster and non-disaster states, respectively. Finally, I define the asset's systematic disaster concern as the difference in its conditional disaster concern given disaster versus non-disaster markets. Intuitively, systematic disaster concern describes how much more likely an asset is expected to experience a disaster if a market-wide disaster is to occur relative to if the market is to perform normally. Put differently, it is a measure of how the disaster concern of an asset is affected by the future market state.

Before estimating the conditional and systematic disaster concern variables from option prices, a fine point is worth noting—option-implied probabilities are under the risk-neutral measure, which are generally different from the corresponding physical probabilities. However, I show that focusing on the conditional disaster probabilities given the state of the market helps link risk-neutral and physical probabilities by "neutralizing" the pricing effect of the market state. I will also provide empirical evidence that the conditional and systematic disaster concern variables, which are estimated under the risk-neutral measure, are strongly informative on the actual realizations of asset disasters and returns in the corresponding market states.

Ross (1976) and Breeden-Litzenberger (1978) show that the risk-neutral return distribution of any security can be estimated from prices of European options written on that security. As such, estimating the conditional disaster probability of an asset given the market state would require options written on the joint values of market and asset returns, which unfortunately are not traded in practice. I show that such options are indeed unnecessary. According to the total probability formula, the unconditional disaster probability of an asset is equal to the weighted average of its conditional disaster probabilities given the market state, with weights equal to the probabilities of different market states. Given this, the conditional disaster probabilities can be estimated from the market index options and individual asset options in two steps. First, I estimate the disaster probabilities of the market and the asset (i.e., market disaster concern and asset disaster concern) from their respective option prices. Second, I estimate the conditional disaster probabilities (i.e., conditional disaster concern) of the asset given the market state as the slope coefficients from regressing the asset disaster probability on the market disaster and non-disaster probabilities over time, subject to the constraint that the estimated conditional disaster probabilities must lie between zero and one.

I next turn to estimating the conditional and systematic disaster concern variables for a large set of stocks. I choose the S&P 500 index as the proxy for the market index, which has 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 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 (non-disaster) state if its monthly return is below (above) -10%. Similarly, a stock is defined to be in the disaster (non-disaster) state if its monthly return is below (above) -25%. These disaster thresholds are chosen based on historical equity return distributions.

The estimated stock conditional disaster concern is on average much higher given disaster markets than given non-disaster markets, resulting in positive systematic disaster concern estimates in most cases. This reflects that investors in general expect higher likelihood of stock-level disasters if the market overall will experience a disaster than if it will not. The conditional and systematic disaster concern variables exhibit wide variations both in the time series and in the cross section. For example, the systematic disaster concern of Microsoft peaked around the Internet Bubble, whereas that of Bank of America (BOA) peaked around the financial crisis, consistent with economic intuitions. The systematic disaster concern variable is positively correlated with the CAPM beta. On the other hand, it has a weak correlation with the market disaster concern beta (i.e., the sensitivity of stock returns to the market disaster concern, commonly used to measure the systematic disaster risk of individual assets), suggesting that these two approaches capture different aspects of individual assets' systematic exposure to disaster risk.

I then ask whether the estimated conditional and systematic disaster concern variables are informative on future realizations of stock disasters and returns. My results show that the conditional disaster concern variables strongly predict the occurrence of stock-level disasters in the corresponding market state. In particular, increasing conditional disaster concern given disaster (non-disaster) markets from zero to one raises the future probability of a stock disaster by 31% (58%) in the 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 this result 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. These findings provide evidence that the comovement of option-implied disaster concern between the market and stocks carries useful forward-looking information on their joint tail distributions.

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 as well as 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 (2018)). Various measures of disaster risk have been proposed to examine the impact of rare disasters on 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 (2018), Gao, Gao, and Song (2018), and Gao, Lu, and Song (2018)). In particular, Bollerslev and Todorov (2011, 2014), Bollerslev, Todorov, and Xu (2015), Gao, Gao, and Song (2018), and Gao, Lu, and Song (2018) focus on inferring the market disaster concern from option prices, which captures investors' perception of future disaster risk of the overall economy. To the best of my knowledge, my paper is the first to study 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. Empirical evidence shows that this return comovement increases during market downturns (e.g., Roll (1988), Jorion (2000), Longin and Solnik (2001), Ang and Chen (2002), Hong, Tu, and Zhou (2007), and Jiang, Wu, and Zhou (2018)). Another strand of research investigates the liquidity commonality of individual stocks with the market (e.g., Chordia, Roll and Subrahmanyam (2000), Hasbrouck and Seppi (2001), Huberman and Halka (2001), Coughenour and Saad (2004), Hameed, Kang, and Viswanathan (2010), and Karolyi, Lee, and van Dijk (2012)). Recently, Christoffersen, Fournier, and Jacobs (2018) shows that the market index is a common factor driving the covariation in stock 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 of estimating forward-looking asset return distributions from option prices. Ross (1976) and Breeden and Litzenberger (1978) show that the risk-neutral probability distribution of asset returns can be extracted from prices of European options written on the asset of interest. Nevertheless, the question of how these risk-neutral distributions inform us of future realized asset returns, which are observed under the physical probability measure, remains a challenge. To resolve this challenge, Ross (2015) proposes that physical return distributions can be uniquely recovered from risk-neutral distributions. Subsequent papers (e.g., Dubynskiy and Goldstein (2013) and Borovička, Hansen, and Scheinkman (2016)) point out that Ross recovery relies on strong assumptions such as bounded state space and transition independence and that unique recovery may not be feasible when these assumptions are relaxed. My paper shows that focusing on the conditional asset return distribution with respect to the market state helps align risk-neutral and physical probability measures by neutralizing the pricing effect of the market state. I provide empirical evidence that my risk-neutral conditional and systematic disaster concern variables indeed carry forward-looking information on the actual realizations of stock disasters and returns in different market states.

The rest of the paper proceeds as follows. Section 2 defines the conditional and systematic disaster concern variables and discusses the link between risk-neutral and physical probability measures. Section 3 explains how the conditional and systematic disaster concern variables can be estimated from option prices. Section 4 estimates these variables for a large set of stocks, examines their empirical properties, and investigates their performance in predicting stock-level disasters and returns in different states of the market. Section 5 concludes. Some technical discussions are delegated to the Appendix.

2 Conditional and Systematic Disaster Concern

In this section, I introduce measures of conditional and systematic disaster concern of an asset with respect to the market index. I define these measures in terms of the ex-ante risk-neutral conditional disaster probabilities of the asset given the market state. I then discuss how focusing on these conditional disaster probabilities helps link measures under the risk-neutral probabilities to the corresponding physical probabilities.

2.1 Definition

Consider a market index M and an individual asset i in a one-period setting. Suppose that the market return 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 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.,

$$
\begin{aligned}
Dis^M &= Q\left(r^M \in D^M\right), \\
Dis^i &= Q\left(r^i \in D^i\right),
\end{aligned}
$$

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. The reason for defining disaster concern under risk-neutral probabilities is because one natural way of extracting ex-ante beliefs is by looking at options prices, and option-implied probabilities are risk-neutral. Intuitively, risk-neutral probabilities are equal to the corresponding physical probabilities adjusted for risk aversion. Therefore, the disaster concern measures increase with higher physical disaster probabilities and higher investor risk aversion.

I then 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 ex-ante risk-neutral conditional disaster probabilities 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.,

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

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

To better understand the economic meaning of the systematic disaster concern measure, it is useful to consider the total probability formula. 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 weights given by 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

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

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 conditional probabilities which take values from 0 to 1, $SysDis^i$ ranges from -1 to 1. In particular, a positive $SysDis^i$ 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 $SysDis^i$ 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 $SysDis^i$ can theoretically be either positive or negative, in practice it should be positive more often, reflecting that investors tend to become more concerned about asset disasters when the market disaster concern is higher.

A common approach used in the literature to gauge the systematic exposure of individual assets to disaster risk is to look at the sensitivity of asset returns to the market disaster risk. In essence, this approach still focuses on market disasters. My systematic disaster concern measure, in comparison, focuses on the disaster risk of an individual asset itself and its systematic variation with the market disaster risk. I will provide empirical evidence in Section 4 that these two approaches lead to distinct measures that indeed capture differing aspects of an asset's systematic exposure to disaster risk.

2.2 From Risk-Neutral to Physical

The conditional and systematic disaster concern measures are defined under risk-neutral probabilities. A natural question that follows is whether these measures are informative on the corresponding physical probabilities of asset disasters in different market states. I will show that while physical and risk-neutral probabilities generally differ due to risk adjustments, conditioning on the market state helps link them by neutralizing the pricing effect of the market state.

To illustrate this point, I assume that the market state is the only priced factor and hence the stochastic discount factor depends solely on the market state. Let P stands for the physical probability. The following proposition shows that under the above assumption, the conditional disaster probability of an asset given any market state is identical under the physical and the risk-neutral measures.

Proposition 1 *Assume that the stochastic discount factor depends solely on the market state. For any* $S^M \in \left\{D^M, N^M\right\}$, $ConDis^i\left(S^M\right) = P\left(r^i \in D^i | r^M \in S^M\right)$.

Proof of Proposition 1: Given any market state $S^M \in \left\{D^M, N^M\right\}$, the conditional disaster concern of asset i can be written as

$$ConDis^i\left(S^M\right) = Q\left(r^i \in D^i | r^M \in S^M\right) = \frac{Q\left(r^i \in D^i, r^M \in S^M\right)}{Q\left(r^M \in S^M\right)}. \tag{4}$$

Since the stochastic discount factor depends solely on the market state, I denote by $\xi\left(D^M\right)$ and $\xi\left(N^M\right)$ the values of the stochastic discount factor in the disaster and non-disaster market states, respectively. Also denote the risk-free rate by r_f. The risk-neutral probabilities in (4) can then be rewritten as

$$Q\left(r^i \in D^i, r^M \in S^M\right) = e^{r_f} \cdot \xi\left(S^M\right) \cdot P\left(r^i \in D^i, r^M \in S^M\right),$$
$$Q\left(r^M \in S^M\right) = e^{r_f} \cdot \xi\left(S^M\right) \cdot P\left(r^M \in S^M\right).$$

Hence, (4) becomes

$$ConDis^i\left(S^M\right) = \frac{P\left(r^i \in D^i, r^M \in S^M\right)}{P\left(r^M \in S^M\right)} = P\left(r^i \in D^i | r^M \in S^M\right),$$

as required. ∎

The idea behind Proposition 1 is simple. If the market state is the only systematically priced factor, then conditional on the market state the occurrence of an asset disaster is purely idiosyncratic and hence should be risk-neutrally priced. This is as if the pricing effect of the market state is being neutralized. As such, the conditional disaster probabilities should be identical under the physical and risk-neutral measures.

Admittedly, the assumption in Proposition 1 is strong, which is unlikely to be satisfied in reality. However, this is only a sufficient condition, and presumably much weaker conditions are needed for my conditional disaster concern measures to generate consistent ranking across assets under physical and risk-neutral probabilities. While I do not explore these weaker conditions here, I will show in Section 4 that empirically the risk-neutral conditional disaster concern variables indeed carry strong cross-sectional predictive power for the relative likelihood of stock-level disasters in the corresponding state of the market.

3 Estimation Methodology

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

In this section, I show that one can actually estimate the conditional and systematic disaster concern measures from prices of options written on the individual asset along with prices of options written on the market index. The covariation in the prices of these options allows me 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 consists of two steps. The first step estimates the market disaster concern and the asset disaster concern from the corresponding option prices following Ross (1976) and Breeden-Litzenberger (1978). In the second step, I estimate the conditional disaster concern of the asset given different market states using the market and asset disaster concern estimates obtained in the first step by a constrained linear regression over time. Below I discuss these two steps in turn.

3.1 Estimating Disaster Concern

I start with the estimation of the market disaster concern Dis^M and the asset disaster concern Dis^i from the corresponding option prices, assuming that both the market index and the individual asset are traded on the options market. Since the market and asset disaster concern can be estimated in the same manner, below I drop the superscript for brevity.

Ross (1976) and Breeden-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 value at maturity can be estimated in a model-free manner. At any time t, consider a European put option maturing 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, i.e.,

$$\begin{aligned} Put\left(K\right) &= e^{-r_f(T-t)} \int_{S_T=0}^{\infty} \left(K - S_T\right)^{+} dF\left(S_T\right) \qquad (5) \\ &= e^{-r_f(T-t)} \int_{S_T=0}^{K} \left(K - S_T\right) dF\left(S_T\right), \qquad (6) \end{aligned}$$

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

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

Solving for $F\left(K\right)$ leads to

$$F\left(K\right) = e^{r_f(T-t)} \frac{\partial Put\left(K\right)}{\partial K}. \qquad (7)$$

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

Assume that the asset is in the disaster state if its return over the period from t to T falls below some disaster threshold $\bar{r}$. Then, the disaster concern of the asset is given by

$$Dis = Q\left(r \leq \bar{r}\right). \qquad (8)$$

[1] One could alternatively estimate $F\left(\cdot\right)$ based on European call option prices. By the put-call parity, theoretically estimation 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.

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, (8) is equivalent to

$$Dis = Q\left(S_T \leq \bar{S}_T\right) = F\left(\bar{S}_T\right), \tag{9}$$

where

$$\bar{S}_T = S_t \left(1 + \bar{r} - d\right). \tag{10}$$

Evaluating (9) then yields the disaster concern of the asset.

Two technical issues entail further discussions. First, evaluating (9) requires differentiating the option price with respect to the strike price at the disaster threshold (see (7)). 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 strike prices around the disaster threshold and a required time to maturity of $T - t$. In practice, option prices are available at discrete strikes and maturities. Additionally, while most stock indexes are represented by European options, individual stock options are generally American-style. To obtain the European option prices with the required strike prices and time to maturity, I adopt a common approach of first fitting the implied volatility surface by kernel smoothing and then estimating the European option prices based on the Black-Scholes (BS) model (Black and Scholes (1973) and Merton (1973)) using the fitted volatilities. (See the Appendix for detailed discussions.)

It is important to note that using the BS model here does not rely on it being the correct option pricing model. The OptionMetrics database provides the BS implied volatility for all European options. For American options, OptionMetrics computes implied volatility based on the Cox-Ross-Rubinstein (CRR) model (Cox, Ross, and Rubinstein (1979)), which converges to the BS model 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 this, estimating European prices using the BS model simply inverts the BS implied volatility calculation from observed option prices. This is in essence no more than a change of variable and hence does not rely on the validity of the BS model.[2]

3.2 Estimating Conditional and Systematic Disaster Concern

I then proceed to estimate the conditional and systematic disaster concern of the individual asset with respect to the market index. The essence here is to estimate the risk-neutral conditional disaster probabilities of the asset given disaster and non-disaster market states. This might seem impossible without options written on the joint values of the asset and the market index. I now show that observing the covariation in the asset disaster concern and the market disaster concern over time indeed makes my task possible.

The key to my estimation lies with the total probability formula (1), or equivalently (3), which shows that the systematic disaster concern $SysDis^i$ captures the sensitivity of the asset disaster concern Dis^i to the market disaster concern Dis^M. This is similar to the CAPM beta, which measures the return sensitivity of an asset to the market return and is typically estimated as the slope coefficient from regressing the asset return on the market return over time. Given this, a natural idea would be to estimate $SysDis^i$ in a similar manner, that is, by regressing Dis^i on Dis^M over time. A problem in doing so 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 $ConDis^i\left(N^M\right)$, both of 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 does not guarantee that this boundedness condition is satisfied.

To fix this problem, I conduct a constrained linear regression. Since the boundedness constraint is on $ConDis^i\left(D^M\right)$ and $ConDis^i\left(N^M\right)$, I choose to estimate these conditional

[2] I choose to conduct kernel smoothing in the implied volatility space rather than directly in the option price space, since doing so is more robust and hence has become standard in the literature.

disaster concern variables directly. By (1), 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 run the following constrained linear regression over time:

$$
\begin{aligned}
& Dis_t^i = b_1^i Dis_t^M + b_2^i \left(1 - Dis_t^M\right) + \varepsilon_t^i, \qquad (11) \\
& s.t. \\
& 0 \leq b_1^i, b_2^i \leq 1.
\end{aligned}
$$

The resulting slope coefficients $\hat{b}_1^i$ and $\hat{b}_2^i$ will be taken as estimates of conditional disaster concern $ConDis^i\left(D^M\right)$ 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 variables 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 variables using a rolling-window approach.[3] 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 measures for a large set of stocks and explore their empirical properties. I investigate the performance of these measures in predicting stock-level disasters and stock returns in different market states. I also construct profitable trading strategies based on the systematic disaster concern measure.

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

[3] The rolling-window approach is widely used in the literature to obtain time-varying values of the CAPM beta.

4.1 Data and Estimation

I use a sample period from January 1996 to December 2015. My main source of data is the OptionMetrics database, which contains daily information on option prices along with prices and dividend payments of the underlying securities. I choose the S&P 500 index as a proxy for the market index, which has actively traded options covering a wide range of moneyness and 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 obtain monthly stock return data from CRSP and the Fama-French and liquidity factors from WRDS.

I define the disasters thresholds in terms of monthly market and stock returns. In particular, the market index is defined to be in the disaster (non-disaster) state if its return over a month is below (above) -0.10. Similarly, a stock is defined to be in the disaster (non-disaster) state if its monthly return is below (above) -0.25. According to these thresholds, disaster events occurred with historical frequencies around 2% for both the S&P 500 index and the group of stocks. The fact that the market index has a higher (i.e., less negative) disaster threshold than the stocks reflects that the market as a whole is less volatile than individual assets.[4]

I estimate the market and stock disaster concern variables on a daily basis according to (9) using prices of options maturing in 30 days. To maintain the accuracy of my estimation, I focus on stocks actively traded on the options market using the following filtering criteria. On each date, I compute the disaster concern of a stock if (1) there are at least 20 different option contracts written on the stock with implied volatility available, (2) the lowest moneyness level (i.e., ratio of strike price to current stock price) of available options written on the stock is no higher than 0.9, and (3) the shortest (longest) time to maturity of available options written on the stock is no longer (shorter) than 30 days.

When estimating disaster concern, I also need the expected dividend yield over the

[4] An alternative way of defining the disaster thresholds is to allow them to vary with volatility both in the time series and in the cross section, i.e., higher volatility commands a more negative disaster threshold. However, the drawback of this approach is that it tends to dampen the time-series and cross-sectional variation in the resulting disaster concern variables, which is in fact key to my analyses. I hence choose to define the disaster thresholds as being constant over time and across stocks in order to generate sufficient variations.

upcoming 30-day period (see (10)). The expected dividend yield paid by the S&P 500 index is directly provided in OptionMetrics. For each stock, 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 upcoming 30 days 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 (11). At the end of each month, I perform estimation for each stock based on daily market and stock disaster concern estimates from the most recent 12-month window, provided that the stock has disaster concern estimates available on at least 200 days during the estimation window. This rolling-window approach generates considerable time variations in my estimates. Since 12 months are required before the first estimation, I obtain monthly conditional and systematic disaster concern estimates 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.

I will also need the CAPM beta of all stocks in some of my analyses. For consistency, I estimate the CAPM beta for each stock at the end of each month by regressing daily excess stock returns on daily excess S&P 500 returns over the preceding 12-month window. Similarly, I obtain monthly estimates of the market disaster concern beta for each stock by regressing daily excess stock returns on daily market disaster concern estimates using the same 12-month rolling windows. This is the common method used in the literature to capture the systematic disaster risk of individual assets. I will compare the empirical properties of my systematic disaster concern variable with those of the market disaster concern beta.

4.2 Descriptive Statistics

Figure 1 plots the market disaster concern along with the cross-sectional average stock disaster concern over time. The two variables tend to move in tandem, and both exhibit wide fluctuations. In particular, there are two periods of substantial increases in the disaster concern of both the market index and individual stocks. The first one is from 1998 to 2002, corresponding to the Internet bubble and the subsequent bubble bursting.

The second one is from 2008 to 2011, corresponding to the recent financial crisis and the subsequent recession.

Figure 2 plots the cross-sectional average conditional disaster concern of stocks given disaster and non-disaster markets over time. The distance between these two curves represents the cross-sectional average systematic disaster concern. The figure shows that the average conditional disaster concern is always higher given disaster markets relative to non-disaster markets, giving rise to positive systematic disaster concern on average. This reveals that investors are on average more concerned about future stock disasters if the market will have a disaster than if it will 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 my key variables. Panel A shows that the market disaster concern (Dis^M), estimated using S&P 500 options, has a mean value of 0.0509, indicating that on average investors expect a market-wide disaster to happen with a risk-neutral probability of 5% throughout my sample period. 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 likelihood of a market disaster is considered close to zero during the safest time but as high as 30% during the riskiest time.

Panel B summarizes the stock-level variables. For each of these variables, I first compute the average value for each stock over time, and then I 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 stock is expected to experience a disaster with a risk-neutral probability of 9%. The minimum and maximum are 0 and 0.7583, respectively, highlighting the wide cross-sectional dispersion in the disaster concern of different stocks.

The conditional disaster concern given disaster markets ($ConDis\left(D^M\right)$) has a cross-sectional mean value of 0.3718, implying that if the market is to fall in the disaster state, an average stock is expected to experience a disaster with a risk-neutral conditional probability of 37%. The cross-sectional standard deviation of $ConDis\left(D^M\right)$ is 0.2419. The minimum and maximum are 0 and 1, respectively. This suggests that disasters are considered impossible for some stocks even if the market itself will experience a disaster, whereas disasters are expected to happen for sure for some other stocks if a market-wide disaster occurs. In comparison, the conditional disaster concern given non-disaster markets ($ConDis\left(N^M\right)$) has a much lower cross-sectional mean of 0.0519. Its standard deviation is 0.0488, also much lower than that of $ConDis\left(D^M\right)$. This reflects that stocks are perceived to be less heterogeneous in terms of how likely a disaster is to happen in non-disaster markets than in disaster markets. The cross-sectional minimum of $ConDis\left(N^M\right)$ is 0, and the maximum is 0.3476.

The systematic disaster concern ($SysDis$) has positive mean and median values of 0.3200 and 0.2872, respectively. This indicates that an average stock is considered more likely to have a disaster in disaster markets than in non-disaster markets. The cross-sectional minimum of $SysDis$ is a negative value of -0.3438, meaning that some stocks are indeed perceived 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. Overall, more than 90% of all stocks have positive $SysDis$ values (not reported in the table).

The cross-sectional mean and median of the CAPM beta ($Beta$) are 1.1210 and 1.0713, both of which are close to 1. All my sample stocks have positive $Beta$ on average, with a cross-sectional minimum of 0.0248 and a maximum of 4.4703. On the other hand, the market disaster concern beta ($DisBeta$) has negative mean and median values of -0.1509 and -0.1301, respectively. This suggests that on average stocks tend to have lower returns as the market disaster concern rises. The cross-sectional standard deviation of $DisBeta$ is 0.1129, and the minimum and maximum are -0.9744 and 0.4804, respectively.

Table 2 reports the pairwise correlations between the stock-level variables. The conditional disaster concern variables $ConDis\left(D^M\right)$ and $ConDis\left(N^M\right)$ have a weak positive correlation of 0.1308. This weak correlation indicates that stocks that are more likely than others to have a disaster in disaster markets are not necessarily more likely than others to have a disaster in non-disaster markets. In addition, $SysDis$ and $Beta$ have a positive correlation of 0.4003. Somewhat surprisingly, $SysDis$ and $DisBeta$ have a very small negative correlation of -0.0693, suggesting that these two measures are likely to capture different aspects of stocks' systematic exposure to disaster risk. Furthermore, $DisBeta$ is negatively correlated with $Beta$ with a correlation coefficient of -0.3707.

Given the comovement in the disaster concern of the market and stocks (see Figure 1), the market disaster concern may be viewed as a factor driving the time variations in the stock disaster concern. To find out what proportion of the time variations in the stock disaster concern is attributable to changes in the market disaster concern, I compute the R-squared from the constrained linear regression (11). Figure 3 plots the cross-sectional average R-squared over time.[5] The figure shows that the average R-squared varies dramatically over the sample period. In particular, it tends to increase during crises. For instance, it rises sharply above 0.5 around 2008–2009, 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 BOA

To provide more intuitions on the time-series and cross-sectional variations in the systematic disaster concern variable, I examine Microsoft and BOA as two examples. I have shown in Figure 1 that there are two periods of substantial increases in the market disaster concern, the 1998–2002 Internet bubble and the 2008–2011 financial crisis. Since Microsoft is a technology firm and BOA is a financial firm, one would wonder whether the systematic disaster concern of these two firms would behave differently over these two periods.

I start by plotting the disaster concern Dis of Microsoft and BOA over time. Figure 4 shows that both stocks exhibit dramatic increases in Dis during both crisis periods, reflecting that the disaster concern of both stocks responds positively to increases in the market disaster concern. Interestingly, the increase in Dis is more pronounced for Microsoft during the 1998–2002 period. In contrast, the increase in Dis is more pronounced for BOA during the 2008–2011 period. This suggests that Microsoft's disaster concern appears to be more sensitive to the increase in the market disaster concern driven by the Internet bubble, whereas BOA's disaster concern 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 $SysDis$ of the two stocks in Figure 5, which directly captures the sensitivity of the stock disaster concern to the market disaster

[5] The R-squared changes over time as a result of the rolling-window estimation approach.

concern. As expected, $SysDis$ of Microsoft rises sharply to around 0.8 during the Internet bubble, compared to a much milder rise during the financial crisis. In contrast, $SysDis$ 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 informativeness of my estimation.

4.4 Conditional 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 future 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 point, two conditional disaster concern variables, $ConDis\left(D^M\right)$ and $ConDis\left(N^M\right)$, can be estimated for each stock 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 $ConDis_{t-1}^i\left(S_t^M\right)$ the conditional disaster concern of stock i estimated at the end of month $t-1$ given the realized market state in month t, i.e.,

$$ConDis_{t-1}^i\left(S_t^M\right) = \begin{cases} ConDis_{t-1}^i\left(D^M\right), & \text{if } r_t^M \leq -0.1 \\ ConDis_{t-1}^i\left(N^M\right), & \text{if } r_t^M > -0.1 \end{cases}.$$

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

$$DisD_t^i = \begin{cases} 1, & \text{if } r_t^i \leq -0.25 \\ 0, & \text{if } r_t^i > -0.25 \end{cases}.$$

If my conditional disaster concern estimates are informative, $ConDis_{t-1}\left(S_t^M\right)$ should positively predict $DisD_t$.

I start by comparing summary statistics of $ConDis_{t-1}\left(S_t^M\right)$ and $DisD_t$. For both variables, I first compute the cross-sectional average values in each month. Table 3 reports the time-series summary statistics of these cross-sectional averages. Over the full sample, $ConDis_{t-1}\left(S_t^M\right)$ has a mean value of 0.0350, suggesting that on average investors expect a stock-level disaster to occur with a risk-neutral probability of 4% conditional on the subsequently realized state of the market. The time-series minimum and maximum of $ConDis_{t-1}\left(S_t^M\right)$ are 0.0053 and 0.5653, respectively. On the other hand, the time-series mean value of $DisD_t$ is 0.0262, indicating that on average an actual stock disaster occurs with a probability of 3% over the sample period. The minimum and maximum of $DisD_t$ are 0 and 0.4278, meaning that in some month no stock has a disaster whereas in some other month about 43% of all stocks experience disasters.

I also compare statistics of $ConDis_{t-1}\left(S_t^M\right)$ and $DisD_t$ over subsamples with realized disaster and non-disaster markets separately. For the 224 months without market disasters ($r_t^M > -0.1$), the average value of $ConDis_{t-1}\left(S_t^M\right)$ is 0.0290, and the average value of $DisD_t$ is 0.0224. For the remaining 4 months with realized market disasters ($r_t^M \leq -0.1$), the average values of $ConDis_{t-1}\left(S_t^M\right)$ and $DisD_t$ are 0.3718 and 0.2349, respectively. This shows that both the conditional disaster concern and realized stock disasters are higher given disaster markets than given non-disaster markets. The fact that $ConDis_{t-1}\left(S_t^M\right)$ is on average higher than $DisD_t$ in both market states may be due to risk adjustments under risk-neutral probabilities relative to physical probabilities.

I next ask if stocks with higher $ConDis_{t-1}\left(S_t^M\right)$ are more likely to experience disasters in the following month. For each month t, I sort all stocks into quintiles by the value of $ConDis_{t-1}\left(S_t^M\right)$. I next compute the realized stock disaster probability of each quintile in month t as the average $DisD_t$ of all stocks in that quintile. Then, I compute the time average of the realized stock disaster probability for each quintile. The results are shown in Table 4. From low to high $ConDis_{t-1}\left(S_t^M\right)$, the average realized stock disaster probabilities for the five quintiles are 0.0092, 0.0136, 0.0187, 0.0318, and 0.0587, which are monotonically increasing. The difference between the bottom and the top quintiles is statistically significant at the 1% level based on the Newey-West standard error.[6] I also look at months with and without realized market disasters separately. The average realized stock disaster probabilities for the five quintiles are 0.1417, 0.1873, 0.2316, 0.2609,

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

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

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.

and 0.3577 conditional on disaster markets, and 0.0068, 0.0104, 0.0149, 0.0277, and 0.0534 conditional on non-disaster markets. In both market states, the average realized stock disaster probability is monotonically increasing as conditional disaster concern becomes higher, and the difference between the two extreme quintiles is strongly significant.

I further use a regression approach to analyze the relation between $ConDis_{t-1}\left(S_t^M\right)$ and $DisD_t$. For each month t, I run a cross-sectional regression of $DisD_t$ on $ConDis_{t-1}\left(S_t^M\right)$, i.e.,

$$DisD_t^i = \gamma_{0,t} + \gamma_{1,t} ConDis_{t-1}^i\left(S_t^M\right) + \eta_t^i.$$

If $ConDis_{t-1}\left(S_t^M\right)$ contains information on the subsequent realization of stock disasters, $\gamma_{1,t}$ should be positive. The last column of Table 4 reports the time average of the estimated $\gamma_{1,t}$. Over the full sample, $\gamma_{1,t}$ has a positive mean value of 0.5781, which is significant at the 1% level. This implies that if $ConDis_{t-1}\left(S_t^M\right)$ increases from 0 to 1, the probability of a stock disaster increases by 58% on average. For subsamples with realized disaster and non-disaster markets, the average values of $\gamma_{1,t}$ are 0.3066 and 0.5830, respectively, both being strongly significant. This means that increasing $ConDis_{t-1}\left(S_t^M\right)$ from 0 to 1 raises the probability of a stock disaster by 31% and 58%, respectively, given disaster and non-disaster markets.

It is worth taking a closer look at each of the four months with realized market disasters. These four months are August 1998, September 2002, October 2008 and February 2009, with monthly market returns being -0.1431, -0.1090, -0.1670, and -0.1036, respectively. Panel B of Table 4 reports the results. For all four months, the realized stock disaster probabilities of the quintile portfolios sorted by $ConDis_{t-1}\left(S_t^M\right)$ have a rising trend. In particular, for two out of the four months (October 2008 and February 2009), the realized stock disaster probability monotonically increases as $ConDis_{t-1}\left(S_t^M\right)$ rises. Using the regression approach, the estimated $\gamma_{1,t}$ is also significantly positive in all four months, with values ranging between 0.2050 and 0.4271.

Overall, my results above show that stocks with higher conditional disaster concern given the subsequently realized market state are indeed more likely to experience disasters in the following month. My estimated conditional disaster concern variables thus provide information on the future occurrence of stock disasters in the corresponding state of the market.

4.5 Systematic Disaster Concern and Future Stock Returns

I now investigate the relation between systematic disaster concern and future stock returns. I start with a portfolio sorts approach. At the end of each month, I sort all stocks into five quintiles by the value of $SysDis$, and then I calculate the equal-weighted return of each quintile portfolio over the next month. Table 5 reports the average returns of the five $SysDis$-sorted portfolios over time. From low to high $SysDis$, the average returns of the five portfolios over the full sample are 0.0078, 0.0096, 0.0104, 0.0085 and 0.0072, respectively. This reveals a hump-shaped relation, where portfolios with the lowest and the highest $SysDis$ yield lower average returns than portfolios in the middle.

To understand what causes the hump-shaped relation, I look at months with positive and negative market returns separately.[7] For the 140 months with positive market returns, the average returns of the five $SysDis$-sorted portfolios are 0.0330, 0.0359, 0.0413, 0.0460, and 0.0531, which are monotonically increasing as $SysDis$ becomes higher. The average return difference between the bottom and the top portfolios is significant at the 1% level. This suggests that stocks with high $SysDis$ outperform stocks with low $SysDis$ when the market 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% conditional on the market return being positive. I then repeat the analysis for the 88 months with negative market returns. The average returns of the five portfolios are -0.0323, -0.0324, -0.0387, -0.0511, and -0.0657, which are monotonically decreasing as $SysDis$ rises. The average return difference between the bottom and the top portfolios is again strongly significant. Hence, stocks with high $SysDis$ underperform stocks with low $SysDis$ when the market 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% conditional on the market return being negative. Overall, opposite relations between systematic disaster concern and future stock returns in good and bad markets together give rise to the hump-shaped relation in the full sample.

The opposite patterns in good versus bad markets are intuitive. The systematic disaster concern describes investors' expectation on the incremental likelihood of a stock disaster if

[7] Here I focus on months with positive versus negative market returns instead of months with and without realized market disasters to obtain more balanced subsamples.

the overall market is to suffer from worse performance than usual. As such, if the market performs poorly (with a negative monthly return), one would expect stocks with high systematic disaster concern to be more heavily affected and hence deliver lower returns than other stocks. In contrast, when the market performs well (with a positive monthly return), stocks with high systematic disaster concern should outperform other stocks. Otherwise, they would be dominated in both market states, and thus no investors would ever be willing to hold them.

It is interesting to ask whether the relation between *SysDis* and future stock returns might be driven by the CAPM beta, especially given the positive correlation between *SysDis* and *Beta* (see Table 2). The idea is that stocks with a larger *Beta* are more procyclical, and as a result they tend to outperform other stocks in good markets and underperform in bad markets. To control for the effect of *Beta*, I use a double sorts approach. In each month, I first sort all stocks into two portfolios with below-median *Beta* and above-median *Beta*, respectively. Within each *Beta*-sorted portfolio, I further sort stocks into quintiles by the value of *SysDis* and compute the equal-weighted return of each quintile over the next month. Table 6 shows that for both low-*Beta* stocks and high-*Beta* stocks, the average future portfolio return increases with *SysDis* when the market return is positive and decreases with *SysDis* when the market return is negative. The differences between the bottom and the top quintiles remain significant. These results suggest that the relation between systematic disaster concern and future stock returns is not driven by the CAPM beta.

I then ask if my result could be driven by the market disaster concern beta *DisBeta*, given that both *SysDis* and *DisBeta* capture some aspects of an asset's systematic exposure to disaster risk. To answer this question, I repeat the double sorts analysis using *DisBeta* as the first sorting variable. As shown in Table 7, the relation between *SysDis* and future stock returns in both market states remains unaffected after controlling for the effect of *DisBeta*. This provides further evidence that *SysDis* contains additional information on future stock returns that is not captured by *DisBeta*.

To further strengthen my result, I control for the effects of *Beta* and *DisBeta* simultaneously using a triple sorts analysis. In each month, I first compute the median values of *Beta* and *DisBeta*. Next I sort all stocks into the following four portfolios: (1)

below-median *Beta* and below-median *DisBeta*, (2) below-median *Beta* and above-median *DisBeta*, (3) above-median *Beta* and below-median *DisBeta*, and (4) above-median *Beta* and above-median *DisBeta*.[8] Within each portfolio, I then sort stocks into quintiles by the value of *SysDis* and compute the equal-weighted return of each quintile over the next month. Table 8 shows that for all four portfolios sorted by *Beta* and *DisBeta*, the relation between *SysDis* and future stock returns is largely unaffected.

My analyses so far are at the portfolio level. To further examine the relation between systematic disaster concern and future stock returns at the individual stock level, I use a regression approach. In each month, I cross-sectionally regress stock returns on the values of *SysDis* estimated as of the end of the previous month, controlling for lagged values of *Beta* and *DisBeta*, i.e.,

$$r_t^i = \delta_{0,t} + \delta_{1,t} SysDis_{t-1}^i + \delta_{2,t} Beta_{t-1}^i + \delta_{3,t} DisBeta_{t-1}^i + \psi_t^i.$$

Table 9 reports the time averages of the regression coefficients. I start by taking *SysDis* as the only independent variable. Over the full sample, the coefficient on *SysDis* is not significantly different from zero. I then split the full sample into subsamples with positive and negative market returns. For months with positive market returns, the coefficient on *SysDis* is positive and significant at the 1% level, implying that stocks with higher *SysDis* tend to deliver higher returns in good markets. On the other hand, for months with negative market returns, the coefficient on *SysDis* is significantly negative, implying that stocks with higher *SysDis* tend to yield lower returns in bad markets. These finding are consistent with earlier results from portfolio sorts.

I then include *Beta* and *DisBeta* (both separately and jointly) in the regression. The coefficient on *SysDis* remains mostly unaffected in terms of both direction and statistical significance. This confirms that the relation between *SysDis* and future stocks returns is not driven by *Beta* or *DisBeta*. In addition, neither *Beta* nor *DisBeta* seems to have a significant effect on future stock returns over the entire sample. During months with positive market returns, stocks with higher *Beta* and lower *DisBeta* tend to deliver higher

[8] Since *Beta* and *DisBeta* have a negative correlation (see Table 2), the four portfolios constructed based on the median values of the two variables typically do not contain equal numbers of stocks. I check to make sure that each portfolio has enough stocks for my analysis.

returns. In contrast, during months with negative market returns, stocks with lower $Beta$ and higher $DisBeta$ tend to perform better.

Overall, my results show that the relation between systematic disaster concern and future stock returns 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 cannot be explained by the CAPM beta or the market disaster concern beta.

4.6 Trading Strategies

Section 4.5 shows that stocks with the lowest and the highest systematic disaster concern on average earn lower future returns than stocks in the middle. This allows me to construct trading strategies by going long in stocks with middle levels of $SysDis$ and shorting a combination of stocks with the lowest and the highest $SysDis$.

Let r_t^j represent the equal-weighted return over month t of the jth quintile portfolio sorted by $SysDis_{t-1}$, 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

$$r_t^{trd} = r_t^3 - x r_t^1 - (1 - x)\, r_t^5, \tag{12}$$

where x takes values from 0 to 1.[9] 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 $SysDis$.

Table 10 reports the average return from the trading strategy with x varying from 0 to 1. The average monthly trading return is positive for all values of x. Statistically, the most significant trading return is obtained when $x = 0.7$, 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. To see if the trading profits can be explained by popular risk factors, I estimate the abnormal returns (i.e., risk-adjusted alphas) with respect to the following three models: (1) the CAPM model in which the

[9] The trading strategy proposed here is a long-short strategy that requires zero net investment. The trading return (12) represents the profit earned for each one dollar engaged in the strategy.

market return is the only source of systematic risk, (2) the Fama-French-Carhart four-factor model (Fama and French (1993) and Carhart (1997)) which uses market, size, value, and momentum as risk factors, and (3) the Fama-French-Carhart four-factor model plus the Pástor and Stambaugh (2003) liquidity factor. Table 10 shows that the abnormal returns are statistically positive for almost all values of x and for all three models examined. This supports that my trading profits are not driven by risk factors related to the market return, firm size, value, momentum, or liquidity.

5 Conclusion

This paper proposes new measures of the conditional and systematic disaster concern of an individual asset with respect to the market. These measures can be estimated based on the comovement in the option prices of the asset and the market index. They have intuitive interpretations in terms of the asset's risk-neutral conditional disaster probabilities given possible future states of the market, reflecting investors' expectations on the asset's disaster risk in different market conditions. While risk-neutral probabilities generally differ from the corresponding physical probabilities, I show that conditioning on the market state helps link them by neutralizing the pricing effect of the market state. Using the S&P 500 index as a proxy for the market, I empirically estimate the conditional and systematic disaster concern variables for a large set of common stocks. I show that these estimated variables exhibit substantial changes 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 in a similar manner. In addition, the constrained regression approach motivated by the total probability formula is nonparametric and does not rely on assumed functional forms of the generating process of asset returns. Hence, it could be useful for uncovering potential nonlinearity in the relation between asset returns and systematic factors. All of this has important implications on theoretical and empirical work in asset pricing, which I will 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 prices of European put options with strike prices around the disaster threshold and some specific time to maturity. Such options are usually not traded on the market. To obtain the prices of these hypothetical options, I adopt the following approach from the literature (e.g., Shimko (1993), Malz (1997), and Figlewski (2010)). For any given date, I start with the implied volatilities provided in OptionMetrics of all traded options written on the asset of interest. Using these traded options, I fit the implied volatility surface across different strike prices and maturities. Then, I plug the fitted implied volatility at the required strike price and maturity into the BS pricing formula to estimate the corresponding European option price.

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 σ^h represent the implied volatility, and let V^h be the option vega (which measures the sensitivity of the option price to volatility). Denote by $mn^h = K^h/S_t$ 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 moneyness range of traded options), time to maturity mt^* (within the maturity range of 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

$$\hat{\sigma}\left(mn^*, mt^*, cp^*\right) = \frac{\sum_{h=1}^{H} V^h \sigma^h \Psi\left(mn^* - mn^h, mt^* - mt^h, cp^* - cp^h\right)}{\sum_{h=1}^{H} V^h \Psi\left(mn^* - mn^h, mt^* - mt^h, cp^* - cp^h\right)}, \tag{13}$$

where the kernel function Ψ 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 implied volatilities of all traded options, where those options with moneyness, maturity, and call-put indicator values close to (mn^*, mt^*, cp^*) are assigned higher weights than those far away. In addition, since I eventually need to compute the European option price from the fitted implied volatility, I also assign higher weights to traded options whose prices have higher sensitivity to volatility (higher vega).

It is worth mentioning that the kernel smoothing formula (13) only applies for values of mn^* and mt^* within the ranges of traded options. In order to estimate the disaster concern, I need European put option prices (and hence implied volatilities) around the disaster threshold. Since disasters are characterized by large negative returns, this means that mn^* may fall below the moneyness range of traded options. In this case, I assume that the implied volatility is flat outside the traded range and therefore set mn^* equal to the lowest moneyness level 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.

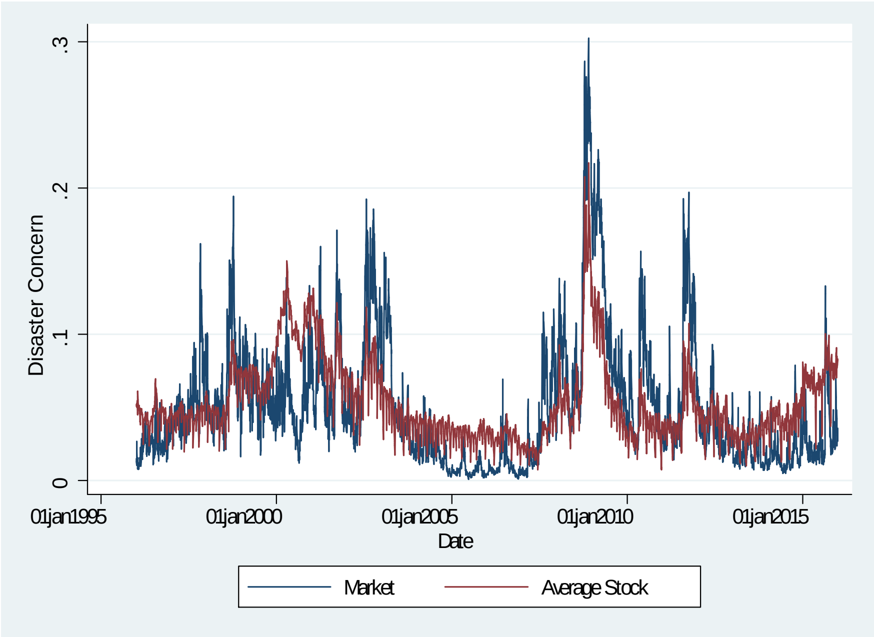


Figure 2: Conditional Disaster Concern

This figure plots the cross-sectional average conditional disaster concern of stocks given disaster and non-disaster markets over time.

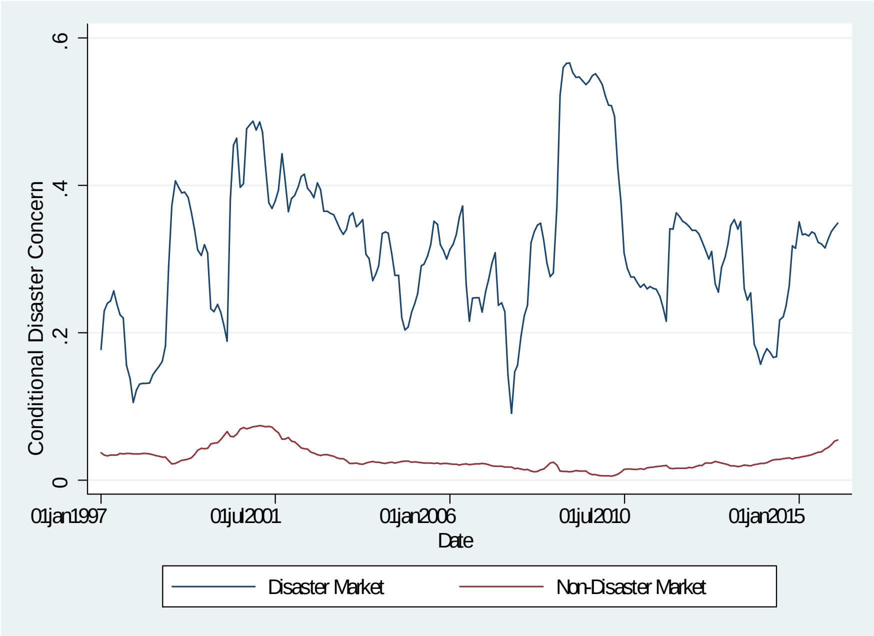


Figure 3: Estimation R-Squared

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

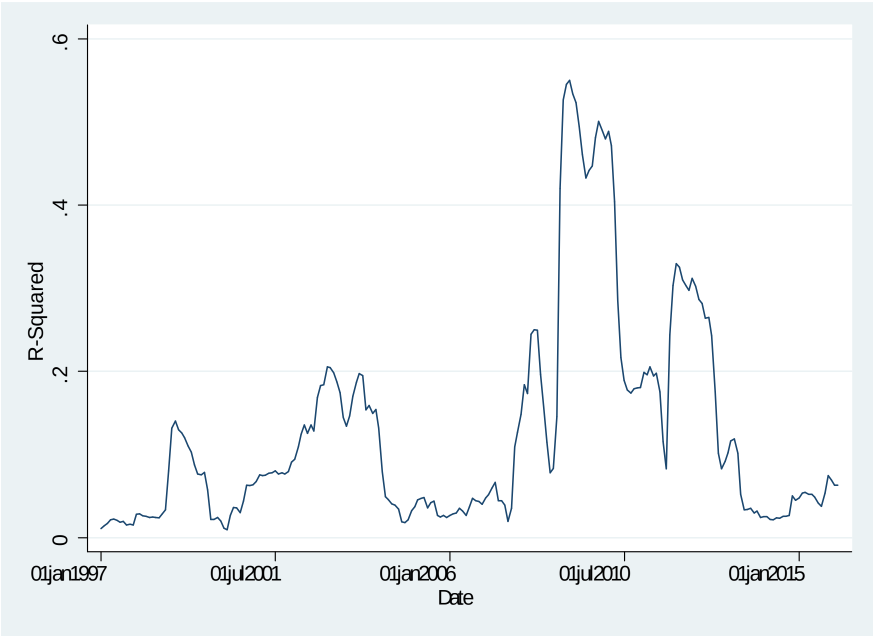


Figure 4: Disaster Concern of Microsoft and BOA

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

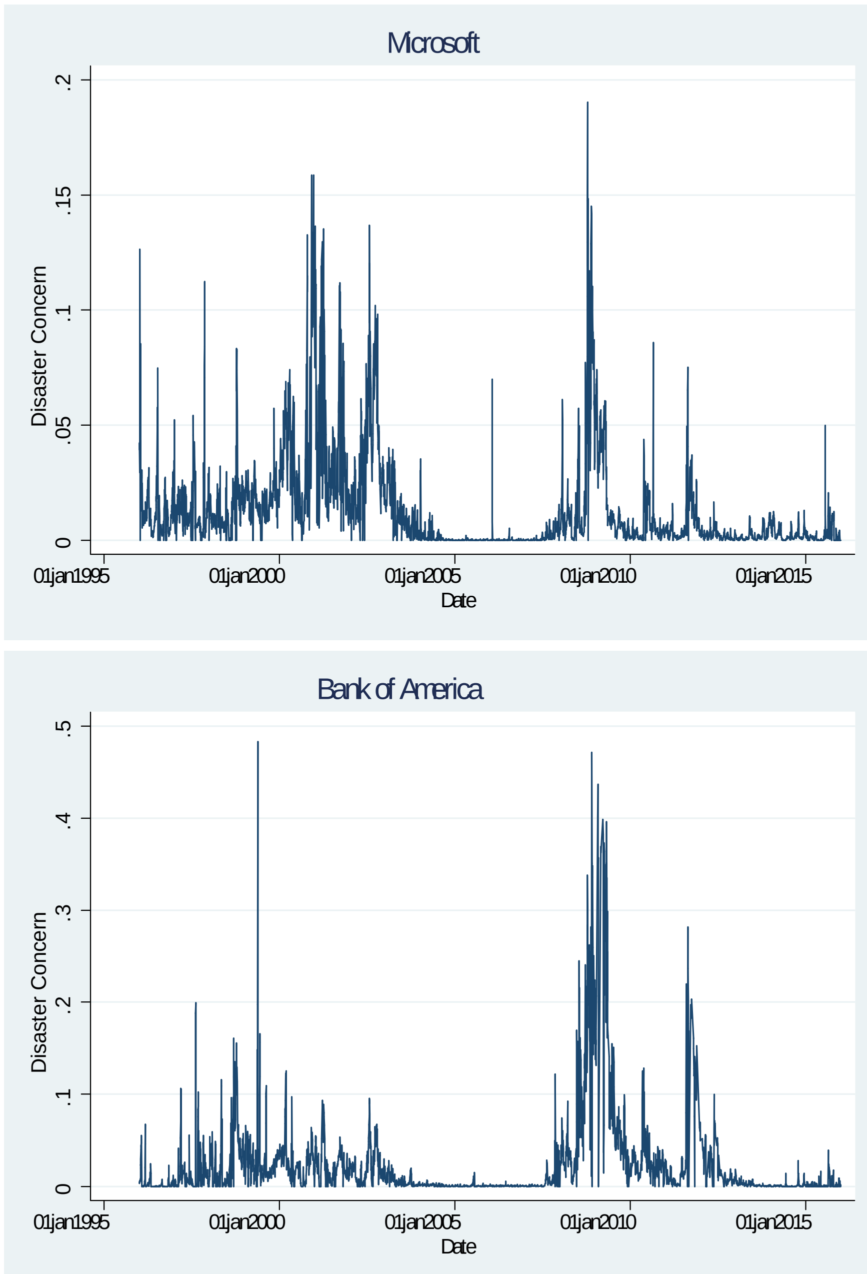
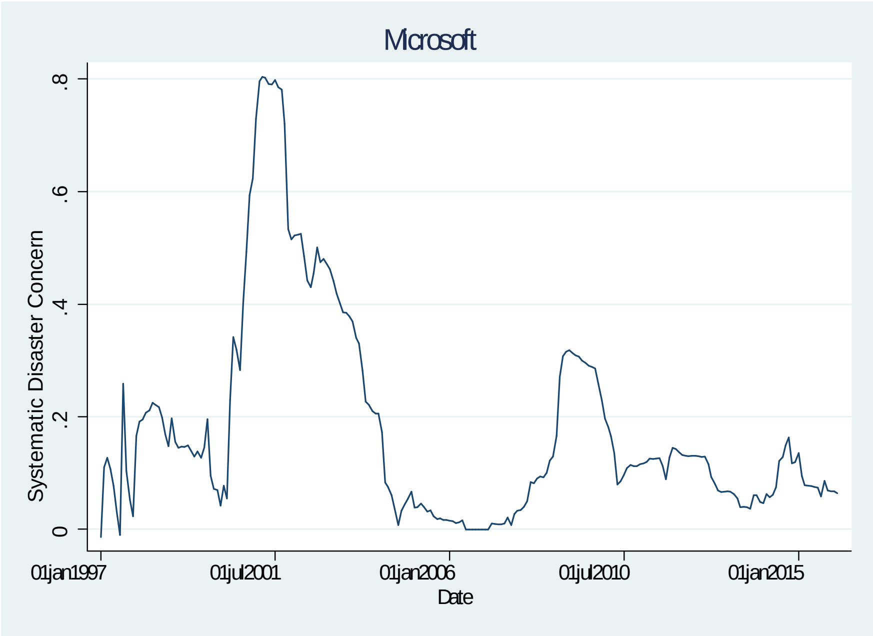


Figure 5: Systematic Disaster Concern of Microsoft and BOA

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



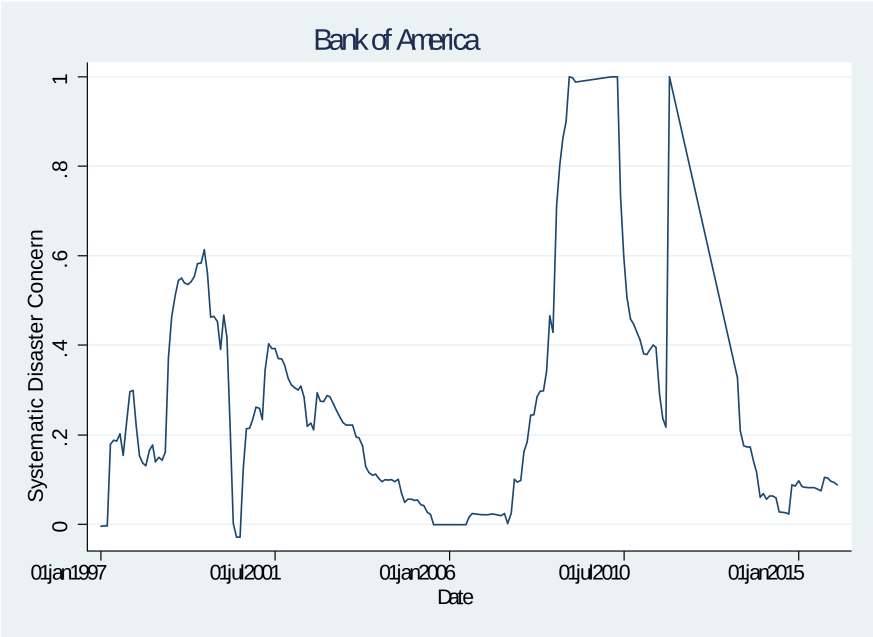


Table 1: Summary Statistics

This table reports summary statistics of market disaster concern (Dis^M) as well as stock-level variables including 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 ($Beta$), 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 time averages.

Panel A: Market Variables					
	Mean	Median	S.D.	Min	Max
Dis^M	0.0509	0.0389	0.0444	0.0008	0.3025
Panel B: Stock Variables					
	Mean	Median	S.D.	Min	Max
Dis	0.0873	0.0661	0.0678	0	0.7583
$ConDis\left(D^M\right)$	0.3718	0.3251	0.2419	0	1
$ConDis\left(N^M\right)$	0.0519	0.0358	0.0488	0	0.3476
$SysDis$	0.3200	0.2872	0.2295	-0.3438	1
$Beta$	1.1210	1.0713	0.4258	0.0248	4.4703
$DisBeta$	-0.1509	-0.1301	0.1129	-0.9744	0.4804

Table 2: Pairwise Correlation

This table reports pairwise correlation of stock-level variables including 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 ($Beta$), and 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 compares conditional disaster concern and future realizations of stock disasters in different market states. For each month t, I compute the cross-sectional average of the lagged conditional disaster concern given the subsequently realized state of the market ($ConDis_{t-1}\left(S_t^M\right)$) and the cross-sectional average of the realized stock disaster dummy ($DisD_t$). The table reports time-series summary statistics of these cross-sectional averages for the full sample as well as for subsamples with realized disaster and non-disaster markets separately.

Panel A: Full Sample (228 Months)					
	Mean	Median	S.D.	Min	Max
$ConDis_{t-1}\left(S_t^M\right)$	0.0350	0.0240	0.0514	0.0053	0.5653
$DisD_t$	0.0262	0.0083	0.0495	0	0.4278
Panel B: Non-Disaster Market (224 Months)					
	Mean	Median	S.D.	Min	Max
$ConDis_{t-1}\left(S_t^M\right)$	0.0290	0.0238	0.0158	0.0053	0.0742
$DisD_t$	0.0224	0.0082	0.0367	0	0.2512
Panel C: Disaster Market (4 Months)					
	Mean	Median	S.D.	Min	Max
$ConDis_{t-1}\left(S_t^M\right)$	0.3718	0.3815	0.1665	0.1591	0.5653
$DisD_t$	0.2349	0.2135	0.1609	0.0846	0.4278

Table 4: Predicting Stock Disasters Using Conditional Disaster Concern

This table shows the relation between conditional disaster concern and future realizations of stock disasters. For each month t, I sort all stocks into quintiles by the lagged value of conditional disaster concern given the subsequently realized state of the market ($ConDis_{t-1}\left(S_t^M\right)$) and then compute the cross-sectional average of the realized stock disaster dummy ($DisD_t$) in each quintile. The table reports the time average of the cross-sectional average $DisD_t$ of each quintile for the full sample as well as for subsamples with realized disaster and non-disaster markets separately. Also reported are the differences between the bottom and the top quintiles. The last column shows the time average of the slope coefficient from cross-sectionally regressing $DisD_t$ on $ConDis_{t-1}\left(S_t^M\right)$ in each month. The table also reports results for each of the four market-disaster months separately, all of which feature monthly market returns (r_t^M) below -0.1. The standard errors are displayed in the parentheses below the corresponding estimates. For full-sample t-tests, I use the Newey-West standard errors with five lags to account for potential autocorrelation. Asterisks denote statistical significance at the 1% (***), 5% (**), and 10% (*) levels.

Panel A: Full Sample, Non-Disaster Market, and Disaster Market							
	Low	2	3	4	High	Low–High	Regression
Full Sample	0.0092	0.0136	0.0187	0.0318	0.0587	-0.0495***	0.5781***
(228 Months)						(0.0095)	(0.0728)
Non-Disaster Market	0.0068	0.0104	0.0149	0.0277	0.0534	-0.0465***	0.5830***
(224 Months)						(0.0054)	(0.0475)
Disaster Market	0.1417	0.1873	0.2316	0.2609	0.3577	-0.2160**	0.3066***
(4 Months)						(0.0418)	(0.0471)
Panel B: Market-Disaster Months							
August 1998	0.2468	0.3333	0.3071	0.2756	0.3858	-0.1390	0.2050**
($r_t^M = -0.1431$)							(0.0943)
September 2002	0.0339	0.0056	0.0449	0.1299	0.2079	-0.1740	0.2685***
($r_t^M = -0.1090$)							(0.0400)
October 2008	0.2526	0.3228	0.4702	0.5088	0.5839	-0.3313	0.4271***
($r_t^M = -0.1670$)							(0.0484)
February 2009	0.0333	0.0875	0.1042	0.1292	0.2531	-0.2198	0.3260***
($r_t^M = -0.1036$)							(0.0433)

Table 5: Systematic Disaster Concern and Portfolio Returns

This table shows the relation between systematic disaster concern and future stock returns based on the portfolio sorts approach. In each month, I sort stocks into quintiles by the lagged value of systematic disaster concern. The table reports the time averages of equal-weighted quintile portfolio returns for the full sample as well as for subsamples with positive and negative market returns separately. Also reported are the differences between the bottom and the top quintiles. The standard errors are displayed in the parentheses below the corresponding estimates. For full-sample t-tests, I use the Newey-West standard errors with five lags to account for potential autocorrelation. Asterisks denote statistical significance at the 1% (***), 5% (**), and 10% (*) levels.

	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 6: Systematic Disaster Concern and Portfolio Returns (Controlling for CAPM Beta)

This table shows the relation between systematic disaster concern and future stock returns based on the portfolio sorts approach controlling for the effect of the CAPM beta (*Beta*). In each month, I first sort all stocks into two portfolios by the lagged value of *Beta*: (1) below-median *Beta*, and (2) above-median *Beta*. Within each *Beta*-sorted portfolio, I further sort stocks into quintiles by the lagged value of systematic disaster concern. The table reports the time average of equal-weighted returns for each of the 2×5 portfolios for the full sample as well as for subsamples with positive and negative market returns separately. Also reported are the differences between the bottom and the top quintiles within each of the two *Beta*-sorted portfolios. The standard errors are displayed in the parentheses below the corresponding estimates. For full-sample t-tests, I use the Newey-West standard errors with five lags to account for potential autocorrelation. Asterisks denote statistical significance at the 1% (***), 5% (**), and 10% (*) levels.

Panel A: Low-*Beta* Stocks						
	Low	2	3	4	High	Low–High
Full Sample	0.0087	0.0089	0.0091	0.0091	0.0092	-0.0005
(228 Months)						(0.0018)
Positive Market Return	0.0307	0.0303	0.0321	0.0347	0.0369	-0.0062***
(140 Months)						(0.0021)
Negative Market Return	-0.0264	-0.0252	-0.0274	-0.0315	-0.0349	0.0085***
(88 Months)						(0.0025)
Panel B: High-*Beta* Stocks						
	Low	2	3	4	High	Low–High
Full Sample	0.0073	0.0114	0.0094	0.0068	0.0072	0.0000
(228 Months)						(0.0035)
Positive Market Return	0.0423	0.0492	0.0514	0.0537	0.0575	-0.0152***
(140 Months)						(0.0036)
Negative Market Return	-0.0485	-0.0488	-0.0574	-0.0676	-0.0727	0.0242***
(88 Months)						(0.0050)

Table 7: Systematic Disaster Concern and Portfolio Returns (Controlling for Market Disaster Concern Beta)

This table shows the relation between systematic disaster concern and future stock returns based on the portfolio sorts approach controlling for the effect of the market disaster concern beta ($DisBeta$). In each month, I first sort all stocks into two portfolios by the lagged value of $DisBeta$: (1) below-median $DisBeta$, and (2) above-median $DisBeta$. Within each $DisBeta$-sorted portfolio, I further sort stocks into quintiles by the lagged value of systematic disaster concern. The table reports the time average of equal-weighted returns for each of the 2×5 portfolios for the full sample as well as for subsamples with positive and negative market returns separately. Also reported are the differences between the bottom and the top quintiles within each of the two $DisBeta$-sorted portfolios. The standard errors are displayed in the parentheses below the corresponding estimates. For full-sample t-tests, I use the Newey-West standard errors with five lags to account for potential autocorrelation. Asterisks denote statistical significance at the 1% (***), 5% (**), and 10% (*) levels.

Panel A: Low-$DisBeta$ Stocks						
	Low	2	3	4	High	Low–High
Full Sample	0.0086	0.0125	0.0113	0.0073	0.0086	0.0000
(228 Months)						(0.0036)
Positive Market Return	0.0400	0.0475	0.0501	0.0516	0.0569	-0.0169***
(140 Months)						(0.0039)
Negative Market Return	-0.0413	-0.0433	-0.0504	-0.0631	-0.0683	0.0270***
(88 Months)						(0.0054)
Panel B: High-$DisBeta$ Stocks						
	Low	2	3	4	High	Low–High
Full Sample	0.0075	0.0087	0.0088	0.0079	0.0059	0.0015
(228 Months)						(0.0026)
Positive Market Return	0.0301	0.0306	0.0341	0.0361	0.0415	-0.0114***
(140 Months)						(0.0026)
Negative Market Return	-0.0285	-0.0262	-0.0315	-0.0371	-0.0507	0.0222***
(88 Months)						(0.0045)

Table 8: Systematic Disaster Concern and Portfolio Returns (Controlling for CAPM Beta and Market Disaster Concern Beta)

This table shows the relation between systematic disaster concern and future stock returns based on the portfolio sorts approach controlling for the effects of the CAPM beta (*Beta*) and the market disaster concern beta (*DisBeta*). In each month, I first sort all stocks into four portfolios by the lagged values of *Beta* and *DisBeta*: (1) below-median *Beta* and below-median *DisBeta*, (2) below-median *Beta* and above-median *DisBeta*, (3) above-median *Beta* and below-median *DisBeta*, and (4) above-median *Beta* and above-median *DisBeta*. Within each *Beta*-*DisBeta*-sorted portfolio, I further sort stocks into quintiles by the lagged value of systematic disaster concern. The table reports the time average of equal-weighted returns for each of the 4×5 portfolios for the full sample as well as for subsamples with positive and negative market returns separately. Also reported are the differences between the bottom and the top quintiles within each of the four *Beta*-*DisBeta*-sorted portfolios. The standard errors are displayed in the parentheses below the corresponding estimates. For full-sample t-tests, I use the Newey-West standard errors with five lags to account for potential autocorrelation. Asterisks denote statistical significance at the 1% (***), 5% (**), and 10% (*) levels.

Panel A: Low-*Beta*, Low-*DisBeta* Stocks						
	Low	2	3	4	High	Low–High
Full Sample	0.0111	0.0094	0.0127	0.0116	0.0095	0.0016
(228 Months)						(0.0034)
Positive Market Return	0.0378	0.0353	0.0418	0.0414	0.0400	-0.0022
(140 Months)						(0.0043)
Negative Market Return	-0.0314	-0.0317	-0.0336	-0.0358	-0.0390	0.0076
(88 Months)						(0.0047)
Panel B: Low-*Beta*, High-*DisBeta* Stocks						
	Low	2	3	4	High	Low–High
Full Sample	0.0079	0.0091	0.0084	0.0076	0.0091	-0.0013
(228 Months)						(0.0016)
Positive Market Return	0.0286	0.0287	0.0298	0.0313	0.0349	-0.0064***
(140 Months)						(0.0019)
Negative Market Return	-0.0251	-0.0221	-0.0256	-0.0302	-0.0319	0.0069**
(88 Months)						(0.0028)
Panel C: High-*Beta*, Low-*DisBeta* Stocks						
	Low	2	3	4	High	Low–High
Full Sample	0.0082	0.0127	0.0088	0.0080	0.0081	0.0001
(228 Months)						(0.0033)
Positive Market Return	0.0456	0.0531	0.0537	0.0560	0.0594	-0.0138***
(140 Months)						(0.0036)
Negative Market Return	-0.0513	-0.0516	-0.0627	-0.0683	-0.0735	0.0222***
(88 Months)						(0.0048)
Panel D: High-*Beta*, High-*DisBeta* Stocks						
	Low	2	3	4	High	Low–High
Full Sample	0.0064	0.0073	0.0089	0.0055	0.0046	0.0018
(228 Months)						(0.0038)
Positive Market Return	0.0408	0.0368	0.0443	0.0433	0.0495	-0.0087*
(140 Months)						(0.0046)
Negative Market Return	-0.0484	-0.0397	-0.0473	-0.0545	-0.0668	0.0185***
(88 Months)						(0.0061)

Table 9: Systematic Disaster Concern and Stock Returns by Regression

This table shows the relation between systematic disaster concern and future stock returns based on regressions. In each month, I cross-sectionally regress monthly stock returns on the lagged value of systematic disaster concern ($SysDis$), controlling for lagged values of the CAPM beta ($Beta$) and the market disaster concern beta ($DisBeta$). The table reports the time averages of the regression coefficients for the full sample as well as for subsamples with positive and negative market returns separately. The standard errors are displayed in the parentheses below the corresponding estimates. For full-sample t-tests, I use the Newey-West standard errors with five lags to account for potential autocorrelation. Asterisks denote statistical significance at the 1% (***), 5% (**), and 10% (*) levels.

Panel A: Full Sample (228 Months)				
SysDis	-0.0017	-0.0009	-0.0031	-0.0014
	(0.0054)	(0.0035)	(0.0042)	(0.0031)
Beta		-0.0000		-0.0007
		(0.0035)		(0.0032)
DisBeta			-0.0248	-0.0204
			(0.0223)	(0.0207)
Constant	0.0088***	0.0085***	0.0075***	0.0081***
	(0.0029)	(0.0029)	(0.0027)	(0.0029)
Panel B: Positive Market Return (140 Months)				
SysDis	0.0261***	0.0080**	0.0163***	0.0055*
	(0.0059)	(0.0036)	(0.0044)	(0.0031)
Beta		0.0205***		0.0168***
		(0.0039)		(0.0037)
DisBeta			-0.0962***	-0.0611**
			(0.0264)	(0.0239)
Constant	0.0317***	0.0159***	0.0251***	0.0152***
	(0.0022)	(0.0031)	(0.0023)	(0.0031)
Panel C: Negative Market Return (88 Months)				
SysDis	-0.0459***	-0.0150***	-0.0339***	-0.0125***
	(0.0076)	(0.0045)	(0.0058)	(0.0039)
Beta		-0.0326***		-0.0285***
		(0.0049)		(0.0045)
DisBeta			0.0888***	0.0444*
			(0.0249)	(0.0241)
Constant	-0.0277***	-0.0033	-0.0204***	-0.0031
	(0.0039)	(0.0045)	(0.0037)	(0.0042)

Table 10: Average Trading Returns and Risk-Adjusted Alphas

This table reports average monthly returns from trading strategies constructed based on the lagged value of systematic disaster concern (*SysDis*). The strategies involve 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-Carhart 4-factor model, and the Fama-French-Carhart 4-factor plus the Pástor-Stambaugh liquidity-factor model. The Newey-West standard errors with five lags are used to account for potential autocorrelation and are displayed in the parentheses below the corresponding estimates. Asterisks denote statistical significance at the 1% (***), 5% (**), and 10% (*) levels.

x	Avg Return	Alpha		
		CAPM	FFC	FFC+LIQ
0	0.0032	0.0065**	0.0041**	0.0035*
	(0.0031)	(0.0027)	(0.0019)	(0.0019)
0.1	0.0031	0.0060**	0.0039**	0.0034**
	(0.0028)	(0.0024)	(0.0017)	(0.0017)
0.2	0.0031	0.0055**	0.0037**	0.0032**
	(0.0025)	(0.0022)	(0.0015)	(0.0015)
0.3	0.0030	0.0050**	0.0036***	0.0031**
	(0.0022)	(0.0020)	(0.0014)	(0.0014)
0.4	0.0030	0.0045**	0.0034***	0.0030**
	(0.0019)	(0.0018)	(0.0013)	(0.0012)
0.5	0.0029*	0.0040**	0.0033***	0.0028**
	(0.0017)	(0.0017)	(0.0012)	(0.0012)
0.6	0.0029*	0.0035**	0.0031***	0.0027**
	(0.0015)	(0.0016)	(0.0011)	(0.0011)
0.7	0.0028**	0.0030**	0.0030**	0.0026**
	(0.0014)	(0.0015)	(0.0012)	(0.0012)
0.8	0.0028*	0.0025*	0.0028**	0.0024**
	(0.0015)	(0.0015)	(0.0012)	(0.0012)
0.9	0.0027*	0.0020	0.0027**	0.0023*
	(0.0016)	(0.0015)	(0.0013)	(0.0014)
1	0.0026	0.0015	0.0025*	0.0022
	(0.0018)	(0.0016)	(0.0015)	(0.0015)