Risk-Return Tradeoff and Serial Correlation in the Chinese Stock Market: A (Bailout-Driven) Crash Feedback Hypothesis

Abstract

This study shows that market crash features can explain the coexistence of the market's puzzling mean-variance relation and the serial correlation of market returns observed in the Chinese stock market. When feedback traders aim to exploit implicit (market-wide) bailout guarantees, their speculative actions could be driven by market features resembling crashes and would lead to low compensation for aggregate market volatility. Thus, crash-like market features can contribute to the weak market's mean-variance relations and positive serial correlation of market returns, without diminishing compensation for taking idiosyncratic volatility. Our results support this hypothesis.

Keywords:

Mean-variance relation; Risk-return tradeoff; Serial correlation; Implicit government guarantees; Feedback trading; Idiosyncratic volatility

1. Introduction

Regarding aggregate stock market behavior, two of the most studied phenomena are (1) the weak (or negative) relationship between the market's expected return and its variance and (2) serial correlation in market returns. These phenomena constitute two major puzzles in financial economics, as standard asset pricing models typically predict a positive risk-return relationship over time and no serial correlation of returns.[1] Attempts to understand these phenomena have generated considerable discussion. The extensive literature in this area focuses predominantly on the largest developed stock markets, such as the U.S. market,[2] and often examines the market's mean-variance relation and serial correlation as two independent phenomena.

This study examines these two phenomena jointly within a simple two-regime specification in the Chinese stock market, the largest emerging stock market. We find that market crash features are useful for capturing the coexistence of the weak market's mean-variance relation and the significant serial correlation of market returns. We also show that market crash features have quite different implications for understanding market- and firm-level mean-variance relations.

We argue that market-wide bailout guarantees, in conjunction with feedback trading, can offer a plausible explanation for these results. In the case of market-wide bailout guarantees, the belief that the government will act to stabilize the financial system in times of crisis can create an incentive for financial market participants to take on more risk than they would

[1]For example, it has been known since Merton (1973, 1980) that there should be a positive relation between the market's expected return and its variance.

[2]See, e.g., French et al. (1987); Baillie and DeGennaro (1990); Campbell and Hentschel (1992); Ghysels et al. (2005); Lundblad (2007); Guo and Whitelaw (2006); Brandt and Kang (2004); Brandt and Wang (2010); Pastor et al. (2008); Campbell (1987); Nelson (1991); Whitelaw (1994); Lettau and Ludvigson (2010); Turner et al. (1989); Glosten et al. (1993); Harvey (2001); Amengual and Sentana (2010); LeBaron (1992); Atchison et al. (1987); Lo and MacKinlay (1988); Sias and Starks (1997); Bogousslavsky (2016); Sentana and Wadhwani (1992). A general discussion on this issue can be found in Guo and Pai (2021).

otherwise because they believe that the government will be there to limit losses. Feedback trading implies that investors behave as if they focus on past price movements as their main information signal. As summarized by Economou et al. (2022), feedback trading is a natural choice in practice when cognitive effort is costly in terms of both information acquisition and deliberation. Considering the substantial uncertainty regarding bailout-driven government actions,[3] feedback trading may no longer be irrelevant for speculators seeking to take advantage of market-wide bailout guarantees. This study combines these two ideas and develops the following "bailout feedback" hypothesis: if feedback traders seek to take advantage of market-wide bailout guarantees, they will speculate more aggressively in periods exhibiting greater market crash features.

The hypothesis suggests that the effect of bailout-driven speculation on risk compensation for volatility would vary greatly between market and firm levels. At the market level, it links the characteristics of market crashes to the compensation for bearing aggregate market volatility because the perception of systematic risk decreases during bailout periods. This speculation can weaken the otherwise positive market's mean-variance relation during high market crash periods, as market participants may be taking too much risk compared to the potential rewards. In this manner, by connecting prior market crash features (which usually means that prior market returns are low) to lower subsequent market premiums, bailout-driven speculation also contributes to the positive serial correlation of market returns.

At the firm level, however, bailout-driven speculation fails to link market crash characteristics to the compensation for bearing idiosyncratic risk. The reason is straightforward: the bailout scheme is designed to support the entire system, rather than individual companies.[4] Under this scenario, market crash features are not expected to shed light on the puzzling

[3]In reality, how and when policymakers (who have different interpretations of market crashes from market participants) perceive market crashes and then take price-protection actions is often ambiguous.

[4]As illustrated by Kelly et al. (2016), the poor performance of any individual stock may not be sufficient to prompt a government bailout.

relationship between idiosyncratic volatility (IVOL) and average returns (see, e.g., the IVOL puzzle documented by Ang et al., 2006).

The bailout feedback hypothesis is relevant to the Chinese stock market for several reasons. First, implicit bailout guarantees are very credible in China's financial markets (e.g., Zhu, 2016). Shiller (2016) further illustrates that "we see today in China a sense that many people trust that the government will prevent any asset prices from falling, will make up for any financial losses, at least in the long run." Second, as Brunnermeier et al. (2022) emphasize, an important observation of China's financial markets is that speculation about government policies plays a central role in driving market dynamics. Numerous commentators of the Chinese stock market have ascribed great importance to the role of government policies in China's financial system, which is often referred to as a "policy" market. Third, the Chinese stock market is characterized by the dominance of inexperienced retail traders (e.g., Brunnermeier et al., 2022; Carpenter and Whitelaw, 2017). For a variety of reasons, financial economists tend to view inexperienced retails as unsophisticated traders who make inferences under the constraint of limited cognitive ability (e.g., Barber and Odean, 2013), which allows more of the bailout-driven feedback trading discussed in this paper.

We construct two crash measures based on, (1) the 1st percentile lower tail of the cross-sectional distribution of all individual stock returns, and (2) the mean of all negative individual stock returns in the previous two months. High-crash periods are those in which a crash measure is above the sample mean. Using data from to 1997-2020 period, we find that the positive relationship between the market's expected excess return and its conditional variance is economically and statistically significant in low-crash periods but collapses in high-crash periods. The empirical results are robust across A-share equal-weighted and value-weighted returns, and two widely used volatility models. Furthermore, we cannot observe similar two-regime mean-variance results when high-crash periods are defined by other percentile distributions, say, the 25th, or even higher. The contrasting results highlight the unique role of extreme negative stock returns as a cue for Chinese investors to form speculative beliefs about government interventions.

Furthermore, we study the serial correlation issue of market returns. The otherwise positive first-order autocorrelation of market returns becomes insignificant in the aforementioned two-regime setting. These results suggest that implicit government guarantees are responsible for the serial correlation puzzle.

Finally, we examine the risk-return tradeoff at the firm level. Firm-level risks are measured by idiosyncratic volatility, and returns are measured by the alpha estimated from Fama and French (1996) three-factor model. We observe a negative IVOL-return relationship throughout the entire sample. In addition, we find that bubble-like market features dominate crash-like market features in explaining the negative IVOL puzzle. This result is consistent with the notion that government interventions are on a market-wide level, which has little effect on compensation for idiosyncratic risk.

Our study contributes to the literature on the risk-return tradeoff and serial correlation. Typically, these market phenomena have been studied in isolation. For example, using their two-regime specification, previous studies rediscover the positive risk-return tradeoff in states of low investor sentiment (Yu and Yuan, 2011; Piccoli et al., 2018), low volatility (Salvador et al., 2014; Rossi and Timmermann, 2010; Ghysels et al., 2014), upper quantiles (Chiang and Li, 2012), and non-financial crises (Ghysels et al., 2016b). However, these studies focus only on the market's mean-variance relation and speak little about either the firm-level risk-return tradeoff or the serial-correlation of market returns. In contrast, this study shows that crash-like market features have distinct implications for capturing the market- and firm-level risk-return tradeoff, which is at the heart of our bailout feedback hypothesis. In a rare case in which the market's risk-return tradeoff and serial correlation are studied jointly, Kinnunen (2014) addresses these issues from the perspective of information frictions. Without making assumptions about information friction, our work proposes that an implicit reliance on government guarantees can offer another simple and realistic explanation for the two puzzles in China. Our study also contributes to the growing literature on asset price behavior in China. In a related study, Cheng et al. (2018) discovered a positive risk-return relationship in the Chinese stock market after controlling for hedging risks proxied by scaled market prices. However, their results were not expected to simultaneously account for serial correlations.

The remainder of this paper is organized as follows. Section 2 develops the hypotheses and presents testable predictions. Section 3 introduces the data and the volatility models. Sections 4 and 5 report empirical results. Section 7 examines the importance of investor sentiment. Finally, we conclude the paper in Section 8.

2. Testable Hypotheses

As outlined in the introduction, the bailout feedback hypothesis stems from the notion that certain feedback traders aim to take advantage of market-wide bailout guarantees. Although there is some disagreement about the overall significance of these bailout-driven feedback traders, it is reasonable to identify two key aspects of their impact. Firstly, their speculative activities have a more pronounced effect during periods of high market crashes, as opposed to low-crash periods. Secondly, their speculative actions have a greater impact on the compensation for systematic risk than on that for idiosyncratic risk. If the bailout feedback hypothesis holds true, there are two testable implications concerning market crash characteristics:

Implication 1. *In periods exhibiting salient market crash features, the positive market's mean-variance trade-off diminishes and the autocovariance of market returns becomes apparent.*

Implication 2. *Although market crash features are useful in identifying the weak market's mean-variance relationship, they may not be as effective in detecting the weak relation between idiosyncratic volatility and average returns.*

In this section, we describe the development of a simple model to clarify these implications. We consider a market containing a riskless asset with a zero rate of return and N

risky stocks traded at each time $t = 0, 1, \ldots, \infty$. We assume that the return on the i-th stock follows a one-factor model:

$$R_{i,t+1} = \mu_{i,t} + \beta_{i,t}\varepsilon_{m,t+1} + \varepsilon_{i,t+1}, \tag{1}$$

where $\mu_{i,t}$ is the expected stock return, $\beta_{i,t}$ is the factor loading, $\varepsilon_{m,t+1}$ is the market-wide shock, and $\varepsilon_{i,t+1}$ is the stock-specific shock. $\varepsilon_{m,t+1}$ and $\varepsilon_{i,t+1}$ are both i.i.d (independent and identically distributed) and normally distributed with mean zero and variance $\sigma^2_{m,t}$ ($\sigma^2_{i,t}$). The realized market-wide shock at time t, $\varepsilon_{m,t}$, is known to investors, which allows us to study how the realized state of the market is related to subsequent risk-taking.

The one-factor model embeds CAPM (Capital Asset Pricing Model) as a special case. Accordingly, Eq. (1) means that the conditional variance-covariance matrix of returns has the form,

$$\Sigma_t = \mathrm{Var}_t[R_{t+1}] = \beta_t\beta_t'\sigma^2_{m,t} + Diag(\sigma^2_{i,t}),$$

where the $N \times 1$ vector of factor loadings (β_t) is the vector of the stocks' market betas and $Diag(\sigma^2_{i,t})$ is a diagonal matrix whose i-th diagonal element $\sigma^2_{i,t}$.

Let $w_{m,t}$ denotes the vector of market portfolio weights at time t, the market's expected excess return is given by

$$\mu_{m,t} = w'_{m,t}\mu_t,$$

where $\mu_t = \mathrm{E}_t[R_{t+1}]$ is the vector of conditional expected excess returns on N risky stocks. The market return and its variance have limiting behavior of

$$R_{m,t+1} \to \mu_{m,t} + \varepsilon_{m,t+1}, \quad \mathrm{Var}_t\left(R_{m,t+1}\right) \to \sigma^2_{m,t}, \tag{2}$$

As in many studies (e.g., Kelly et al., 2016), we assume that the market portfolio consists of enough stocks and hence the above limits hold with equality.

The representative investor at time t chooses his or her portfolio $w_{p,t}$ to maximize

$$E_t U \equiv w'_{p,t}\mu_t - \frac{\gamma}{2} w'_{p,t}\Sigma_t w_{p,t},$$

where $\gamma > 0$ is the coefficient of risk aversion and $\mu_t = \mathrm{E}_t[R_{t+1}]$ is the vector of conditional expected excess returns on N risky stocks. The vector of investor demand at time t is then given by

$$w_{p,t} = \frac{1}{\gamma}\Sigma_t{}^{-1}\mu_t. \tag{3}$$

At time t, we also have $w_{p,t} = w_{m,t}$ in equilibrium. Then, Eq. (3) yields a positive market mean-variance relation:

$$\mu_{m,t} = w'_{m,t}\mu_t = \gamma\sigma^2_{m,t}. \tag{4}$$

As Merton (1980) demonstrates, there is a positive relation between the market's expected return and variance.

To explain deviations from the positive mean-variance relation, one must rely on an excessive risk-taking factor that contributes to investors' willingness to sacrifice risk compensation. Accordingly, we modify the specification (3) as follows:

$$w_{p,t} = \frac{1}{\gamma}\Sigma_t{}^{-1}\mu_t + f_t, \tag{5}$$

where f_t represents the N-vector of excessive stock demand at time t. The vector f_t can be decomposed into two parts:

$$f_t = \underbrace{\lambda_t w_{m,t}}_{\binom{market-level}{speculation}} + \underbrace{\delta_t w_{ind,t}}_{\binom{firm-level}{speculation}}, \tag{6}$$

where $\lambda_t \in [0, 1]$ and $\delta_t \in [0, 1]$ are time-varying loading coefficients of an N-vector market portfolio weight $w_{m,t}$ and that of an N-vector portfolio weight $w_{ind,t}$ (orthogonal to the market portfolio), respectively. There are two primary drivers of excessive risk-taking, as indicated by Eq. (6). To put it simply, the first component, $\lambda_t w_{m,t}$, represents market-level speculation by investors, while the second component, $\delta_t w_{ind,t}$, represents firm-level investor speculation. For expositional simplicity, we also assume that $w_{ind,t}$ is a zero-beta ($\beta_t' w_{ind,t} = 0$) portfolio.

In equilibrium, market clearing based on Eq. (5) requires $w_{p,t} = w_{m,t}$ or

$$(1 - \lambda_t)w_{m,t} = \frac{1}{\gamma}{\Sigma_t}^{-1}\mu_t + \delta_t w_{ind,t}.$$

Multiplying both sides of the above equation by $w_{m,t}'\Sigma_t$ gives

$$(1 - \lambda_t)w_{m,t}'\Sigma_t w_{m,t} = \frac{1}{\gamma}w_{m,t}'\Sigma_t{\Sigma_t}^{-1}\mu_t = \frac{1}{\gamma}w_{m,t}'\mu_t. \tag{7}$$

From Eq. (7), we obtain the equilibrium expected excess returns as

$$\mu_{m,t} = \gamma(1 - \lambda_t)\sigma_{m,t}^2. \tag{8}$$

Analogously, we can obtain the mean-variance relation of idiosyncratic-level returns as

$$\alpha_t = \mu_t - \beta_t\mu_{m,t} = -\gamma\delta_t Diag(\sigma_{i,t}^2)w_{ind,t}, \tag{9}$$

which is similar to that in Stambaugh et al. (2015).

As discussed in the introduction, the bailout feedback effect arises because bailout-driven feedback traders rely on crash-like market features to take advantage of market-wide government bailouts, thereby yielding a relationship between realized bad market states and subsequent speculative motives. To characterize this relationship in the model analytically, we formalize this bailout feedback effect by defining an indicator function:

$$1_{\{\varepsilon_{m,t}<\varepsilon^-\}} = \begin{cases} 0, & \text{if } \varepsilon_{m,t} \geq \varepsilon^- \\ 1, & \text{if } \varepsilon_{m,t} < \varepsilon^- \end{cases} \tag{10}$$

and technically writing λ_t as

$$\lambda_t = c1_{\{\varepsilon_{m,t}<\varepsilon^-\}}|\varepsilon_{m,t}|, \tag{11}$$

where c is a positive constant to ensure $\lambda_t \leq 1$ and $\varepsilon^- < 0$ is the left-tail threshold for the aggregate shock. When $\varepsilon_{m,t}$ is sufficiently low, investors observe a salient crash-like market feature, and the bailout feedback effect kicks in, thereby causing excessive risk-taking.

Rewriting (8) with (11) gives

$$\mu_{m,t} = \gamma\big(1 - c1_{\{\varepsilon_{m,t}<\varepsilon^-\}}|\varepsilon_{m,t}|\big)\sigma^2_{m,t}. \tag{12}$$

Combining Eqs. (2) and (12), we can get

$$\begin{aligned} R_{m,t} &= \gamma(1 - c1_{\{\varepsilon_{m,t-1}<\varepsilon^-\}}|\varepsilon_{m,t-1}|)\sigma^2_{m,t-1} + \varepsilon_{m,t}, \\ R_{m,t+1} &= \gamma(1 - c1_{\{\varepsilon_{m,t}<\varepsilon^-\}}|\varepsilon_{m,t}|)\sigma^2_{m,t} + \varepsilon_{m,t+1}. \end{aligned}$$

Hence, the autocovariance of market portfolio returns is

$$\mathrm{Cov}(R_{m,t}, R_{m,t+1}) = c\gamma 1_{\{\varepsilon_{m,t}<\varepsilon^-\}}\sigma^4_{m,t} \geq 0. \tag{13}$$

In words, the bailout feedback effect can give rise to the positive first-order autocorrelation under the scenarios of $\varepsilon_{m,t} < \varepsilon^-$. The underlying intuition for the first-order autocorrelation is that a negative aggregate shock, which typically generates a contemporaneous negative unexpected return, may trigger excessive risk taking and thus results in subsequent low risk premiums. In turn, such positive autocorrelation can be removed by properly taking the next-period risk premium into account, i.e.,

$$\mathrm{Cov}\Big(R_{m,t}, R_{m,t+1} - \gamma(1 - c1_{\{\varepsilon_{m,t}<\varepsilon^-\}}|\varepsilon_{m,t}|)\sigma^2_{m,t}\Big) = 0. \tag{14}$$

Consistent with Implication 1, these equations (see, e.g., (12) and (13)) indicate that the bailout feedback effect, $1_{\{\varepsilon_{m,t}<\varepsilon^-\}}$, contributes to both the weak market mean-variance relation and the autocorrelation of market returns.

Also, the bailout feedback hypothesis means that $1_{\{\varepsilon_{m,t}<\varepsilon^-\}}$ is not important for generating positive values of δ_t, although it is critical for generating positive values of λ_t. So Eqs. (8) and (9) are consistent with Implication 2: $1_{\{\varepsilon_{m,t}<\varepsilon^-\}}$ contributes to the weakness of the market's mean-variance relation but not to that of the firm-level mean-variance relation. In this sense, the bailout feedback effect leads to a divergence between the market- and firm-level risk-return relations.

Our bailout feedback hypothesis stands out from other explanations due to its distinct implications on market- and firm-level risk-return tradeoffs. For instance, market declines may entice contrarians to trade aggressively, whose behaviors have the potential to bias the risk pricing. Another example is that a market decline may trigger losses for many investors. According to the prospect theory (Kahneman and Tversky, 1979; Tversky and Kahneman, 1992), investors are more risk-seeking in the loss region, thus undermining the market's mean-variance relation. However, if these two stories hold, the pricing effects should also hold at the firm level, as psychological biases typically persist longer in the idiosyncratic dimension than in the market-wide dimension.

Implications 1 and 2 are based on the argument that market-level speculation is driven by a crash-like market state. If the speculation is actually triggered by a bubble-like market state, then the positive market's mean-variance slope will flatten out, and such bubble-like market features favor negative instead of positive serial correlation. The predictions derived in this case are in sharp contrast to those in the bailout feedback case, but are consistent with the investor sentiment literature (e.g., De Long et al., 1990; Yu and Yuan, 2011). Our empirical findings contradict this scenario.

3. Data and Summary Statistics

The return data are obtained from the China Stock Market and Accounting Research (CSMAR) database for the period January 1997 to December 2020, covering a total of 288 months. We collect the entire set of A-shares listed in China and available in CSMAR. We use A-share equal- and value-weighted returns as proxies for stock market returns.[5] The monthly market excess return (R) is calculated as the realized monthly market return minus the one-month interest rate in China.

3.1. Volatility models

In this study, we adopt two widely used volatility models to estimate the market's conditional variance: the GARCH (1,1) and the rolling window models. The GARCH (1,1) model calculates the conditional variance of market returns in month $t+1$ as follows:

$$\mathrm{Var}_t(R_{t+1}) = 22 \sum_{d=1}^{N_t} \frac{1}{N_t} h_{t-d}, \tag{15}$$

$$r_{d+1}^{raw} = \mu + \varepsilon_{d+1},$$

$$h_{d+1} = \omega + \alpha \varepsilon_d^2 + \beta h_d,$$

where r_{d+1}^{raw} is the daily raw return, h_d is the conditional variance of the daily returns, and N_t is the number of trading days in month t (approximately 22 in one month).

[5]CSMAR offers the market returns of two A-share composite indexes, called "Aggregate A Share" and "Aggregate A Share and GEM" in the database, respectively. The two indexes lead to almost the same results in the regressions of this paper. For the sake of brevity, we only report the results based on the former index.

The rolling window model uses the realized variance in month t as the conditional variance of the return in month $t+1$, that is,

$$\mathrm{Var}_t(R_{t+1}) = 22 \sum_{d=1}^{N_t} \frac{1}{N_t} r_{t-d}^2, \tag{16}$$

where r_{t-d} is the daily demeaned return in month t computed by subtracting the within-month mean return from the daily raw return and N_t is the number of trading days in month t (roughly 22 in one month).

In unreported tests, we employ alternative models to estimate the conditional variance, including the rolling window model with a mixed data sampling approach (Ghysels et al., 2005), the asymmetric GARCH (1, 1) model (Glosten et al., 1993), and the GARCH-in-mean model (Engle et al., 1987). The market-level mean-variance relation and serial correlation results are essentially similar and are available upon request.

3.2. Measures of market crash features

As the focus of this paper is on market crash features that can be directly perceived by market participants, we choose an intuitive definition of a market crash in Wikipedia as the guiding principle of this paper,[6] that is, a stock market crash is a dramatic decline in stock prices across a significant cross-section of a stock market. Based on this definition, we construct crash measures to capture market-wide price declines at the cross-sectional level.

Our first measure of crash-like market features, denoted by $CRASH_1$, is constructed based on the cross-sectional distribution of all individual stock returns. Given this cross-sectional distribution of stock returns r, for a given confidence level $1-\alpha$, we can define a market-wide indicator P_α as

$$\mathrm{Prob}(r \geq P_\alpha) = 1 - \alpha,$$

where P_α is the α-percentile of the cross-sectional distribution of the realized stock returns.

[6]See https://en.wikipedia.org/wiki/Stock_market_crash

Specifically, our measure is defined based on the 1st percentile (P_1) of the log monthly return distribution pooled across all A-shares in the market over the past two months[7]:

$$CRASH_{1,t} = -P_1(r_t^1, r_{t-1}^1, \ldots, r_t^i, r_{t-1}^i, \ldots, r_t^n, r_{t-1}^n), \tag{17}$$

where r_t^i and r_{t-1}^i are the log monthly returns of stock i in months t and $t-1$, respectively. This definition highlights the importance of extreme realized returns. Recent literature has emphasized the role of salient characteristics in attracting the attention of unsophisticated investors, such as, causing individual investors to buy stocks following extreme returns (Barber and Odean, 2008). Given that the Chinese stock market is largely populated by inexperienced retail investors (e.g., Brunnermeier et al., 2022), the above crash measures are believed to capture the crash-like feature of a stock market perceived by the average investor.

Our second measure of crash-like features is constructed based solely on negative stock returns. Specifically, for month t, we compute $CRASH_2$ as the mean of the negative returns:

$$CRASH_{2,t} = -\mathrm{E}[r|r<0] = -\frac{\sum_{j=0}^{1}\sum_{i=1}^{n} r_{t-j}^i 1_{\{r_{t-j}^i<0\}}}{\sum_{j=0}^{1}\sum_{i=1}^{n} 1_{\{r_{t-j}^i<0\}}}, \tag{18}$$

where $1_{\{r<0\}}$ is an indicator function equal to one if the realized stock return r is negative.

We can then define a high-crash month as one in which the crash measure is above its sample median. Figure 1 shows the two crash measures from January 1997 to December 2020. The shaded areas represent high-crash periods defined by the corresponding measure, which reliably identifies historically well-known slumps in China's stock market, such as the 2004-2005 bust, the 2008 financial crisis, and the 2015 turbulence. The figure shows that these two measures exhibit highly correlated patterns; most of the high-crash months defined by $CRASH_1$ are also high-crash months defined by $CRASH_2$. Given that the two

[7]We consider two months to increase the likelihood of capturing extreme price declines. Our results also hold when measuring crash-like features over the past one or three months. See Table 6.

crash measures tend to generate similar results, we focus on the $CRASH_1$-related results in the following analysis.

As an additional test, we examine whether investors tend to pay more attention to the implicit put protection provided by the government, which is typically referred to as "rescue market" (in Chinese) by Chinese market participants, when $CRASH_1$ is higher. Recent finance research shows that Internet search volume captures investor attention in a direct manner (Da et al., 2011). In China, the search volume reported by Baidu is most likely representative of the internet search behavior of the general population. Thus, we calculate the average search volume per day of the term "rescue market" by month and use the logarithm of this monthly variable, the Baidu index, as a proxy for Chinese investors' attention to government bailouts. Figure 2 shows $CRASH_1$ and Baidu indices for the period 2008-2020. The sample period is determined by the availability of the search volume index reported by Baidu. As expected, the figure illustrates that $CRASH_1$ is positively correlated with the Baidu index.[8]

3.3. Summary statistics

Table 1 presents the descriptive statistics for monthly market excess returns and realized variance in low- and high-crash periods as defined by $CRASH_1$. The mean excess returns in high-crash periods is lower than in low-crash periods. The average investor does not earn more in high-crash periods, which is consistent with the notion that policy-adapting investors are likely to be excessively optimistic in times of trouble. Additionally, the skewness of excess returns is positive overall and in low-crash periods, but negative in high-crash periods. The two-regime pattern of return skewness suggests that market-level downside risk is higher in high-crash periods. Moreover, the mean and volatility of the realized variance are much higher in high-crash periods, suggesting that market instability is more prominent in high-

[8]Nevertheless, the Internet search index itself is not a market price feature and thus has not a direct relationship with feedback trading.

crash periods.

4. Risk-return tradeoff on the market level

4.1. Baseline regression

We use the developed crash measures to distinguish between high- and low-crash periods and employ this two-regime perspective to test Implication 1. Following the empirical designs of Yu and Yuan (2011), we use the typical risk-return tradeoff model as the baseline model, against which we test our alternative specification by augmenting it with our crash measures. We specify the baseline model as:

$$R_{t+1} = a + b\mathrm{Var}_t(R_{t+1}) + \varepsilon_{t+1}, \tag{19}$$

and the augmented model as:

$$R_{t+1} = a_1 + b_1\mathrm{Var}_t(R_{t+1}) + a_2 D_t + b_2 D_t \mathrm{Var}_t(R_{t+1}) + \varepsilon_{t+1}, \tag{20}$$

where R_{t+1} is the monthly market excess return, $\mathrm{Var}_t(R_{t+1})$ is the conditional variance, and D_t is a dummy that equals 1 if month t is a high-crash month, as defined in Section 3.

If there is no direct evidence of a positive risk-return tradeoff, we expect that coefficient b in Eq. (19) is insignificant. Alternatively, according to Implication 1, we expect coefficient b_1 in Eq. (20) to be significantly positive, as the typical risk-return tradeoff should dominate in low-crash periods, and the coefficient b_2 to be significantly negative, as excessive risk-taking in high-crash periods undermines the tradeoff.

Table 2 presents the regression results, which employ the GARCH (1,1) model to calculate conditional variance. Panel A of Table 2 presents the results for equal-weighted returns. The mean-variance relation is insignificant in the baseline specification (19) (b is 0.729 with a t-statistic of 1.10). In augmented specification (20), however, there is a significantly positive relationship between expected return and conditional variance in low-crash periods (b_1 is

6.428 with a t-statistic of 3.48). Meanwhile, such a relation subsides dramatically in high-crash periods (b_2 is -6.379 with a t-statistic of -3.21). We can also find that the sum of the mean-variance coefficients in high-crash periods, $b_1 + b_2$, is indistinguishable from zero. Moreover, the augmented equation explains the expected return better than the baseline equation does, with R^2 increasing from 0.4% to 4.2%.

We find the same results for the value-weighted returns in Panel B. The mean-variance relation is 0.238 with a t-statistic of 0.33 in the baseline specification, while it is 6.179 with a t-statistic of 3.81 in the augmented specification in low-crash periods. The difference between the two regimes is -7.150 with a t-statistic of -3.92. Similarly, R^2 increases from 0.0% to 5.8%.

Table 3 reports the results where the conditional variance is constructed using the rolling window. The point estimates of coefficients of primary interest differ due to the different functional forms, but the patterns in the coefficient estimates are virtually identical.

Table 4 reports the coefficients and t-statistics of the augmented specification with $CRASH_2$. Again, we obtain the same conclusions that have been found with $CRASH_1$. For the sake of parsimony, we report the regression results based only on $CRASH_1$ in the following analysis.

All these results are consistent with our hypothesis that the bailout feedback effect undermines an otherwise positive mean-variance relation in high-crash periods.

4.2. A horse race among different percentiles

Implicit government guarantees imply that the more the stock market plunges, the more likely it is that the government will bail it out. Therefore, the bailout feedback effect is expected to decrease when the shock is less extreme in the cross-sectional distribution. To investigate this possibility, we define $D_t = 1$ when the percentile is below the sample median for the 10th, 25th, and 50th percentiles. Within our bailout feedback hypothesis, the two-regime pattern is expected to dissipate as the percentile increases.

Table 5 reports the results using value-weighted returns. As the percentile departs from

1% to 50%, the absolute value of t-statistics experiences a monotonous decrease from 3.92 to 1.33, and from 3.27 to 1.35, with GARCH and rolling window, respectively, as the conditional variance models. The results suggest that the role of the bailout feedback effect in the mean-variance relation diminishes as a shock becomes milder. Our conclusion is unaltered when resorting to the equal-weighted returns (unreported in Table 5 for brevity).

To rule out the concern that the observed monotonous patterns are purely technical coincidences, we redefine $D_t = 1$ when the percentile is above its sample median for the 75th, 90th, and 99th percentiles, and rerun the regression model. If bubble-like market features are also attributed to a monotonically increasing paradigm of t-statistics of b_2, then our results are ambiguous. However, as shown in Table 5, this was not the case. The t-statistics start at 1.73 at the 75th percentile, decrease to 1.21 at the 90th percentile, and finally become negative at the 99th percentile with GARCH as the conditional variance model.

These results highlight the unique role of the left tails of the cross-sectional return distribution in explaining the market's mean-variance relation in China.

4.3. Robustness checks

This section presents several tests to examine whether the results are robust to different variable definitions and model specifications.

First, our crash measures are defined based on the distribution of monthly stock returns over the past two months thus far. To ensure that our results are not driven by specific choices of the calculation time window, Table 6 reports the regression results with two modified $CRASH_1$ measures. One crash measure is calculated based on monthly returns over the past one month, that is,

$$CRASH_{1,t} = -P_1(r_t^1, \ldots, r_t^i, \ldots, r_t^n) \tag{21}$$

and the other is calculated based on monthly returns over the past three months, that is,

$$CRASH_{1,t} = -P_1(r_t^1, r_{t-1}^1, r_{t-2}^1, \ldots, r_t^i, r_{t-1}^i, r_{t-2}^i, \ldots, r_t^n, r_{t-1}^n, r_{t-2}^n). \tag{22}$$

Panel A (B) of Table 6 reports the one-month (three-month) results. We repeat the regression analysis for different return weighted methods and conditional variance estimation models in each time window. The previous two-regime patterns in the mean-variance relation continue to hold throughout, with b_1 significantly positive and b_2 significantly negative. Again, their sum, $b_1 + b_2$, is indistinguishable from zero.

Second, we rewrite the augmented model, Eq. (20), as

$$R_{t+1} = f_0 + f_1 D_t + (g_0 + g_1 CRASH_{1,t} D_t)\mathrm{Var}_t(R_{t+1}) + \varepsilon_{t+1}. \tag{23}$$

The specification can be considered as a data-generating process underlying model (12), and might be termed as "the linear impact model." Table 7 presents the regression results for this specification. The estimates of g_0 across the different return-weighted methods and conditional variance models are all significantly positive. For example, in the case of equal-weighted returns and rolling-window variance, the estimate of g_0 is 3.369 and its t-statistic is 2.81. The result indicates that holding the price crash measure constant, the expected excess return is significantly positively related to conditional variance. Meanwhile, the estimates of g_1 are all significantly negative, for example, g_1 is -5.834 with a t-statistic of -2.55 in the above case, revealing that the coefficients of the mean-variance relation decrease linearly with the increase in the price crash measure in high-crash periods.

Together, these results confirm and strengthen our previous findings on the link between crash-like market features and the market's mean-variance relation.

5. Serial correlation

Based on Implication 1, the serial correlation in market returns is expected to disappear after the crash-like market features are taken into account. To better understand this issue, we incorporate the current market return R_t into the independent variables on the right-hand side of Eq. (19) and (20), and estimate the following regressions:

$$R_{t+1} = a + b\text{Var}_t(R_{t+1}) + cR_t + \varepsilon_{t+1}, \tag{24}$$

$$R_{t+1} = a_1 + b_1\text{Var}_t(R_{t+1}) + a_2 D_t + b_2 D_t \text{Var}_t(R_{t+1}) + cR_t + \varepsilon_{t+1}. \tag{25}$$

Table 8 reports the regression results with conditional variance derived from the GARCH model. The two-regime pattern survives the inclusion of the serial correlation term. Take the case of value-weighted returns for example. The coefficient of b_1 (b_2) is 5.879 (-6.767) as shown in Panel B, which is quantitatively similar to 6.179 (-7.150) in Table 2. Another intriguing result in Table 8 is that the coefficient of R_t, capturing the serial correlation of stock returns, is significantly positive in the baseline model (24) (the estimate of c is 0.129 with a t-statistic 2.20 in the case of value-weighted returns), but not in the augmented model (25) (the estimate of c is 0.037 with a t-statistic 0.57 in the case of equal-weighted returns). Similar results can be found when constructing the conditional variance based on the rolling window as shown in Table 9. The results suggest that our crash-augmented mean-variance model is useful for understanding the puzzling serial correlation of market returns in China.

A potential concern with our analysis is that the serial correlation pattern is because of non-synchronous trading. Then, the disappearance of serial correlation in our augmented model might only reflect the high correlation between our crash dummy and the magnitude of non-synchronous trading. To rule out this possibility, we include a liquidity index constructed following the methods of Amihud (2002) from CSMAR to capture the liquidity effect in the Chinese stock market. The results (unreported) remain virtually unchanged.

6. Idiosyncratic volatility and stock returns

The previous finding confirms Implication 1 that the bailout feedback effect is a source of both the weakness of the market's mean-variance relation and the serial correlation of market returns. This finding is consistent with the view that bailout-driven speculation influences compensation for systematic risk. If this bailout speculation effect matters, the market- and firm-level mean-variance relations are expected to diverge during the periods with high crash-like market features (Implication 2). About such a divergence, Eqs. (8) and (9) further illustrate that the bailout feedback effect should be mostly irrelevant to the firm-level mean-variance relation, despite having strong explanatory power for the market-level mean-variance relation. The previous analysis provide direct evidence in favor of the role of the bailout feedback effect in the market's mean-variance relation. This section focuses on the relationship between IVOL and average returns.

We first conduct a panel regression of firm returns on IVOL:

$$\alpha^i_{t+1} = a_1 + b_1 \mathrm{Var}_t(\epsilon^i_{t+1}) + b_2 D_t \mathrm{Var}_t(\epsilon^i_{t+1}) + \theta_t + \theta_i + \varepsilon_{t+1}, \tag{26}$$

where α^i_{t+1} is the intercept in a regression of stock i's daily excess returns in month $t+1$ on the daily Fama and French three factors; $\mathrm{Var}_t(\epsilon^i_{t+1})$ is the variance of residuals in a regression of stock i's daily excess returns in month t on the daily Fama and French three factors; D_t is a dummy that equals 1 if at month t, the market is characterized by a salient crash-like feature, and zero otherwise; θ_t and θ_i are time- and firm-fixed effects controlling for time-invariant and firm-invariant confounding factors. D_t is excluded owing to its collinearity with time-fixed effects θ_t. We winsorize α^i_{t+1} and $\mathrm{Var}_t(\epsilon^i_{t+1})$ at the 1% and 99% levels, respectively, to mitigate the interference effects of outliers. The sample period is from January 1997 to December 2020.

Table 10 reports the results. The coefficients of b_1 are significantly negative across different specifications. The negative pricing effect of IVOL is consistent with the previous studies on Chinese IVOL puzzle (Gu et al., 2018). By contrast, the coefficients of b_2 are significantly positive, and the magnitudes are relatively small compared to b_1, suggesting that the bailout feedback effect slightly dampens rather than magnifies the IVOL puzzle. As a pseudo test, we redefine $D_t = 1$ when the percentile is above its sample median for the 90th, 95th, or 99th percentile, and rerun the regression. The results reported in the last three rows in Table 10 are in striking contrast to those in the first three rows. The coefficients of b_2 are now significantly negative and the magnitudes are similar to those of b_1. This suggests that bubble-like market features dominate crash-like market features in explaining the negative IVOL puzzle. However, exploring the economic forces behind bubble-like market features is beyond the scope of the present paper.

We further use the portfolio-sorting method to explore the role of the bailout feedback effect in the negative IVOL puzzle. For each firm i in month t, $\text{Var}_t(\epsilon^i_{t+1})$ is calculated as the variance of residuals in a regression of each stock's daily excess returns in month t on the daily Fama and French three factors (MKT, SMB, and HML). At the end of each month $t+1$, stocks are sorted into quantiles based on $\text{Var}_t(\epsilon^i_{t+1})$. The risk-adjusted returns of these portfolios are calculated as α by regressing the monthly excess returns in month $t+1$ on the monthly Fama and French three factors.

Table 11 reports the results. Panel A considers the whole sample. Stocks with low IVOL in quantile 1 deliver an average risk-adjusted return of 0.140% (t-statistic = 1.05) per month, while stocks with high IVOL in quantile 5 show an average risk-adjusted return of -0.901% (t-statistic = -5.38) per month. The quantile 5 portfolio underperforms the quantile 1 portfolio by 1.041% (t-statistic = 4.24) monthly, indicating a negative IVOL puzzle. In Panel B and C, we divide the whole sample into the crash-like subsample with $D_t = 1$ and the non-crash-like subsample with $D_t = 0$, respectively. In each panel, we construct the crash dummy based on different distribution cutoffs, varying from the 1st percentile ($-P1$) to the 10th percentile ($-P10$). If the bailout feedback effect contributed to the negative pricing effect of IVOL, we should observe higher IVOL premiums in crash-like periods. This, however, is not true. Take the $-P1$ cutoff for example, the IVOL premium in the non-crash-like subsample is -1.435% (t-statistic $= -4.29$), which is twice as large as its counterpart -0.740 (t-statistic $= -2.24$) in the crash-like subsample.

Consistent with Implication 2, the results lend support to the bailout-feedback effect story and distinguish our story from other alternative explanations. For example, the contrarian story raises a concern that excess risk taking during times of trouble is because of contrarian beliefs rather than bailout expectations. The prospect theory story suggests that people exhibit higher risk tolerance in the loss region, leading to the observed excess risk-taking in the crash period. Such stories predict a puzzling risk-return tradeoff at both the individual and market levels, which is not consistent with our results shown in Tables 10 and 11.

7. Does investor sentiment matter?

Yu and Yuan (2011) use the investor sentiment index developed by Baker and Wurgler (2006) to identify high- and low-sentiment periods and study the ability of this index to explain the mean-variance relation in the U.S. stock markets. Their findings are consistent with the investor sentiment hypothesis that the presence of sentiment traders during high-sentiment periods undermines an otherwise positive mean-variance relation. This section examines this non-mutually exclusive hypothesis in the context of China.

First, we consider the skewness preference, a preference for gambles on highly right-skewed payoffs (e.g., Kahneman and Tversky, 1979), which is widely documented as a source of excessive risk-taking in the investment domain (e.g., Kumar, 2009). In the literature, there have been both theoretical and empirical evidence on the overpricing of stocks with lottery-like payoffs (e.g., Brunnermeier et al., 2007; Barberis and Huang, 2008; Green and Hwang, 2012). To establish the skewness-augmented model, we employ the measure of market skewness used by Green and Hwang (2012) and Ghysels et al. (2016a) defined as

$$MarketSkew_t = \frac{(P_{99} - P_{50}) - (P_{50} - P_1)}{(P_{99} - P_1)},$$

where P_j is the jth percentile of the cross-sectional distribution of all individual stock returns over the previous two months, calculated in the same way as P_1 in $CRASH_1$. If skewness preference, as an important dimension of investor sentiment, indeed has a strong bearing on the risk-return tradeoff, we expect coefficient b_1 to be significantly positive and coefficient b_2 to be significantly negative.

For brevity, we report only the results that employ the GARCH (1,1) model to calculate conditional variance. The results are virtually unchanged when rolling-window variance is used. The rows labeled "Mrkt Skew" in Table 12 show the results. While b_1 and b_2 are marginally significant in the equal-weighted cases, they are insignificant in the value-weighted cases. One potential explanation for the unstable results is that skewness preference is concentrated in small stocks, and equal-weighted returns tend to overestimate the role of small stocks in the whole sample. By contrast, the benchmark results are robust through different functional forms as shown in the rows labeled "Crash 97-20".

Second, we use a more general sentiment index called "CICSI" from CSMAR. Based on the methodology defined by Baker and Wurgler (2006) and the features of the Chinese stock market, CSMAR comprises six proxies of investor sentiment to construct this CICSI sentiment index: fund discount, share turnover, number of IPOs, average first-day returns of IPOs, number of new accounts, and the consumer confidence index. We estimate the augmented regression (20) in the period between January 2007 and December 2020. The sample period is determined by the availability of the CICSI sentiment index in the database. To capture the influences of investor sentiment, the dummy variable D_t equals 1 in the month when the CICSI sentiment index is above the sample median, and 0 in the month when the CICSI sentiment index is below the sample median. The rows labeled "CICSI" in Tables 12 report the regression results. b_1 and b_2 are mostly insignificant, and their signs are the opposite of those in Table 2. For comparison, we repeat the augmented regression analysis in Tables 2 and 3 over the subperiod 2007-2020. The rows labeled "Crash 07-20" in Tables 12 report the regression results. Both b_1 and b_2 are significant and have the expected signs similar to those within the entire sample. The statistical power is slightly weaker, probably owing to the smaller number of observations.

Third, many studies (e.g., Baker et al., 2012) argue that the price difference of dual-listed shares is a more direct proxy for investor sentiment.[9] As an additional test, we use an index measuring the price disparity between China firms' A-share and H-share prices as an alternative proxy for investor sentiment from 2006 to 2020.[10] The sample period is also determined by data availability. The rows labeled "AH premium" in Table 12 show the results. Again, the results show that all coefficients are insignificant, and the signs are the opposite of those in Table 2, indicating the weak explanatory power of this sentiment proxy.

Together, the above results indicate that our crash-augmented model performs much better than the sentiment-augmented model during the considered period. It then points to a suspicion whether the investor sentiment hypothesis itself is a primary candidate for explaining the market's mean-variance relation observed in China, although it is useful for detecting a positive mean-variance relation in the U.S. market.

8. Conclusion

Either a weak market mean-variance relation or serial correlation is puzzling within conventional asset pricing models. To explain these two coexisting puzzles in China, we combine market-wide bailout guarantees with the feedback trading process in financial markets. The combination of these two concepts allows us to move from stringent rational expectation models to a bailout feedback hypothesis, in which realized crash-like market movements can facilitate excessive risk-taking when feedback investors seek to take advantage of market-wide government guarantees.

[9] Dual-listed shares are pairs of securities that claim equal cash flows but trade in different markets.

[10] The index is produced by the Hang Seng Indexes Company. See http://www.hsi.com.hk/HSI-Net/HSI-Net for information about the index. The key difference between these shares is that A shares can only be held by Chinese investors, while H shares can only be held by foreign investors before November 2014.

To test this hypothesis, we develop market price crash indices to capture the crash-like features of a stock market perceived by investors. We find robust evidence that the market's expected excess return is positively related to its conditional variance in low-crash periods but not in high-crash periods. Such two-regime results cannot be found at the individual-stock level, which helps to isolate our bailout feedback story from other confounding factors, such as the prospect theory. Further, we observe that the positive serial correlation vanishes after considering the crash indices. All the evidence is consistent with our bailout feedback hypothesis. Given that intensive government interventions are involved in China, we believe that the bailout feedback effect deserves consideration as a possible solution for the coexistence of the market's weak risk-return tradeoff and serial correlation in the Chinese stock market.

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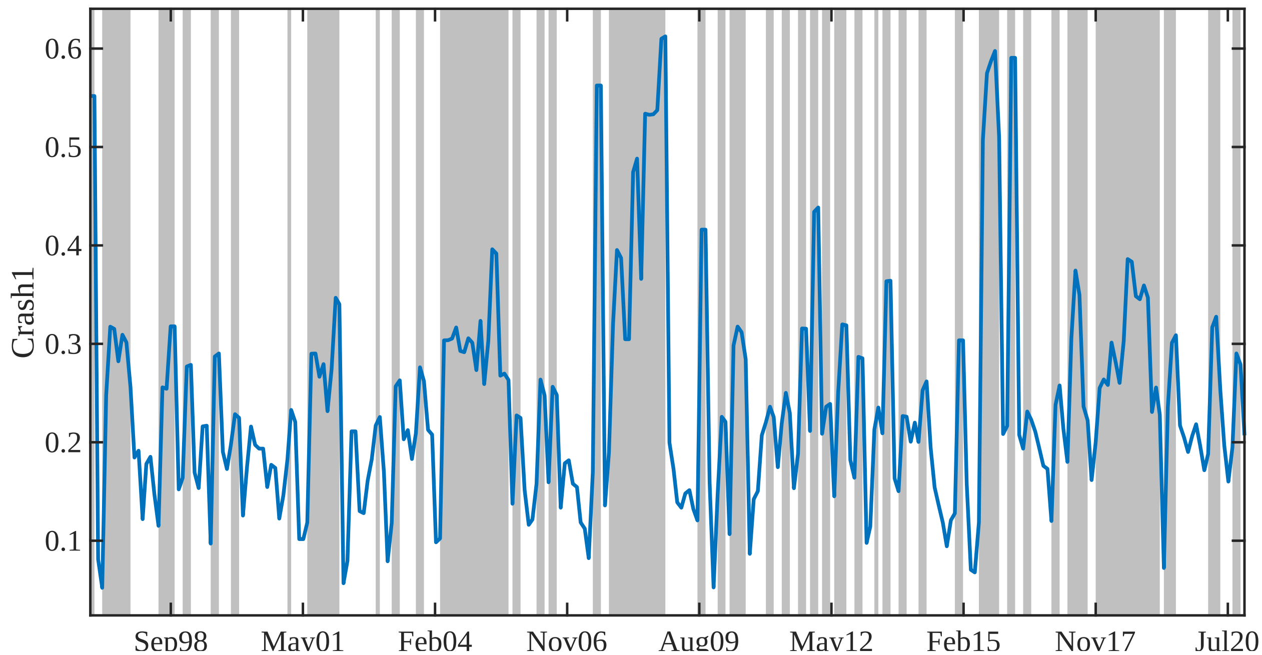

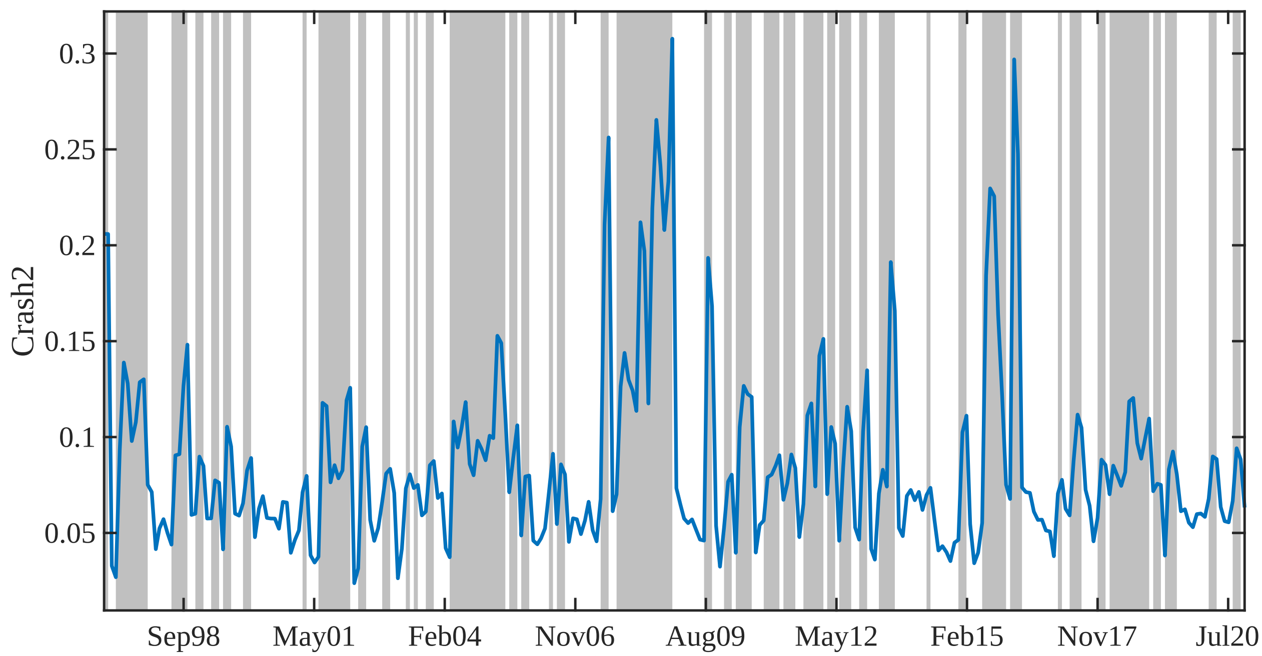

(b) $Crash_2$

Figure 1: Market crash measures

The figure plots two market crash indexes, $CRASH_1$ and $CRASH_2$, from January 1997 to December 2020. Shading denotes high-crash periods, i.e., the value of market crash indexes in those periods are above the sample median.

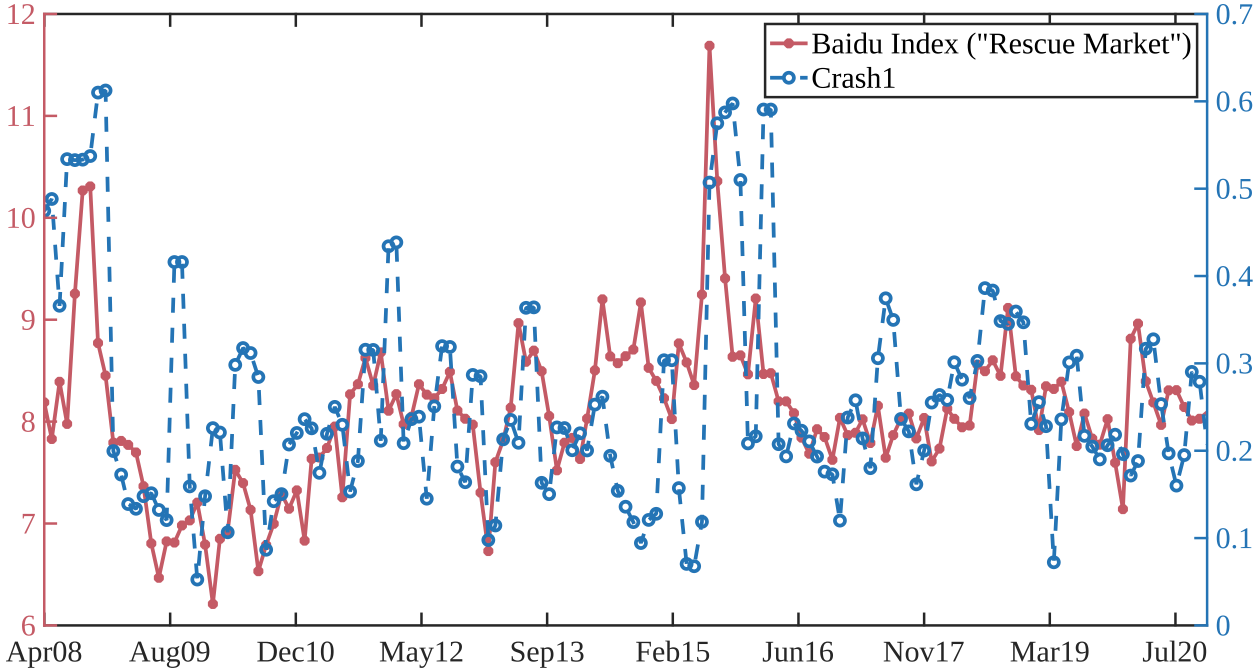

Figure 2: The Baidu search results for “rescue market” (in Chinese) and the crash measure. The figure plots the logarithm of Baidu search intensity for the term “rescue market” (in Chinese) with the red solid line, and plots the crash index, $CRASH_t$ (based on $CRASH_1$) with the blue dotted line for comparison. The sample period is April 2008 to December 2020.

Table 1: Descriptive statistics of monthly market excess returns and realized variance.

	Excess Return				Realized Variance			
	Mean$\times 10^2$	Var $\times 10^2$	Skew	Kurt	Mean$\times 10^3$	Var$\times 10^5$	Skew	Kurt
Panel A: Equal-weighted returns								
Full Sample	1.317	0.863	0.308	4.237	8.404	6.340	3.577	22.143
Low Crash	1.626	0.881	0.634	4.758	6.353	2.230	2.444	10.310
High Crash	1.007	0.849	−0.039	3.584	10.454	9.650	3.077	16.036
Panel B: Value-weighted returns								
Full Sample	0.826	0.663	0.244	4.940	6.781	4.170	2.112	7.672
Low Crash	1.394	0.703	0.714	5.406	5.123	1.920	2.218	8.445
High Crash	0.258	0.620	−0.349	3.992	8.439	5.890	1.676	5.366

The monthly market excess return is calculated as the realized monthly market return minus the one-month interest rate in China. The realized variance is computed from the within-month daily returns. The sample period is January 1997 to December 2020. High-crash and low-crash months are defined based on $CRASH_1$ as defined in Eq. (17).

Table 2: Relation between market excess return and GARCH variance.

Model	$a(a_1)$	$b(b_1)$	a_2	b_2	R^2
Panel A Equal-weighted returns					
Baseline	0.007	0.729			0.004
	(0.88)	(1.10)			
Augmented	−0.024*	6.428***	0.033*	−6.379***	0.042
	(−1.72)	(3.48)	(1.88)	(−3.21)	
Panel B Value-weighted returns					
Baseline	0.007	0.238			0.000
	(0.95)	(0.33)			
Augmented	−0.018*	6.179***	0.029**	−7.150***	0.058
	(−1.66)	(3.81)	(1.99)	(−3.92)	

This table reports the regression estimates of the baseline model (19): $R_{t+1} = a + b\text{Var}_t(R_{t+1}) + \varepsilon_{t+1}$, and the augmented model (20): $R_{t+1} = a_1 + b_1\text{Var}_t(R_{t+1}) + a_2 D_t + b_2 D_t \text{Var}_t(R_{t+1}) + \varepsilon_{t+1}$. D_t is a high-crash dummy that is defined based on $CRASH_1$. This table uses GARCH, Eq. (15), to model the conditional variance. The sample period is January 1997 to December 2020. ***, ** and * show the significance at the level of 1%, 5% and 10%, respectively. The numbers in parentheses are t-statistics.

Table 3: Relation between market excess return and rolling-window variance.

Model	$a(a_1)$	$b(b_1)$	a_2	b_2	R^2
		Panel A Equal-weighted returns			
Baseline	0.009	0.487			0.003
	(1.32)	(0.98)			
Augmented	−0.008	4.389***	0.019	−4.428***	0.038
	(−0.77)	(3.30)	(1.29)	(−3.08)	
		Panel B Value-weighted returns			
Baseline	0.007	0.193			0.000
	(1.12)	(0.32)			
Augmented	−0.004	3.909***	0.013	−4.642***	0.042
	(−0.49)	(3.17)	(1.05)	(−3.27)	

This table reports the regression estimates of the baseline model (19): $R_{t+1} = a + b\text{Var}_t(R_{t+1}) + \varepsilon_{t+1}$, and the augmented model (20): $R_{t+1} = a_1 + b_1\text{Var}_t(R_{t+1}) + a_2D_t + b_2D_t\text{Var}_t(R_{t+1}) + \varepsilon_{t+1}$. D_t is a high-crash dummy that is defined based on $CRASH_1$. This table uses RW, Eq. (16), to model the conditional variance. The sample period is January 1997 to December 2020. ***, ** and * show the significance at the level of 1%, 5% and 10%, respectively. The numbers in parentheses are t-statistics.

Table 4: Regression results with $CRASH_2$.

Model	a_1	b_1	a_2	b_2	R^2
		Panel A Equal-weighted returns			
GARCH	−0.020	6.371***	0.024	−6.085***	0.040
	(−1.40)	(3.26)	(1.35)	(−2.91)	
RW	−0.003	4.079***	0.009	−3.943***	0.034
	(−0.29)	(2.97)	(0.64)	(−2.67)	
		Panel B Value-weighted returns			
GARCH	−0.013	5.698***	0.020	−6.415***	0.050
	(−1.22)	(3.46)	(1.41)	(−3.47)	
RW	0.001	3.295***	0.004	−3.716**	0.032
	(0.07)	(2.61)	(0.35)	(−2.57)	

This table reports the regression estimates of the baseline model (19): $R_{t+1} = a + b\text{Var}_t(R_{t+1}) + \varepsilon_{t+1}$, and the augmented model (20): $R_{t+1} = a_1 + b_1\text{Var}_t(R_{t+1}) + a_2D_t + b_2D_t\text{Var}_t(R_{t+1}) + \varepsilon_{t+1}$. D_t is a high-crash dummy that is defined based on $CRASH_2$. This table uses GARCH, Eq. (15), and RW, Eq. (16), to model the conditional variance. The sample period is January 1997 to December 2020. ***, ** and * show the significance at the level of 1%, 5% and 10%, respectively. The numbers in parentheses are t-statistics.

Table 5: Regression results with different percentiles.

	GARCH Model					Rolling Window				
	a_1	b_1	a_2	b_2	R^2	a_1	b_1	a_2	b_2	R^2
−P1	−0.018*	6.179***	0.029**	−7.150***	0.058	−0.004	3.909***	0.013	−4.642***	0.042
	(−1.66)	(3.81)	(1.99)	(−3.92)		(−0.49)	(3.17)	(1.05)	(−3.27)	
−P10	−0.013	5.563***	0.020	−6.307***	0.050	−0.001	3.584***	0.006	−4.107***	0.038
	(−1.20)	(3.44)	(1.40)	(−3.47)		(−0.07)	(2.87)	(0.50)	(−2.87)	
−P25	−0.006	4.594***	0.010	−5.273***	0.050	0.001	3.500***	0.001	−4.050***	0.047
	(−0.62)	(3.11)	(0.71)	(−3.10)		(0.16)	(2.95)	(0.10)	(−2.94)	
−P50	0.006	1.894	−0.006	−2.150	0.023	0.009	1.524	−0.010	−1.747	0.023
	(0.57)	(1.39)	(−0.44)	(−1.33)		(1.02)	(1.41)	(−0.78)	(−1.35)	
P75	0.004	−1.086	0.004	2.510*	0.022	0.005	−1.321	0.005	2.550**	0.033
	(0.47)	(−1.10)	(0.28)	(1.73)		(0.63)	(−1.50)	(0.37)	(2.14)	
P90	0.003	−0.836	0.009	1.778	0.028	0.004	−1.150	0.008	2.056*	0.027
	(0.28)	(−0.83)	(0.64)	(1.21)		(0.47)	(−1.26)	(0.65)	(1.70)	
P99	−0.003	0.208	0.024*	−0.500	0.016	0.000	−0.407	0.018	0.470	0.016
	(−0.31)	(0.17)	(1.69)	(−0.32)		(0.02)	(−0.36)	(1.41)	(0.35)	

This table reports the regression estimates of the augmented model (20): $R_{t+1} = a_1 + b_1 \mathrm{Var}_t(R_{t+1}) + a_2 D_t + b_2 D_t \mathrm{Var}_t(R_{t+1}) + \varepsilon_{t+1}$. D_t is a dummy that is defined based on various percentiles according to their sample medians. This table uses GARCH, Eq. (15) and RW, Eq. (16), to model the conditional variance. The sample period is January 1997 to December 2020. ***, ** and * show the significance at the level of 1%, 5% and 10%, respectively. The numbers in parentheses are t-statistics.

Table 6: Regression results with two modified crash measures.

Model	Weight	a_1	b_1	a_2	b_2	R^2
Panel A One Month						
GARCH	Equal	−0.006	3.778**	0.008	−3.594**	0.032
		(−0.42)	(2.58)	(0.48)	(−2.19)	
GARCH	Value	−0.006	3.293**	0.015	−4.250***	0.031
		(−0.56)	(2.51)	(1.10)	(−2.70)	
RW	Equal	0.001	3.399***	0.002	−3.235**	0.034
		(0.08)	(2.71)	(0.12)	(−2.37)	
RW	Value	−0.001	2.721**	0.008	−3.336**	0.028
		(−0.06)	(2.39)	(0.60)	(−2.49)	
Panel B Three Month						
GARCH	Equal	−0.014	5.367**	0.016	−4.820**	0.025
		(−0.90)	(2.43)	(0.85)	(−2.07)	
GARCH	Value	−0.008	4.840**	0.011	−5.003**	0.028
		(−0.72)	(2.52)	(0.75)	(−2.39)	
RW	Equal	−0.002	3.874**	0.007	−3.571**	0.024
		(−0.20)	(2.41)	(0.48)	(−2.11)	
RW	Value	0.002	2.943**	0.001	−3.030*	0.020
		(0.21)	(2.01)	(0.04)	(−1.88)	

This table reports the regression estimates of the augmented model (20): $R_{t+1} = a_1 + b_1 \mathrm{Var}_t(R_{t+1}) + a_2 D_t + b_2 D_t \mathrm{Var}_t(R_{t+1}) + \varepsilon_{t+1}$. D_t is a high-crash dummy that is defined based on the modified crash measures. We pool all A-share monthly returns over the past one month or three months to calculate the modified crash measures based on $CRASH_1$. This table uses GARCH, Eq. (15), and RW, Eq. (16), to model the conditional variance. The sample period is January 1997 to December 2020. ***, ** and * show the significance at the level of 1%, 5% and 10%, respectively. The numbers in parentheses are t-statistics.

Table 7: Regression results with linear impact of crash measure in high-crash periods.

Model	f_0	f_1	g_0	g_1	R^2
Panel A Equal-weighted returns					
GARCH	−0.008	0.001	3.866**	−5.901**	0.021
	(−0.60)	(0.10)	(2.35)	(−1.97)	
RW	−0.002	0.002	3.369***	−5.834**	0.028
	(−0.24)	(0.14)	(2.81)	(−2.55)	
Panel B Value-weighted returns					
GARCH	−0.003	−0.001	3.253**	−6.458**	0.024
	(−0.27)	(−0.06)	(2.26)	(−2.24)	
RW	0.001	−0.001	2.833**	−6.299***	0.030
	(0.08)	(−0.06)	(2.54)	(−2.62)	

This table reports the coefficients and t-statistics of the augmented specification (23): $R_{t+1} = f_0 + f_1 D_t + (g_0 + g_1 CRASH_{1,t} D_t)\mathrm{Var}_t(R_{t+1}) + \varepsilon_{t+1}$. D_t is a high-crash dummy that is defined based on $CRASH_1$. This table uses GARCH, Eq. (15), and RW, Eq. (16), to model the conditional variance. The sample period is January 1997 to December 2020. ***, ** and * show the significance at the level of 1%, 5% and 10%, respectively. The numbers in parentheses are t-statistics.

Table 8: Serial correlation and the relation between market return and GARCH variance.

Model	$a(a_1)$	$b(b_1)$	a_2	b_2	c	R^2
			Panel A Equal-weighted returns			
Baseline	0.003	0.923			0.151**	0.052
	(0.43)	(1.40)			(2.58)	
Augmented	−0.022	5.513***	0.032*	−5.317**	0.087	0.075
	(−1.61)	(2.79)	(1.83)	(−2.48)	(1.29)	
			Panel B Value-weighted returns			
Baseline	0.005	0.404			0.129**	0.019
	(0.65)	(0.55)			(2.20)	
Augmented	−0.017	5.879***	0.029**	−6.767***	0.037	0.060
	(−1.64)	(3.44)	(1.98)	(−3.48)	(0.57)	

This table reports the regression estimates of the baseline model (24): $R_{t+1} = a + b\text{Var}_t(R_{t+1}) + cR_t + \varepsilon_{t+1}$, and the augmented model (25): $R_{t+1} = a_1 + b_1\text{Var}_t(R_{t+1}) + a_2D_t + b_2D_t\text{Var}_t(R_{t+1}) + cR_t + \varepsilon_{t+1}$. D_t is a high-crash dummy that is defined based on $CRASH_1$. This table uses GARCH, Eq. (15), to model the conditional variance. The sample period is January 1997 to December 2020. ***, ** and * show the significance at the level of 1%, 5% and 10%, respectively. The numbers in parentheses are t-statistics.

Table 9: Serial correlation and the relation between market return and rolling-window variance.

Model	$a(a_1)$	$b(b_1)$	a_2	b_2	c	R^2
Panel A Equal-weighted returns						
Baseline	0.004	0.815			0.164***	0.029
	(0.60)	(1.62)			(2.75)	
Augmented	−0.010	3.764***	0.020	−3.538**	0.111	0.047
	(−0.95)	(2.73)	(1.40)	(−2.31)	(1.65)	
Panel B Value-weighted returns						
Baseline	0.004	0.461			0.134**	0.018
	(0.67)	(0.76)			(2.27)	
Augmented	−0.005	3.625***	0.014	−4.178***	0.057	0.045
	(−0.57)	(2.83)	(1.08)	(−2.75)	(0.85)	

This table reports the regression estimates of the baseline model (24): $R_{t+1} = a + b\mathrm{Var}_t(R_{t+1}) + cR_t + \varepsilon_{t+1}$, and the augmented model (25): $R_{t+1} = a_1 + b_1\mathrm{Var}_t(R_{t+1}) + a_2 D_t + b_2 D_t \mathrm{Var}_t(R_{t+1}) + cR_t + \varepsilon_{t+1}$. D_t is a high-crash dummy that is defined based on $CRASH_1$. This table uses RW, Eq. (16), to model the conditional variance. The sample period is January 1997 to December 2020. ***, ** and * show the significance at the level of 1%, 5% and 10%, respectively. The numbers in parentheses are t-statistics.

Table 10: Idiosyncratic volatility and stock returns

Model	b_1	b_2	Firm Fixed	Time Fixed	Obs	R^2
−P1	−0.948***	0.314***	YES	YES	459,129	0.034
	(−36.21)	(9.30)				
−P5	−0.894***	0.242***	YES	YES	459,129	0.034
	(−36.08)	(7.27)				
−P10	−0.892***	0.246***	YES	YES	459,129	0.034
	(−36.60)	(7.41)				
P90	−0.547***	−0.391***	YES	YES	459,129	0.034
	(−21.59)	(−11.69)				
P95	−0.523***	−0.409***	YES	YES	459,129	0.034
	(−19.89)	(−12.12)				
P99	−0.488***	−0.433***	YES	YES	459,129	0.034
	(−17.50)	(−12.55)				

This table reports the regression estimates of the model (26): $\alpha^i_{t+1} = a_1 + b_1 \mathrm{Var}_t(\epsilon^i_{t+1}) + b_2 D_t \mathrm{Var}_t(\epsilon^i_{t+1}) + \theta_t + \theta_i + \varepsilon_{t+1}$. α^i_{t+1} is the intercept in a regression of stock i's daily excess returns in month $t+1$ on the daily Fama and French three factors; $\mathrm{Var}_t(\epsilon^i_{t+1})$ is the variance of residuals in a regression of stock i's daily excess returns in month t on the daily Fama and French three factors; D_t is a dummy defined based on various percentiles according to their sample medians; θ_t and θ_i are time fixed effects and firm fixed effects. The sample period is from January 1997 to December 2020. ***, ** and * show the significance at the level of 1%, 5% and 10%, respectively. The numbers in parentheses are t-statistics.

Table 11: Portfolio sorting based on idiosyncratic volatility

IVOL Rank	1	2	3	4	5	$5-1$
			Panel A: Whole Sample			
Whole Sample	0.140	0.185	0.059	-0.226	-0.901	-1.041***
	(1.05)	(1.75)	(0.52)	(-1.73)	(-5.38)	(-4.24)
			Panel B: Subsample: Crash			
Crash ($-$P1)	0.093	0.361	0.256	0.005	-0.647	-0.740**
	(0.51)	(3.27)	(1.99)	(0.03)	(-2.87)	(-2.24)
Crash ($-$P5)	0.159	0.373	0.231	-0.131	-0.839	-0.998***
	(0.88)	(3.28)	(1.67)	(-0.92)	(-4.38)	(-3.27)
Crash ($-$P10)	0.181	0.365	0.216	-0.132	-0.807	-0.988***
	(1.02)	(3.19)	(1.62)	(-0.93)	(-4.17)	(-3.26)
			Panel C: Subsample: Non-Crash			
Non-Crash ($-$P1)	0.185	0.009	-0.108	-0.475	-1.25	-1.435***
	(1.16)	(0.06)	(-0.66)	(-2.42)	(-5.08)	(-4.29)
Non-Crash ($-$P5)	0.137	0.03	-0.101	-0.356	-1.095	-1.232***
	(0.80)	(0.18)	(-0.58)	(-1.55)	(-3.96)	(-3.29)
Non-Crash ($-$P10)	0.117	0.032	-0.08	-0.366	-1.13	-1.247***
	(0.70)	(0.20)	(-0.44)	(-1.59)	(-4.13)	(-3.38)

This table reports risk-adjusted portfolio returns sorted by IVOL. For each firm i in month t, $\text{Var}_t(\epsilon^i_{t+1})$ is calculated as the variance of residuals in a regression of each stock's daily excess returns in month t on the daily Fama and French three factors (MKT, SMB, and HML). The risk-adjusted returns are calculated as α by regressing monthly excess returns in month $t+1$ on the monthly Fama and French three factors. The sample period is from January 1997 to December 2020. ***, ** and * show the significance at the level of 1%, 5% and 10%, respectively. Newey et al. (1987) t-statistics with six lags are shown in parentheses.

Table 12: Investor sentiment and the relation between market return and GARCH variance.

Model	Sample	a_1	b_1	a_2	b_2	R^2
		Panel A Equal-weighted returns				
Mrkt Skew	97-20	−0.010	1.869**	0.028**	−1.766*	0.021
		(−0.87)	(2.17)	(2.02)	(−1.92)	
CICSI	07-20	0.021	−0.501	−0.032	3.779*	0.020
		(1.61)	(−0.57)	(−1.56)	(1.87)	
AH Premium	06-20	0.028	−2.510	−0.001	2.508	0.010
		(1.35)	(−0.90)	(−0.05)	(0.85)	
Crash	97-20	−0.024*	6.428***	0.033*	−6.379***	0.042
		(−1.72)	(3.48)	(1.88)	(−3.21)	
Crash	07-20	−0.024	6.364**	0.044*	−6.825**	0.037
		(−1.16)	(2.43)	(1.69)	(−2.45)	
		Panel B Value-weighted returns				
Mrkt Skew	97-20	−0.001	0.448	0.015	−0.222	0.007
		(−0.15)	(0.49)	(1.21)	(−0.21)	
CICSI	07-20	0.023**	−1.349	−0.025	2.900	0.014
		(2.03)	(−1.35)	(−1.51)	(1.38)	
AH Premium	06-20	0.025*	−3.268	−0.004	2.678	0.012
		(1.71)	(−1.30)	(−0.21)	(0.98)	
Crash	97-20	−0.018*	6.179***	0.029**	−7.150***	0.058
		(−1.66)	−3.81	−1.99	(−3.92)	
Crash	07-20	−0.021	6.652***	0.039**	−8.341***	0.075
		(−1.44)	(3.13)	(2.01)	(−3.54)	

This table reports the coefficients and t-statistics of the augmented two-regime specification (20): $R_{t+1} = a_1 + b_1 \mathrm{Var}_t(R_{t+1}) + a_2 D_t + b_2 D_t \mathrm{Var}_t(R_{t+1}) + \varepsilon_{t+1}$. D_t is a dummy that equals 1 if the corresponding sentiment measure is larger than its sample median. Sentiment measures include market skewness ("Mrkt Skew"), CICSI sentiment index ("CICSI") and Hang Seng China AH Premium Index ("AH premium"). This table uses GARCH, Eq. (15), to model the conditional variance. ***, ** and * show the significance at the level of 1%, 5% and 10%, respectively. The numbers in parentheses are t-statistics.