DEPARTMENT OF ECONOMICS
WORKING PAPERS

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Do Hedge Funds Reduce Idiosyncratic Risk?

by

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2012/15

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Abstract

This paper studies the effect of hedge-fund trading on idiosyncratic risk. We hypothesize that while hedge-fund activity would often reduce idiosyncratic risk, high initial levels of idiosyncratic risk might be further amplified due to fund loss limits. Panel-regression analyses provide supporting evidence for this hypothesis. The results are robust to sample selection and are further corroborated by a natural experiment using the Lehman bankruptcy as an exogenous adverse shock to hedge-fund trading. Hedge-fund capital also explains the increased idiosyncratic volatility of high-idiosyncratic-volatility stocks as well as the decreased idiosyncratic volatility of low-idiosyncratic-volatility stocks over the past few decade.

Acknowledgements

We thank Francesco Franzoni, Andras Fulop, Rene Garcia, Carole Gresse, Robert Korajczyk, Juhani Linnainmaa, Stefan Negal, Lubos Pastor, David Thesmar, and seminar participants at Bentley University, Boston College, Central European University, ECB, MKE Budapest, the 3rd Annual Conference on Hedge Funds, and the 4th Financial Risks International Forum for helpful comments and suggestions.

1. Introduction

The debate whether profit maximizing speculators are stabilizing or destabilizing asset prices touches upon the heart of financial theory and dates back to the classic argument by Friedman (1953). One aspect of this debate is that whenever investors sell or buy assets for non-fundamental reasons, some other market participants should be ready to take the other side of the trade, preventing the price from further deviating from the fundamental value. In other words, some market participants should act as de facto market makers by absorbing non-fundamental shocks. However, many studies (e.g., Shleifer and Vishny (1997)) point out that professional investors—the prime candidates for such market making activity—are subject to various frictions which might limit their capacity to play this role in certain states of the world. In these states, their activity might even amplify the original price shock.

In this paper, we hypothesize that professional investors absorb small shocks, but amplify large shocks.[1] To illustrate our highlighted mechanism, consider a hypothetical hedge fund specializing in the relative mispricing of stocks. In particular, we suppose a strategy of buying (selling) a stock when its price is low (high) relative to its exposure to systematic factors and of taking an opposite position in a portfolio with the same exposure to systematic risk. In "normal" times, if a sufficiently large amount of capital is dedicated to the strategy, this activity reduces idiosyncratic return volatility by partially absorbing idiosyncratic shocks. However, most institutional traders have implicit or explicit limits on their loss-bearing capacity.[2] Regardless of its source, this constraint might force funds to reduce their positions after a series of adverse shocks. Thus, when the initial idiosyncratic shock increases to a

[1]We formalize our hypothesis in a stylized model whereby professional traders engage in long-short positions to profit from the mean reversion of non-fundamental shocks subject to traders' limited loss-bearing capacity. The model is presented in Appendix D.

[2]The loss limit can come from various sources, including internal or external value-at-risk (VAR) constraints, wealth effects, constraints on equity or debt, margin requirements or expected or realized fund-flow response to poor performance. See the related theoretical (e.g., Shleifer and Vishny (1997), Xiong (2001), Danielsson, Shin, and Zigrand (2004), Brunnermeier and Pedersen (2009), Kondor (2009), and Guerrieri and Kondor (2012)) and empirical (e.g., Coval and Stafford (2007) and Greenwood and Thesmar (2011)) literature.

particularly high level, the induced loss on the funds following the long-short strategy triggers forced liquidation. Thus, if this strategy is sufficiently wide spread to affect prices, it will lead to an attenuation of small to moderate shocks and an amplification of large shocks.

In our empirical analyses, we test two main hypotheses. First, the larger the invested capital of hedge funds in a given stock, the higher (lower) *level* of estimated idiosyncratic volatility for the stock relative to the period-average idiosyncratic volatility, provided that the stock belongs to the top (bottom) decile of the cross-sectional distribution in the period. Second, larger invested capital implies, in expectation, a larger positive (negative) *change* in idiosyncratic volatility for stocks in the top (bottom) decile. That is, loosely speaking, larger fund activity results in wilder period-to-period changes of idiosyncratic volatility. Additionally, we also argue that these effects must be stronger for less liquid stocks, and when the loss-bearing capacity of the group of funds is smaller.

Figures 1 and 2 show preliminary support for our first hypothesis. It has been well documented that the share in the US equity market and trading assets of various financial institutions, especially hedge funds, have been steadily increasing over the last decades.[3] According to our hypothesis, this increasing share of hedge funds implies that large idiosyncratic shocks should have become larger and small idiosyncratic shocks should have become smaller compared to the average idiosyncratic shocks over time. In other words, the cross-sectional distribution of idiosyncratic volatility of US equities should become more skewed over time. Figure 1 illustrates that it is indeed the case.

In Figure 2, we use a simple non-parametric measure similar to the standard Lorenz curve to further investigate the first hypothesis. First, we order the stocks in each month into deciles based on their estimated idiosyncratic volatility. Then, as in the construction of a Lorenz curve, we develop a measure for the contribution of each decile to the aggregate

[3]While almost 50% of the US equities were held directly in 1980, this proportion decreased to around 20% by 2007 (see French (2008)) due to both the increased activity of mutual funds and hedge funds. See also the presidential address of Allen (2001) for an elaborate discussion on the importance of the role of financial intermediaries.

idiosyncratic volatility. Just as the top 10% of US households can own more than 10 percent of total wealth, the stocks in a given decile can be responsible for more or less than 10 percent of the aggregate idiosyncratic volatility in a given month. Figure 2 shows that the share of the top deciles has steadily increased, while that of the bottom decile has steadily decreased over time. In fact, the value-weighted share of the top decile of idiosyncratic volatility has increased from 10% to 19%, while that of the bottom decile decreased from 13% to 3% over the period 1963–2008. Time-series regressions show that there is indeed a connection between these trends and the increasing assets under management (AUM) of hedge funds over and above a shared time trend.

Figure 3 provides descriptive evidence for our second hypothesis. First, we consider stocks in the top or bottom decile of idiosyncratic volatility in a given period. We sort these stocks into four groups according to the fraction of their shares owned by hedge fund at the beginning of the period. Then, we plot the average change in idiosyncratic volatility of each group. The columns above the x-axis show the changes in idiosyncratic volatility of stocks in the top decile, averaged within each ownership group. Not surprisingly, all the groups in the top decile display a positive average change, as increasing idiosyncratic volatility pushes stocks to the top decile. Yet, a higher share of hedge-fund ownership is associated with a larger positive change in idiosyncratic volatility. Similarly, the columns below the x-axis show the average changes in idiosyncratic volatility for stocks in the bottom decile. Again, the change of each group is negative, as decreasing idiosyncratic volatility pushes the stocks to the bottom decile. However, the changes in the idiosyncratic volatility are again larger in absolute terms for groups with higher hedge-fund ownership. This is consistent with our second testable hypothesis.

Motivated by Figure 3, we start with firm-level, panel-regression analyses using subsamples as our baseline case. Three subsamples are constructed based on stocks' idiosyncratic volatility: The sample of firms of Decile 1, that of firms of Decile 10, and that of firms of

Deciles 2–9. For each subsample, we regress the change in idiosyncratic volatility of a given stock on its hedge-fund ownership and various stock-level controls. Consistent with Figure 3, we find that higher hedge-fund ownership is associated with larger absolute changes in idiosyncratic volatility. We also find that this connection between hedge-fund ownership and idiosyncratic volatility is stronger for less liquid stocks.

There are two potential concerns with the baseline case. The first issue is that we might select stocks with different observable characteristics for different subsamples. These differences in characteristics might not be independent from changes of idiosyncratic risk and from hedge-fund ownership, resulting in the spurious relation between the two variables. To alleviate this concern, we follow a control-group approach. We construct control groups in two ways. First, we use each firm in the extreme decile samples as its own control. Thus, we collect observations on stocks in periods $t-2$ and $t+2$, if the stocks belong to an extreme decile in period t. Then, the control group is constructed using the firm-quarters from $t+2$ to $t+2$, but excluding the firm-quarters at t. Second, we use the propensity score matching (PSM) method to construct a control group. Specifically, we estimate the probability of a firm falling in an extreme decile in a given period based on observed characteristics. Then, individual firm-quarters with similar propensity scores as those of the firms in the extreme deciles are selected to create the propensity score matching (PSM) control groups. In both cases, we show that firms that reside in the extreme deciles display a stronger relation between hedge-fund ownership and the changes in idiosyncratic volatility, compared to stocks in the control groups. This is consistent with our second hypothesis.

The second concern is reverse causality. It is possible that the activity of hedge funds does not have any effect on volatility, but rather hedge funds choose to hold stocks with an extreme change in idiosyncratic volatility. If hedge funds pick these stocks using characteristics which we do not observe, then the control-group approach does not alleviate this problem. To address this issue, we use the Lehman bankruptcy as a natural experiment (e.g., Aragon and

Strahan (2011)). Specifically, we consider the Lehman bankruptcy as an exogenous adverse shock triggering forced liquidation by hedge funds that use Lehman as their prime broker. Then, we test whether the idiosyncratic volatility of stocks held by the affected hedge funds increase. We show that the idiosyncratic volatility of stocks primarily held by hedge funds with Lehman as their prime broker increased post Lehman bankruptcy, while that of stocks primarily held by other hedge funds did not. This evidence enhances the results of the control-group approach.

We provide further supporting evidence for the hypothesis that the amplification of high-idiosyncratic shocks by hedge funds is channelled through a funding-liquidity mechanism, by which limits on hedge funds' loss-bearing capacity forces managers to liquidate their positions. First, we examine whether the effects of hedge-fund trading are indeed weaker among stocks that are held by hedge funds with less funding constraints. We use two measures for funding constraints: fund leverage and lockup provision. Consistent with the funding-liquidity explanation, we find that the effect of hedge funds is stronger for stocks that are held by hedge funds that use leverage or do not apply a lockup period for Decile 1 stocks. For Decile 10 stocks, the hedge-fund effect is stronger for stocks that have higher ex-ante illiquidity and owned by hedge funds with leverage or without a lockup provision, which is also consistent with our hypothesis. Second, we examine whether the stocks with both high-idiosyncratic volatility in quarter t and high-hedge-fund ownership in quarter $t-1$ are traded intensely by hedge funds, which would be consistent with a sell-off of high-volatility stocks during a fire sale. Indeed, we find this to be the case. Moreover, the sell-off is concentrated in liquid stocks, consistent with the findings of recent literature (e.g., Sadka (2010) and Ben-David, Franzoni, and Moussawi (2012)).

Next, we return to the patterns displayed in Figure 1 and 2 and test whether the effects that we identify at the firm-level have the potential to explain the aggregate trends in idiosyncratic volatility. In particular, we study whether proxies of the trading activity of various financial institutions explain the diverging trends of the top and bottom deciles of idiosyncratic return volatility. Specifically, we run time-series regressions of the shares of extreme deciles in the aggregate idiosyncratic volatility on the aggregate idiosyncratic cash-flow volatility, the AUM of Long/Short-Equity hedge funds, and various controls. We also control for the changing cost of financing short positions proxied by the TED spread. We find that the downward trend in the bottom decile of idiosyncratic volatility is significantly related to the increase in AUM of Long/Short-Equity funds. We also find evidence that the upward trend in the top decile of idiosyncratic volatility is significantly related to fundamental factors, such as cash-flow risk and firm leverage. However, after controlling for the TED spread, we find that the interaction between AUM of Long/Short-Equity and the TED spread also plays a significant role in explaining this upward trend in the top decile. All these results are consistent with our hypotheses.

This paper is the first to expose the fact that idiosyncratic shocks have become more extreme during the last decades and to relate this fact to the increasing role of hedge funds in absorbing and amplifying idiosyncratic shocks. This paper is mostly related to the literature that provides systematic evidence on whether arbitrageurs amplify or reduce economic shocks. Hong, Kubik, and Fishman (2011) identify amplification by documenting overreaction to earnings shocks for stocks with a large short-interest. Gamboa-Cavazos and Savor (2005) find that short sellers close their positions after losses and add to their positions after gains. Similarly, Lamont and Stein (2004) find a negative correlation between market returns and the aggregate short-interest ratio. Unlike these papers, we find evidence that whether shocks are amplified or reduced depends on the size of the shocks. The paper is also related to the literature that studies the relation between firm-ownership structure and stock-price volatility (see, e.g., Sias (1996 and 2004), Bushee and Noe (2000), Koch, Ruenzi, and Starks (2009), and Greenwood and Thesmar (2010)). Our main novelty compared to this literature is that we show that the direction of the relation is conditional on whether the stock experiences a particularly high volatility.

The time-series properties of the extreme deciles of idiosyncratic volatility that we document in this parer are related to the literature on the time trend of the aggregate idiosyncratic volatility started by Campbell, Lettau, Malkiel, and Xu (2001), who document the increasing time trend in the aggregate idiosyncratic volatility. Some papers relate the upward trend to the fundamentals of firms' business environment (e.g., Gaspar and Massa (2006) and Irvine and Pontiff (2009)). Other papers relate the time trend to the changes in trading activities of market participants (e.g., Xu and Malkiel (2003) and Brandt, Brav, Graham, and Kumar (2008)). Yet, there are much evidence that the upward trend is reversed when the sample period is extended over 2000 (see, e.g., Brandt, Brav, Graham, and Kumar (2009) and Bekaert, Hodrick, and Zhang (2010)).

In contrast to the aforementioned literature, we are concerned with the dynamics of extreme realizations in the cross-section as opposed to the time trend of aggregate idiosyncratic volatility. In particular, we are interested in the trend of the top and bottom decile of the cross-section. Although the existence of the time trend documented in Campbell, Lettau, Malkiel, and Xu (2001) has been questioned in the extended sample, this caveat does not apply to our work. While examining the trend of the extreme deciles, we construct our measure by dividing the idiosyncratic volatility of each decile by the aggregate idiosyncratic volatility. Thus, the measure is independent from the potential trend in the aggregate idiosyncratic volatility.

The structure of the paper is as follows. In the next section, we describe our sample and estimation methods. Section 3 tests our main hypotheses, using both panel and cross-sectional regressions. In Section 4, we perform time-series analyses. Section 5 concludes.

2. Data and main variables

In this section, we describe the variables for our empirical tests. We follow Ang, Hodrick, Xing, and Zhang (2006) and Irvine and Pontiff (2009) in estimating idiosyncratic return volatility and idiosyncratic cash-flow volatility for an individual firm, respectively. We then develop a measure that describes the extreme realizations of idiosyncratic volatility in the cross-sectional distribution. Using this measure, we highlight a new stylized fact; the cross-sectional distribution of the idiosyncratic volatility of common stocks has become more skewed over time.

A. Idiosyncratic return volatility and its cross-sectional distribution

We estimate idiosyncratic volatility relative to the Fama-French three-factor model. We examine both monthly and quarterly idiosyncratic volatility using daily return data. Specifically, for period t and stock i, we estimate the following regression model

$$r_{i,s} = \alpha_i + \beta_{i,MKT} MKT_s + \beta_{i,SMB} SMB_s + \beta_{i,HML} HML_s + \varepsilon_{i,s}, \tag{1}$$

where $r_{i,s}$ is the return (excess of the risk-free rate) of stock i on day s during the period t. The idiosyncratic volatility of stock i during period t is defined as the average of the squared residuals of the regression over the number of trading days in period t, $D_{i,t}$:

$$IV_{i,t} = \frac{1}{D_{i,t}} \sum_{s \in t} \varepsilon_{i,s}^2. \tag{2}$$

Note that our estimation method of idiosyncratic volatility is somewhat different than that applied in Campbell, Lettau, Malkiel, and Xu (2001), who estimate idiosyncratic volatility as the difference between a stock's daily return and its industry or market average. Our specification relaxes the assumption of a unit beta for every stock, while also allowing for other sources of systematic risk. Nevertheless, we show in the next section that our estimate displays quite similar time trends to those shown in the literature.

We use daily return data and daily risk-free rate and Fama-French factors from CRSP. Only common stocks (share code 10 and 11) of firms traded on NYSE, AMEX, and Nasdaq are included in the sample. To alleviate the effects of bid/ask spread on the volatility estimation, we limit the sample to stocks with a prior calendar year-end price of \$2 or higher. Following Amihud (2002), we require that stocks have more than 100 nonmissing trading days during the previous calendar year. Following Ang, Hodrick, Xing, and Zhang (2006), we also require that stocks have more than 15 trading days for each monthly idiosyncratic volatility estimated, and 25 trading days for quarterly estimation. The sample period is from July 1963 to December 2008.

Having obtained the idiosyncratic volatilities of individual stocks, we estimate their cross-sectional moments for each given period, using market capitalizations as weights. Specifically, we use the following value-weighted measures for the cross-sectional mean, variance, skewness, and kurtosis of idiosyncratic volatility:

$$M_t = \sum_i w_{i,t} IV_{i,t} \tag{3}$$

$$V_t = \sum_i w_{i,t} (IV_{i,t} - M_t)^2 \tag{4}$$

$$S_t = \frac{1}{N_t} \sum w_{i,t}^{\frac{3}{2}} \Big(\frac{IV_{i,t} - M_t}{\sqrt{V_t / N_t}} \Big)^3 \tag{5}$$

$$K_t = \frac{1}{N_t} \sum w_{i,t}^{2} \Big(\frac{IV_{i,t} - M_t}{\sqrt{V_t / N_t}} \Big)^4 - 3, \tag{6}$$

where $w_{i,t}$ is the weight for stock i based on its market capitalization at the end of period $t-1$ and N_t is the number of firms in the cross-section at period t.

To further examine the shape of the cross-sectional distribution of idiosyncratic volatility in a given period, we also calculate the relative contribution of each decile to the cross-sectional mean. First, at period t, we rank stocks into deciles based on their idiosyncratic volatility. Then, using prior-period-end market capitalization as weights, we calculate the share of the k^{th} decile in the aggregate idiosyncratic volatility during period t as follows:[4]

$$d_{k,t} = \sum_{i \in k} w_{i,t} IV_{i,t} / M_t. \tag{7}$$

Therefore, the shares of the deciles sum to unity. Using this measure, we evaluate the contribution of each decile to the aggregate idiosyncratic volatility in a point in time.

Diverging time trends of the extreme deciles Figure 1 shows the time trends of the cross-sectional moments of monthly idiosyncratic volatility, estimated using Equations (3)–(6). The first panel plots the 12-month moving average of the cross-sectional mean of idiosyncratic volatility (annualized). The panel confirms the result of Brandt, Brav, Graham, and Kumar (2009) and others that the level of the aggregate idiosyncratic volatility increase until early 2000, but falls below its pre-1990 level by 2007. However, a large spike is apparent at the end of the sample period, reflecting the increase in volatility during the financial crisis of 2008.

Instead of focusing on the trend in the cross-sectional mean, our purpose is to examine the shape of the cross-sectional distribution. The second to fourth panels plot the time series of other statistical properties of the cross-sectional distribution. Panels B, C, and D show the 12-month moving averages of the cross-sectional variance, skewness, and kurtosis, respectively. Unlike the cross-sectional mean, the time trends of the higher moments are much more visible, especially the upward slopes in skewness and kurtosis. The increasing

[4]The results reported in this paper are robust to using equal weights in estimating the cross-sectional moments of idiosyncratic volatility, as well as the share of the k^{th} decile, $d_{k,t}$. These terms display similar time trends as their value-weighted counterparts. In the next section, we formally test the divergence of trends between d_{10} and d_1. Using equal weights, this divergence is statistically significant and of similar magnitude as that using value weights. In this paper, we follow most works in the literature and only report the value-weighted results for brevity.

skewness indicates that firms with high volatility, compared to the cross-sectional mean, have become more volatile over time, while the increasing kurtosis suggests both the proportion of relatively high-volatility firms and the proportion of relatively low-volatility firms, compared to the mean, have increased.

To further examine the shape of the cross-sectional distribution, we divide firms into decile groups based on their idiosyncratic volatility level. Then, as in Equation (7), we compute the share of each decile in the total cross-section, $d_{k,t}$, to evaluate the contribution of the decile to the aggregate idiosyncratic volatility. Figure 2 shows the time trend of our measure of each decile share. Panel A plots all deciles, while Panel B shows only the trends of Deciles 1 and 10. The noticeable feature of Panel A is that the share of Decile 1 has almost disappeared over time, while that of Decile 10 has more than doubled. In December 1964, the 12-month moving average of d_1 is 12.5%, while it is 2.8% in December 2008. Conversely, d_{10} is 10.3% in December 1964 and 18.6% in December 2008. The middle deciles (d_3 to d_8) do not display much change over time. Thus, we focus on the extreme deciles in Panel B. We normalize each of the time series by its beginning-of-the-sample value, and plot the normalized time series to compare the trends in the extreme deciles. The panel shows the diverging time trend in the extreme deciles more clearly. The slopes in both deciles appear prominent with opposite signs. Stocks with high idiosyncratic volatility compared to the average idiosyncratic volatility become more volatile compared the mean. Likewise, stocks with low volatility become less volatile.[5]

In Section 4 below, we formally show that the time trends in the extreme deciles are statistically significant. We also show that these diverging trends in the extreme deciles are related to the increasing capital of hedge funds. Interestingly, Panel C of Figure 1 and Panel

[5]In Appendix A, we show that the diverging time trends of the extreme deciles are robust to alternative measures of idiosyncratic risk. Specifically, using the market model, adding a momentum factor to the Fama-French three factors, or applying he method of Campbell, Lettau, Malkiel, and Xu (2001) results with qualitatively similar time trends to those obtained using the Fama-French three-factor model in Equation (1). Appendix A also shows that the diverging time trends are robust to the number of listed firms, firm size, liquidity, industry affiliation, and other characteristics.

B of Figure 2 exhibit weak trends during earlier periods (1960's and 1970's) when presumably hedge funds played a relatively minor role in stock markets, while there exist strong trends after the 1980's as hedge funds have become influential investors. This suggests that these time trends are related to the increasing impact of hedge-fund trading.

B. Idiosyncratic cash-flow volatility

Our main control variable for the fundamental process driving idiosyncratic risk is the idiosyncratic cash-flow volatility. To estimate idiosyncratic cash-flow volatility, we generally follow the method proposed by Irvine and Pontiff (2009), with some additional modifications. Unlike idiosyncratic return volatility, we estimate idiosyncratic cash-flow volatility only at the quarterly frequency due to data availability.[6] Quarterly idiosyncratic cash-flow volatility is estimated as follow. In a given quarter t, the cash-flow innovation (dE) for each firm is defined as $dE_{i,t} = (E_{i,t} - E_{i,t-4})/B_{i,t-1}$, where $E_{i,t}$ is the firm's cash-flow measure and $B_{i,t-1}$ is the book value of the firm's equity at $t-1$. We use earnings per share before extraordinary items (Compustat Item EPSPXQ) as the proxy for cash flows. For book equity, we use Compustat Item CEQQ and add short- and long-term deferred taxed items (Items TXDITCQ and TXPQ) if they are available.

Using the cash-flow innovation, we estimate the pooled cross-sectional time-series regres-

[6] Irvine and Pontiff (2009) construct monthly series of an idiosyncratic cash-flow volatility index by averaging firms of different reporting months over a three-month rolling period. This approach is inappropriate for the purpose of this study because we are interested in estimating the volatilities of individual stocks. Therefore, we construct only quarterly series of idiosyncratic cash-flow volatilities. Since we work with calendar quarters, the firms whose fiscal quarter-ends occur during a calendar quarter are pooled together with the firms whose reporting period is precisely the end of that calendar quarter.

sion separately for each Fama-French 48 industry (Fama and French (1997)):[7]

$$dE_{i,t} = \alpha + \beta_1 dE_{i,t-1} + \beta_2 dE_{i,t-2} + \beta_3 dE_{i,t-3} + \beta_4 dE_{i,t-4} + \epsilon_{i,t}. \tag{8}$$

The residuals from the above regressions are the individual firms' cash-flow shocks. As Irvine and Pontiff point out, at any point in time, the residuals of individual firms may not sum to zero. Therefore, from these individual shocks, we first calculate the marketwide idiosyncratic cash-flow shock by averaging across all the individual cash-flow shocks

$$\epsilon_{m,t} = \frac{1}{N_t} \sum \epsilon_{i,t}. \tag{9}$$

The squared difference between a firm's cash-flow shock and the marketwide cash-flow shock is the firm's idiosyncratic cash-flow volatility during period t

$$IV_{i,t}^{CF} = (\epsilon_{i,t} - \epsilon_{m,t})^2. \tag{10}$$

Idiosyncratic cash-flow volatilities are divided into deciles based on the firms' idiosyncratic return volatility rank. The share of the k^{th} return volatility decile in the entire cross-section of idiosyncratic cash-flow volatility is calculated using market weights as follows

$$d_{k,t}^{CF} = \sum_{i \in k} w_{i,t} IV_{i,t}^{CF} / \sum_{j} w_{j,t} IV_{j,t}^{CF}. \tag{11}$$

Quarterly EPS and book equity data are obtained from the intersection of Compustat and the CRSP sample.[8] The sample firms are required to have at least 8 consecutive quarters

[7] Irvine and Pontiff (2009) do not scale the cash-flow innovation by book equity. Instead, they use the unscaled innovation $\Delta E_{i,t} = E_{i,t} - E_{i,t-4}$ as the regression variables in Equation (8). The regression residuals are then scaled by previous end-of-quarter stock prices, which is analogous to our regression residual, $\epsilon_{i,t}$, from Equation (8). However, we find that pooling firms without scaling their earnings causes inaccurate estimates of the residuals. Since our purpose is to examine the entire cross-section of idiosyncratic volatility rather than its mean value, we wish to obtain individually sensible estimates for the idiosyncratic cash-flow volatilities, and therefore we scale by book equity before running the regression.

[8] Since we lose observations from the CRSP sample when we take the intersection of Compustat and

of available EPS data. We also require that book equity at the end of the previous quarter is nonmissing and positive. We winsorize the bottom and top 0.5% of cash-flow innovation (dE) to avoid potential accounting errors and to alleviate the impact of outliers in the regression. The sample period for the pooled regression in (8) is from January 1972 to December 2008 due to the availability of book-equity data.

3. Firm-level analyses

In this section, we document empirical patterns of idiosyncratic volatility of common stocks which support our main hypotheses. In particular, we present firm-level evidence in line with the hypothesis that a larger invested capital implies a larger positive (negative) *change* in idiosyncratic volatility for stocks in the top (bottom) decile. As an argument against reverse causality, we also present a natural experiment implying that exogenous shocks to the loss bearing capacity of hedge funds induce increased idiosyncratic volatility of the stocks they hold. To further examine whether large idiosyncratic shocks are amplified by hedge-funds trading through a funding liquidity mechanism, we investigate the effect of hedge-fund leverage and trading patterns of hedge funds subsequent to idiosyncratic volatility shocks.

A. Baseline results: Regressions of subsamples

In this subsection, we perform firm-level analyses to investigate the mechanism through which the trading activity of hedge funds and the cash-flow volatility affect the idiosyncratic volatility of individual firms and whether the mechanism is affected by the liquidity level of the stocks.

To identify the contrasting effect of hedge-fund trading depending on the level of id-

the CRSP sample, the stocks in $d_{k,t}^{CF}$ do not exactly correspond to the stocks in $d_{k,t}$. To consider the loss of observations in the Compustat and the CRSP sample intersection, we re-rank stocks in the intersection sample based on their idiosyncratic return volatilities. Then we calculate $d_{k,t}^{CF}$ for return decile k of the intersection sample.

iosyncratic volatility, we divide the full sample into three subsamples: Samples of firms in Decile 1, Decile 10, and the middle deciles. Although analyses using subsamples may suffer a sample-selection bias, subsample results can give a good benchmark for further analysis. We will address the potential sample-selection bias using several different methods in the next subsections.

For the firm-level analyses, we compute the hedge-fund ownership per stock using a matched sample of hedge fund names from Lipper/TASS and financial institution names as reported on the 13F filings available through Thomson Financial. We exclude major U.S. and foreign investment banks and their asset management subsidiaries, because their hedge-fund assets constitute only a small portion of their asset holdings reported in 13F. The matched sample totals 1,252 funds.

For each subsample, we estimate the following regression model:

$$\Delta IV_{i,t} = \alpha + \beta_1 HF_{i,t-1} + \beta_2 \Delta CF_{i,t} + \beta_3 IO_{i,t-1} + \sum_{q \in \{1,5\}} \delta^q Q^q_{i,t-1} HF_{i,t-1} + \gamma' \mathbf{X}_{i,t-1} + \varepsilon_{i,t}, \quad (12)$$

where $\Delta IV_{i,t}$ is the change in idiosyncratic volatility (measured each quarter) of firm i from quarter $t-1$ to t, $\Delta CF_{i,t}$ is the change in cash-flow volatility, $HF_{i,t-1}$ is the level of hedge-fund ownership, $IO_{i,t-1}$ is the non-hedge-fund institutional ownership, $\mathbf{X}_{i,t-1}$ is a vector of control variables which includes firm leverage, illiquidity, and size, and the dummy variables $Q^q_{i,t-1}$, whose values equal one if a stock belongs to illiquidity Quintile q ($q = 1$ for liquid firms and $q = 5$ for illiquid firms) and zero otherwise. Firm leverage is measured as total liability divided by total assets. Illiquidity is estimated following Amihud (2002), using daily observations during a given quarter. We use first differences of idiosyncratic return volatility and idiosyncratic cash-flow volatility to eliminate the potential time trends. We estimate this model using both the panel and Fama-MacBeth regressions. For the panel regressions, standard errors are clustered within each firm, and the time (quarter) fixed-effect is included for each regression.

Table 1 reports the results. Panel A reports the summary statistics of regression variables and the lagged decile for each subsample.[9] The lagged decile shows that the average decile affiliation at quarter $t-1$ of firms in each subsample. For example, firms in Decile 1 at t are in Decile 2 at $t-1$, while firms in Decile 10 at t are in Decile 9 at $t-1$, on average. Panel A shows that firms in the extreme deciles display quite different characteristics from firms in the middle deciles. For example, firms in Decile 1 have higher leverage ratios, and are more liquid and larger than firms in the middle deciles. Also, hedge funds and other institutions tend to own less of Decile 1 firms than firms in the middle deciles. The differences in the means between the extreme deciles and the middle deciles are statistically significant. The significant differences between each sample may raise the issue of sample selection bias. We will test whether the selection bias drives our results in the next parts.

Panel B reports the panel regression results, while Panel C shows the results of Fama-MacBeth regressions. For each subsample, we use three different regression specifications: Model (1) includes only $\Delta CF_{i,t}$, $HF_{i,t-1}$, and $IO_{i,t-1}$; Model (2) includes the control variables, $\mathbf{X}_{i,t-1}$; and Model (3) includes the liquidity-quintile dummy interaction term. As a first step, it is useful to check that regression results are consistent with the intuition that cash-flow shocks increase the idiosyncratic return volatility. The results confirm this intuition; cash-flow volatility is positive and significant except firms in Decile 1. Thus, Table 1 shows that generally, cash-flow volatility positively affects idiosyncratic volatility for all deciles.

Second, consistent with our main hypothesis, hedge-fund ownership induces different

[9] This panel shows that the number of observations of each decile is not equal to one tenth of the entire observations. The reason that the number of observations is uneven is the loss of observations at the intersection of CRSP data, Compustat data, and institutional ownership data (CDA/Spectrum database of Thompson Financials). We first sort firms in the CRSP universe into deciles based on idiosyncratic risk, and then we match the firms with additional information from the other databases—a matching process that causes an uneven loss of observations from each decile. To address the concern regarding any sampling bias for Decile 1 and Decile 10 through this matching process, we repeat the analysis while first matching CRSP and other datasets, and then sorting stocks in the matched sample into idiosyncratic-risk deciles. We re-run Regression (12), and arrive at consistent results.

effects on stocks with high and low idiosyncratic volatility. Both the panel and Fama-MacBeth regressions show that although the results for hedge-fund ownership for the stocks in the middle deciles of idiosyncratic volatility are mixed, hedge-fund ownership displays a negative and significant coefficient for stocks in Decile 1, but a positive and significant coefficient for stocks in Decile 10. Moreover, compared to the stocks in the middle deciles, the effect of hedge-fund trading on the idiosyncratic volatility of stocks in the extreme deciles is much stronger insofar as economic magnitude. For example, the coefficient of HF in Model (3) of the panel regressions for the middle-decile sample is 0.05, while it is 0.56 and 0.17 (in absolute value), respectively for Decile 1 and Decile 10. This result suggests that hedge-fund trading activities reduce the volatility of low-volatility stock and increase the volatility of high-volatility stocks.

Also, the effects of hedge-fund ownership are generally stronger for highly illiquid firms when stocks belong to the top volatility decile. In the panel regression, the interaction term of hedge-fund ownership with Q_5 is significantly positive for Decile 10, while it is positive but not significant for Fama-MacBeth regression. In contrast, the interaction term of hedge-fund ownership with Q_1 is negative for Decile 10, indicating the amplification of volatility due to hedge-fund trading is concentrated in less liquid stocks. Additionally, non-hedge-fund institutional ownership generally exhibits a positive effect on idiosyncratic volatility. This finding is consistent with the findings in the literature that institutional ownership is positively related to idiosyncratic volatility (see, e.g., Xu and Malkiel (2003)).

Finally, we investigate whether we observe monotonic effects across deciles. Specifically, we run Regression (12) for each decile group. Figure 4 plots the hedge-fund coefficient and t-statistic for each regression. The figure indicates that hedge-fund effects are generally monotonic (in economic magnitude) across deciles. Therefore, this monotonicity of hedge-fund trading across deciles might explain the mixed and insignificant coefficient on HF for the middle decile subgroup.

To summarize, the panel regressions using subsamples provide evidence that hedge-fund trading activity is associated with the decrease of volatility of low-idiosyncratic-volatility stocks, and the increase of volatility of high-idiosyncratic-volatility stocks. This effect is stronger for more illiquid stocks.

B. Panel regressions of matched samples

The subsample approach in Table 1 might be subject to a self-selection bias. In other words, selecting firms in the extreme deciles might be equivalent to selecting firms with a high hedge-fund effect. In particular, we consider the following alternative hypothesis to our results. Suppose that there is a group of "wild stocks" with an unusually large fluctuation in month-to-month idiosyncratic volatility. These stocks frequently switch from very high volatility periods to very low volatility periods. Suppose that hedge funds prefer to trade these stocks, perhaps because they provide more perceived opportunities to generate abnormal returns. Then, even if their activity does not affect idiosyncratic volatility, one will observe an association between the hedge-fund ownership in stocks and both large negative and large positive movements of idiosyncratic volatility. Let us call this reasoning the "wild stock hypothesis."

Using a control-group approach, we provide evidence that our main results are not driven by the wild stock hypothesis. The implicit assumption of an effective control-group approach is that the econometrician's information set used to identify wild stocks has a significant overlap with that of hedge-fund managers. Note, however, we might not fully observe all the characteristics of wild stocks, in which case we propose a natural experiment discussed in the next subsection. The control-group approach creates two subsamples: The treatment sample and the control sample. Both samples have similar characteristics except that one is being treated and the other is not. In our case, the treatment is residing in the extreme volatility deciles and the treatment effect is hedge-fund trading effect on volatilities.

Suppose an assignment to the treatment group (Decile 1 or Decile 10) is completely random. Then, holding other variables constant, the hedge-fund ownership effect on idiosyncratic volatility can be measured by the difference of the hedge-fund effect on firms in the treatment group and those in the control group. Specifically, we measure the hedge-fund effect as

$$E[\Delta IV_{i,t}|D_{i,t}=1, HF_{i,t-1}] - E[\Delta IV_{i,t}|D_{i,t}=0, HF_{i,t-1}], \tag{13}$$

where $D_{i,t}$ is a dummy variable that equals one when firm i belongs to the treatment group at time t and zero otherwise. Therefore, the hedge-fund effect (i.e. the treatment effect), holding HF constant, is

$$E[\beta_T HF_{i,t-1}|D_{i,t}=1] - E[\beta_C HF_{i,t-1}|D_{i,t}=0] = \beta_T - \beta_C, \tag{14}$$

where the subscript T signifies the "treatment group" and C signifies the "control group."

However, an assignment to the treatment group might not be random, since the variable $IV_{i,t}$ influences both the outcome ($\Delta IV_{i,t}$) and the treatment assignment (whether $D_{i,t}=1$). Now, suppose that it is possible to observe variables that influence both the outcome and the treatment assignment. Let a set of those variables be $\mathbf{x}_{i,t}$. Suppose also that we can obtain pairs of observations matched by the common $\mathbf{x}_{i,t}$, one with $D_{i,t}=1$ and the other with $D_{i,t}=0$. Provided a sufficient number of pairs, one can average over the population of $\mathbf{x}_{i,t}$ to obtain the treatment effect. Thus, the average treatment effect is simply estimated by a matching estimator, $\hat{\beta}_T - \hat{\beta}_C$, where $\hat{\beta}$ is obtained from a regression using each group matched based on $\mathbf{x}_{i,t}$.

We use two different approaches to find the common $\mathbf{x}_{i,t}$. First, as firms enter and exit the extreme volatility deciles, we create a control group using the same firms in the treatment group, but in periods in which they do not belong to the extreme deciles. Specifically, we use firm-quarters from $t-2$ to $t+2$, excluding t, for the control groups, where t is the quarter during which the firms belong to the extreme deciles. Overall, this approach compares a firm to itself over different periods.

Second, we match firms by a propensity score, which is the probability of placing in one of the extreme deciles given the common observables, $\mathbf{x}_{i,t}$. To create the propensity-score-matching (PSM) control groups, individual firm-quarters are paired with those of similar propensity scores. To obtain the propensity scores, we run the following logistic regressions:

$$Prob\big(D^1_{i,t} \text{ (or } D^{10}_{i,t}) = 1\big) = \alpha + \beta_1 d_{i,t-1} + \beta_2 \Delta CF_{i,t} + \beta_3 HF_{i,t-1} + \beta_4 IO_{i,t-1} + \gamma \mathbf{X}_{i,t-1} + \varepsilon_{i,t}, \quad (15)$$

where $D^1_{i,t}$ ($D^{10}_{i,t}$) is the dummy variable that equals one when firm i belongs to Decile 1 (Decile 10) at time t and zero otherwise, $d_{i,t-1}$ is the decile number at $t-1$, and the other variables are defined in the same manner as in Equation (12). Each individual observation in the treatment group is then paired with the firm-quarter that has the same probability (up to two digits) to create the matched sample. Unmatched observations in the treatment groups are excluded from the treatment samples.

Once the control groups are created, we run regression (12) separately for the treatment and control groups. Then, we test the following null hypothesis:

$$\mathbf{H_o} : \beta_T - \beta_C \leq 0 \;\text{ for } D^{10} \;(\geq 0 \text{ for } D^1). \quad (16)$$

Table 2 presents the results of the control-group approach when the control groups are created using the same firms as in the treatment groups. Panel A shows the summary statistics and Panel B reports the regression results as well as the hypothesis testing of Equation (16). Panel A shows that the difference in firm characteristics between the control group and the treatment group is statistically significant except for the cash-flow volatility, although the magnitude is much smaller than that reported in Table 1. When a firm enters the Decile 1 sample, it tends to be less leveraged, more liquid, and bigger than itself at other points in time, while a firm entering Decile 10 sample shows the opposite characteristics. Also, Panel A reports the persistence of volatility, indicating that firms in Decile 1 (Decile 10) also tend to have low (high) volatility in other points in time.

Panel B shows that even though firms in the extreme deciles tend to have persistent volatility, the hedge-fund effect is much stronger when those firms are in the extreme deciles. The treatment effect ($= \beta_T - \beta_C$) is statistically significant for both Decile 1 and Decile 10 at 10% level[10], except for one case in Decile 10. For Decile 10, after controlling for the interaction term between hedge-fund ownership and the liquidity dummy (Model (3)), the treatment effect becomes insignificant. However, the coefficient of the interaction term with Q^5 for the treatment group is higher than that for the control group and is statistically significant, implying that the hedge-fund effect is stronger among illiquid stocks.

Table 3 reports the results of the PSM control groups. Panel A shows that although the differences between the control group and the treatment group are significant for some firm characteristics, they are not economically meaningful, as they are close to zero in most cases. Thus, the firms in treatment groups and the control groups have similar characteristics, when the PSM method is used. For example, the lagged volatility-decile affiliation of firms in the control groups is almost identical with that of firms in the treatment groups, although the difference between the two groups for Decile 10 (0.03) is statistically significant.

Panel B of Table 3 reports the regression results of PSM method. Consistent with previous tables. The null hypothesis of Equation (16) is rejected at the 10% level, except for the case in Decile 10 where the interactions with the liquidity dummies are included (Model (3)). In this case, however, we observe a positive and significant coefficient for the Decile 10 treatment group, contrary to the control groups. This implies that the coefficient of hedge-fund ownership is subsumed by the interaction term with liquidity dummies for the treatment group. Also, a more positive coefficient on the interaction term with Q^5 for

[10] Since an one-sided test is appropriate in this case, the 5% critical value is 1.65 and 10% critical value is 1.28

Decile 10 is consistent with our hypothesis that the hedge-fund effect is stronger for more illiquid firms. We also test for whether the interaction term with Q^5 of Decile 10 treatment group is statistically different from that of the control group (not reported in the table for brevity). The t-statistics of this test is 2.92. Therefore, the control-group approach offers consistent evidence with the baseline regressions in Table 1, confirming that hedge-fund ownership is associated with the decrease of volatility of low-idiosyncratic-volatility stocks, and the increase of volatility of high-idiosyncratic-volatility stocks.[11]

C. A natural experiment: The Lehman bankruptcy

If hedge funds pick wild stocks by characteristics that we cannot observe, then the control-group approach described in the previous part will not completely alleviate concerns that the wild stock hypothesis drives our results. To address the issue, we adopt a natural experiment approach. In our panel regressions, we think of extreme realizations of idiosyncratic volatility as the trigger for forced liquidation, which in turn amplifies the initial idiosyncratic shock. Instead, in this section, we use an exogenous instrument for such forced liquidations. In particular, we use the Lehman bankruptcy as a natural experiment in the spirit of Aragon and Strahan (2011). We show that the idiosyncratic volatility of stocks held by hedge funds with Lehman as their prime broker increased following the Lehman bankruptcy, while the idiosyncratic volatility of stocks held by other hedge funds did not. Thus, this case indicates that the direction of causality is as suggested by our hypothesis: hedge funds facing adverse shocks amplify idiosyncratic volatility.

[11] To further exclude the "wild stock hypothesis," we also examine the relation between a stock-level measure of volatility-of-volatility and hedge-fund ownership. Specifically, we estimate the future stock-level volatility-of-volatility (at the end of time $t-1$) as the variance of the percentage change in volatility, that is $(IV_{i,t} - IV_{i,t-1})/IV_{i,t-1}$, calculated over the four-quarter rolling window of t to $t+3$. Then, we use this measure of volatility-of-volatility as the dependent variable in Equation (12). We find that the coefficient on hedge-fund ownership is mostly negative or insignificant (except for Decile 1 stocks), while the wild stock hypothesis predicts a positive coefficient. These results reported in Table A2 and discussed in the appendix.

For this analysis, we run the following cross-sectional regression:

$$\Delta IV_i = \alpha + \beta_1 HF_i^L + \beta_2 HF_i^{NL} + \beta_3 IO_i + \sum_{q\in\{1,5\}} \delta_1^q Q_i^q HF_i^L + \sum_{q\in\{1,5\}} \delta_2^q Q_i^q HF_{i,t-1}^{NL} + \gamma' \mathbf{X}_i + \varepsilon_i, \quad (17)$$

where ΔIV_i is the difference between the pre-crisis and the post-crisis idiosyncratic volatility of firm i, HF_i^L is the fraction of the stock i owned by hedge funds that used Lehman as their prime broker, HF_i^{NL} is the non-Lehman hedge-fund ownership, and other variables are defined in the same manner as in Regression (12). The pre-crisis period is 07/01/2008–08/31/2008 and the post-crisis period is 09/15/2008–11/30/2008. Illiquidity is measured during the pre-crisis period, while all other variables are estimated at the end of 06/30/2008. Standard errors are clustered at the Fama-French 48 industry level.

Table 4 reports the results of the regressions.[12] This table shows that only Lehman-related hedge-fund ownership is positively associated with increase in idiosyncratic volatility during the Lehman bankruptcy. Non-Lehman hedge-fund ownership and other institutional ownership are negatively related to the changes in idiosyncratic volatility. The coefficient on Lehman hedge fund is positive and statistically significant for all specifications, while the coefficient on non-Lehman hedge fund is negative and significant for most specifications. These results provide strong evidence consistent with our hypothesis: In normal times, hedge-funds absorb economic shocks. However, facing large shocks while subject to liquidity constraints (in this case the Lehman bankruptcy), hedge funds lose their ability to provide liquidity, and, in turn, amplify the original shocks.

D. Further evidence: Funding liquidity and fire sales

In this subsection, we further investigate whether large idiosyncratic shocks can be amplified by hedge-fund trading through a funding liquidity mechanism, in which limits on hedge

[12] We thank Goerge O. Aragon and Philip E. Strahan for providing their dataset for this table.

funds' loss bearing capacity forces managers to liquidate their positions. First, we examine the long-horizon volatility. As suggested in Coval and Stafford (2007), the fire-sale effects on idiosyncratic volatility should be temporary and subsequently reversed. Thus, we study whether the hedge-fund effect on long-horizon idiosyncratic volatility deteriorates with the increase in estimation horizon. Specifically, we compute the (log) changes in idiosyncratic volatility from Period $t-1$ to the average idiosyncratic volatility over the expanding windows over the Period t to $t+j$ (where j=1, 2, and 3). We replace these variables as the dependent variable of Equation (12) and re-estimate the regression models. Figure 5 reports the regression results. Consistent with the temporary effect induced by an event of a fire-sale, Figure 5 shows that the hedge-fund effect on idiosyncratic volatility diminishes as j increases.

Next, we examine whether the effects of hedge-fund trading are indeed weaker among stocks that are held by hedge funds subject to less funding constraints. We use two measures for funding constraints: fund leverage and lockup provision. Specifically, we divide hedge funds into two groups based on their funding constraints and calculate the stock ownership of each group. Then, we re-estimate Regression (12) for Decile 1 and Decile 10, using the ownership of each hedge-fund group as a main independent variable. In other words, instead of using the entire hedge-fund ownership, $HF_{i,t-1}$, we separately use the ownership of hedge funds that use leverage (or lockup provision) and the ownership of hedge funds that do not use leverage (or lockup provision). Both hedge funds that use leverage and/or hedge funds without a lockup provision are considered to be more funding constrained.[13]

Table 5 reports the results. The table shows that the effect of hedge funds is stronger for stocks that are held by hedge funds that use leverage or do not apply a lockup period, for Decile 1 stocks. For Decile 10 stocks, the hedge-fund effect is not particularly stronger for stocks that are held by leveraged hedge funds or those without a lockup period. However,

[13]Leverage is obtained from the Lipper/TASS database, which includes a dummy variable for hedge funds that state that they apply leverage. Similarly, the data includes information about fund lockup period; conditional on applying a lockup, the distribution is narrowly centered around one year, therefore we simply separate funds into those that apply and do not apply a lockup provision.

for Decile 10 stocks, the hedge-fund effect is stronger for stocks that have higher ex-ante illiquidity and owned by hedge funds with leverage or without a lockup provision, which is consistent with the funding-liquidity explanation.

Finally, we examine whether there is a fire-sale effect during a high-volatility period for stocks with high-hedge-fund ownership. Specifically, one would expect that the stocks with both high-idiosyncratic volatility in Quarter t and high-hedge-fund ownership in Quarter $t-1$ would be traded more intensely by hedge funds in Quarter t. To examine this fire-sale effect, we run the following regression

$$\begin{aligned} \Delta HF_{i,t} &= \alpha + \beta_1 HF_{i,t-1} + \sum_{d\in\{1,10\}} \beta_2^d D_{i,t}^d + \sum_{d\in\{1,10\}} \delta_1^d D_{i,t}^d HF_{i,t-1} \\ &\quad + \sum_{d\in\{1,10\}} \sum_{q\in\{1,5\}} \delta_2^{d,q} D_{i,t}^d Q_{i,t-1}^q HF_{i,t-1} + \gamma' \mathbf{X}_{i,t-1} + \varepsilon_{i,t}, \end{aligned} \tag{18}$$

where $\Delta HF_{i,t}$ is the change in hedge-funds ownership (measured each quarter) of firm i from quarter $t-1$ to t, and $D_{i,t}^1$ ($D_{i,t}^{10}$) is a dummy variable that equals one when firm i belongs to Decile 1 (Decile 10) at time t and zero otherwise. The control variables, $\mathbf{X}_{i,t-1}$, are defined in the same manner as in Equation (12). The results are reported in Table 6. Consistent with the fire-sale explanation, Table 6 shows a significant negative coefficient on the interaction between D^{10} and the lag of hedge-fund ownership. This is indicative of a sell-off for stocks with both high-idiosyncratic volatility in Quarter t and high-hedge-fund ownership in Quarter $t-1$. Also, a negative and significant coefficient on the interaction term of D^{10}, HF, and Q_1 suggests that the fire-sale is concentrated in more liquid stocks, which is consistent with recent works (e.g., Sadka (2010) and Ben-David, Franzoni, and Moussawi (2012)). Overall, the results reported in this subsection provide additional evidence for the hypothesis that large idiosyncratic shocks are further amplified by hedge funds through a funding-liquidity mechanism.

4. Time-Series Analyses

In this section, we present time-series evidence in line with the hypthosis that the larger the invested capital of hedge funds in a given stock, the higher (lower) level of estimated idiosyncratic volatility for the stock relative to the period-average idiosyncratic volatility, provided that the stock belongs to the top (bottom) decile of the cross-sectional distribution in the period.

A. Time-Trend Tests

In the Section 2, we show the descriptive evidence of the diverging time trend of the extreme deciles. In this section, we formally test the significance of the time trend, using monthly computed idiosyncratic volatility. Specifically, we run the following regression model with autocorrelated errors

$$\begin{aligned} d_{k,t} &= \alpha + \delta t + \nu_t; \\ \nu_t &= \sum_{j=1}^{m} \rho_j \nu_{t-j} + \varepsilon_t. \end{aligned} \tag{19}$$

We correct for the autocorrelation in the error terms for up to six lags ($m = 6$). We use maximum likelihood to estimate the model. The result of the regression is reported in Table 7. For Deciles 1 and 2, the time trend is significantly negative, while the trend is significantly positive for Deciles 5 through 10. In addition, the time-trend coefficients increase monotonically across deciles, from -2.14 ($\times 10^{-4}$) to 1.30 ($\times 10^{-4}$). Also, the trend coefficient of Decile 10 is noticeably higher than those in other positive-trend deciles. For example, the trend of Decile 10 is about six times larger than that of Decile 5. Also, as shown in the last row of the table, the diverging trend of the extreme deciles is strongly apparent. The coefficient of the time trend of $d_{10} - d_1$ is 3.57 ($\times 10^{-4}$) with a t-statistic of 7.35.

We also test whether the trend in d_k is stochastic by running a Phillips-Perron unit-root test with only a constant term and with a constant term and a time-trend term. Specifically, Phillips-Perron unit-root tests are based on the following autoregressive models

$$d_{k,t} = \alpha + \gamma d_{k,t-1} + u_t; \tag{20}$$

$$d_{k,t} = \alpha + \delta t + \gamma d_{k,t-1} + u_t. \tag{21}$$

The last two columns of Table 7 report the p-values of the Phillips-Perron tests. For the test that uses a constant term alone (Equation (20)), we reject a unit root for d_{10} at the 5% level, and for d_1, d_8, and d_9 at the 10% level, while for other deciles, we cannot reject a unit root. However, a unit-root process is significantly rejected for the difference $d_{10} - d_1$. For the test that includes a time-trend term (Equation (21)), we reject a unit root for all deciles, including the difference $d_{10} - d_1$, at conventional levels. Thus, we conclude that the time series can be described as at least trend-stationary processes.

The results of the time-trend regressions of the idiosyncratic volatility deciles confirm the existence of deterministic trends, with a downward slope in the low deciles and an upward slope in the high deciles. It also shows that the time trends are monotonic in the rankings of idiosyncratic volatility. The time trend is the most negative for Decile 1 and the most positive for Decile 10. This implies that the contribution of the low deciles to the aggregate idiosyncratic volatility has become smaller while the contribution of high deciles has become larger. Notice that the observed time trend of d_k is independent of the level of the aggregate idiosyncratic volatility because in estimating d_k, we divide the decile idiosyncratic volatility by the cross-sectional mean. Doing so effectively discards the trend in the aggregate idiosyncratic volatility from our d_k measure. Therefore, the trends in the aggregate idiosyncratic volatility reported in Campbell, Lettau, Malkiel, and Xu (2001) and other studies do not affect our results. Since the time-trend coefficients monotonically increase with the decile ranking, from now on we focus only on the extreme deciles, d_1 and

d_{10}, and the difference between these two extreme deciles, $d_{10} - d_1$.

B. Time-series regressions: Determinants of the time trend

In this subsection, we study the potential determinants of the diverging time trends in the extreme deciles of idiosyncratic volatility. We run the following time-series regression

$$d_{k,t} = \alpha + \delta t + \beta_1 d_{k,t}^{CF} + \beta_2 LSE_{t-1} + \gamma' \mathbf{X}_{t-1} + \theta_1 TED_{t-1} + \theta_2 TED_{t-1} \times LSE_{t-1} + \varepsilon_t, \quad (22)$$

where $d_{k,t}$ is the share of decile k in the aggregate idiosyncratic volatility during period t (we study d_1, d_{10}, and $d_{10} - d_1$), $d_{k,t}^{CF}$ is the share of idiosyncratic cash-flow volatility of the corresponding decile, LSE_t is the total AUM of Long/Short-Equity funds at the end of period t, TED_t is the difference between the three month T-bill interest rate and the three-month LIBOR at the end of period t, and $\mathbf{X}$ is the vector of control variables. The dependent variables and all the explanatory variables except the time trend and TED are log-transformed. Note, since some of the variables are available only at quarterly frequency, Regression (22) is estimated using quarterly observations (the time trends in idiosyncratic volatility described in the previous subsection are also present at the quarterly frequency).

We use AUM of Long/Short-Equity funds as a proxy for hedge-fund trading activity in the equity market.[14] Fund AUMs are obtained from Lipper/TASS database. We consider TED as a proxy for the financing costs of long-short positions. The control variables include illiquidity and firm leverage. Illiquidity is estimated quarterly following Amihud (2002) and firm leverage is measured as total liability over market equity. (Similar results are obtained while using book equity instead of market equity.)

We also control for the trading activity of different types of institutions: non-Long/Short-

[14]Note, for the panel regressions in the previous section, we use the fraction of shares held by hedge funds, irrespective of fund investment style. For the time-series regressions in this section, we use total fund AUM, but to assure the use of AUM of funds that mostly trade in the equities market, we focus on the AUM of Long/Short-Equity funds.

Equity funds, and other institutional investors. As only a small fraction of total institutional ownership is due to hedge funds, we use the total dollar amount owned by institutions to proxy for the trading activity of non-hedge-fund institutions. Note, since we use hedge-fund AUM for the time-series tests, we measure institutional ownership in terms of capital amount rather than percentage ownership. Therefore, institutional ownership is measured as the total market capital owned by institutions for each decile of idiosyncratic return volatility at the end of previous quarter. Specifically, we calculate the market capitalization owned by institutions for each individual firm, and then add up all the market capitalizations owned by institutions for the firms in each decile. Due to the availability of hedge fund data, the sample period for the regressions is January 1994 through December 2008. Variables for trading activities and firm leverage are the values at the end of previous quarter, while the idiosyncratic cash-flow volatility and illiquidity are contemporaneously measured with d_k.

We keep the time trend as one of the independent variables throughout different specifications. By adding the time trend, both dependent and independent variables are effectively detrended. Therefore, Equation (22) is equivalent to the regression model where the residuals from a regression of d_k on a time trend are regressed on the set of residuals obtained from regressions of each independent variable on a time trend. The reported t-statistics are Newey-West adjusted using four lags.

Table 8 reports the regression results. Panel A reports the time trend of each of the dependent and independent variables. Note that the diverging trends in d_1 and d_{10} reported in Section 2 for the period 1964–2008 (using monthly observations) also hold for the more recent period 1994–2008 (using quarterly observations). The t-statistics of the time trends for d_1 and d_{10} are -1.92 and 4.11, respectively. Illiquidity for Decile 1 display a significantly negative trend, while firm leverage for Decile 10 is significantly positive. Hedge-fund AUMs display strong positive trends, and institutional ownership appears with a significant positive trend for both the top and bottom deciles.

Panel B reports the time-series regression results for nine different models. The first model includes a time trend and the cash-flow volatility. The coefficient of cash-flow volatility, β_1, is significant for all three dependent variables. However, the inclusion of cash-flow volatility does not weaken the significance of the time trends. The second model considers a time trend and the AUM of Long/Short-Equity fund, LSE, as independent variables. The signs of the coefficients of LSE are consistent with our hypothesis. Its coefficient for d_1 is significantly negative, while it is positive, albeit insignificant, for d_{10}. Also, the inclusion of LSE flips the signs of time trends for both d_1 and d_{10}. The trend of d_1 becomes significantly positive, while that of d_{10} changes to negative, though not statistically significant. Thus, this evidence suggests that to the extent that LSE represents the trading activity of hedge funds in equities, Long/Short-Equity funds trade in a manner that reduces the volatility of stocks with low-idiosyncratic volatility and increases the volatility of stocks with high-idiosyncratic volatility. Also, based on the sign of the coefficients of the time trend, we conclude that without the trading activity of Long/Short-Equity funds, the observed trends of the extreme deciles would have been converging rather than diverging.

The third model includes both cash-flow volatility and LSE. Note, although the diverging trend in $d_{10} - d_1$ is attributed to both cash-flow volatility and LSE, the two variables contribute to the diverging trends in opposite ways. The increasing trend in d_{10} is mirrored by the trend of cash-flow volatility, while the decreasing trend in d_1 is associated with the trading activity of Long/Short-Equity funds. By Models (4), (5), and (6), we illustrate that the effects of these two variables are robust to different model specifications. Nevertheless, a comparison of Models (4) and (6) highlights that the variables that proxy for institutional trading are important for understanding the time trends in the extreme deciles, because the inclusion of variables unrelated to the institutional trading is not sufficient for eliminating the significance of this time trend. Model (6) also shows that after various controls are included, the cash-flow volatility becomes insignificant for explaining the trend in d_1.

In Models (7), (8), and (9), we control for the financing costs of a long-short position by including the TED spread. We also include the interaction term between the TED spread and the AUM of Long/Short-Equity funds. Model (7) includes these two new variables along with our main explanatory variables, but not the controls. Model (8) includes the TED spread and the interaction term, in addition to LSE and the controls related to trading activity, while Model (9) also includes cash-flow volatility and firm leverage. Interestingly, all three models show that the interaction term has a significantly positive coefficient for the d_{10} regression, but not for the d_1 regression. This is consistent with our proposed mechanism. We argue that as the trading activity of hedge funds increase, large idiosyncratic shocks are further amplified, especially when the cost of financing long-short positions is high. High financing costs make the loss limit of financial institutions more stringent and cause more frequent fire-sales. According to this argument, d_1 is less likely to be affected by the interaction term, because for stocks experiencing small shocks, the financing costs of short-positions have much less of an effect on the trading activity of arbitrageurs.[15]

We conclude that our time-series results provide evidence that the trend in the bottom decile is mostly related to the activity of financial institutions, while the trend in the top decile is both associated with the changes in the distribution of the underlying cash flows and the increasing activity of financial institutions.

[15] We further test whether the effects of the increasing trading activity of hedge funds are amplified with the illiquidity of the stock. Specifically, we divide the sample into illiquidity quintiles and estimate Regression (22) within illiquidity Quintile 1 (most liquid stocks) and Quintile 5 (least liquid stocks) for the sample period 1994–2008. Consistent with our hypothesis, we find evidence that the effects of Long/Short-Equity funds' trading activity are stronger for less liquid stocks. The results are reported in Table A3 and discussed in Appendix C. We also test whether our results are driven by the financial crisis of 2008 by estimating Regression (22) on the shorter sample period of January 1994 through December 2007. The results, not reported for brevity, show that our conclusions are not driven by the financial crisis.

5. Conclusion

Periods with extreme idiosyncratic shocks embody an important risk for financial institutions performing arbitrage under loss limits. In this paper, we hypothesize that the aggregate trading activity of these institutions also feeds back to the probability of extreme idiosyncratic shocks. In particular, we argue that the trading activity of hedge funds reduce the volatility of low-idiosyncratic-volatility stocks but amplify that of high-idiosyncratic-volatility stocks.

Our empirical results are consistent with this hypothesis. First, from our sample period 1963–2008, we discover that the cross-sectional distribution of idiosyncratic volatility of US stocks has been increasingly skewed. The share of top decile of idiosyncratic volatility in the aggregate idiosyncratic volatility has doubled over the period, while the share of bottom decile has almost vanished. These trends are observed regardless of firms' industry, liquidity, and size, as well as the sign of price change.

Second, from firm-level regressions for a shorter sample period, 1994–2008, we provide evidence for a strong relation between hedge-funds' ownership of a stock and the changes of idiosyncratic volatility of that stock. Hedge-fund ownership is strongly associated with a decrease in idiosyncratic volatility if the stock belongs to the bottom decile, while it is related to an increase in volatility if the stock belongs to the top decile. A natural experiment using the Lehman bankruptcy also corroborates our hypothesis.

Finally, using time-series regressions, we show that the AUM of hedge funds plays an important role in explaining both the increasing share of the top decile and the decreasing share of the bottom decile. All these results are consistent with our proposed mechanism that increasing capital of hedge funds exacerbates idiosyncratic volatility of the top decile but attenuates that of the bottom decile.

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Table 1: Regressions of Idiosyncratic Volatility Deciles

The table reports the results of regressions of three subsamples that are formed based on idiosyncratic volatility deciles. Panel A reports the summary statistics. Panel B shows the results of panel regressions, while Panel C reports the results of Fama-MacBeth regressions. The dependent variable is the changes in the log of idiosyncratic volatility, and the independent variables are $\Delta CF_{i,t}$, the changes in the log of idiosyncratic cash-flow volatility, $HF_{i,t-1}$, the level of hedge-fund ownership at the end of quarter t-1, $IO_{i,t-1}$, the non-hedge-fund institutional ownership at the end of quarter t-1, $ILLIQ_{i,t-1}$, the Amihud (2002) illiquidity in quarter t-1, firm leverage in quarter t-1, size at the end of t-1, and the dummy variables, $Q^q_{i,t-1}$, that equal one if a stock belongs to illiquidity Quintile q (q=1 for liquid firms and q=5 for illiquid firms) and zero otherwise. Idiosyncratic cash-flow volatility is estimated following Irvine and Pontiff (2010). Hedge-fund ownership is the percentage holdings of institutions which are identified as hedge funds from a list of hedge fund names obtained from Lipper/TASS. Institutional holding data based on 13F filings are available through the CDA/Spectrum database of Thompson Financials. Size is the log of market capitalization. For panel regressions in Panel B, standard errors are clustered within each firm, and the time (quarter) fixed effect is included. The t-statistics are reported in square brackets. The sample period is 1994–2008.

Panel A: Summary Statistics

Subsample	Middle Deciles (M)		Decile 1		Mean Difference (1-M)		Decile 10		Mean Difference (10-M)	
Variable	Mean	Std	Mean	Std	Difference	t value	Mean	Std	Difference	t value
N	219,129		12,035				23,527			
ΔCF	0.05	3.23	0.07	3.21	0.02	[0.50]	0.20	3.45	0.15	[6.61]
HF	0.12	0.11	0.09	0.09	-0.03	[-29.34]	0.07	0.10	-0.05	[-64.94]
IO	0.28	0.24	0.27	0.21	-0.01	[-5.59]	0.14	0.18	-0.15	[-92.09]
Leverage	0.53	0.25	0.63	0.22	0.10	[42.58]	0.47	0.25	-0.07	[-39.28]
ILLIQ	-17.43	3.03	-18.82	2.60	-1.39	[-49.18]	-14.63	2.93	2.80	[135.32]
Size	12.80	1.89	13.93	1.84	1.13	[64.12]	10.84	1.48	-1.96	[-154.25]
Lagged decile	5.61	2.44	1.86	1.40	-3.75	[-167.15]	9.06	1.33	3.45	[213.43]

Panel B: Panel Regressions

Subsample	Middle Decile			Decile 1			Decile 10		
Variable\Model	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
Intercept	-0.07	-0.37	-0.40	-0.25	-1.52	-1.57	0.22	-0.83	-0.87
	[-6.80]	[-29.73]	[-30.04]	[-7.72]	[-16.63]	[-16.00]	[5.60]	[-12.92]	[-13.03]
ΔCF (× 100)	0.30	0.30	0.30	0.35	0.35	0.35	0.41	0.37	0.38
	[6.28]	[6.29]	[6.29]	[1.47]	[1.50]	[1.47]	[2.44]	[2.23]	[2.26]
HF	-0.03	0.04	0.05	-0.86	-0.72	-0.56	0.43	0.32	0.17
	[-2.18]	[2.90]	[3.47]	[-5.90]	[-4.81]	[-3.42]	[5.52]	[4.23]	[1.81]
IO	0.12	0.01	0.02	0.43	0.05	0.06	0.63	0.26	0.29
	[21.06]	[2.31]	[3.38]	[7.94]	[0.82]	[1.13]	[14.16]	[5.69]	[6.15]
$Q_1 \cdot HF$			-0.12			-0.38			-0.05
			[-8.33]			[-1.97]			[-0.34]
$Q_5 \cdot HF$			0.09			-0.76			0.33
			[2.98]			[-1.00]			[2.79]
Leverage		0.12	0.13		-0.12	-0.11		0.19	0.20
		[27.72]	[28.02]		[-2.38]	[-2.28]		[8.85]	[8.85]
ILLIQ		-0.01	-0.01		-0.11	-0.11		-0.01	-0.01
		[-6.17]	[-7.18]		[-8.00]	[-8.22]		[-2.57]	[-3.32]
Size		0.01	0.01		-0.05	-0.05		0.08	0.08
		[6.56]	[6.70]		[-2.68]	[-2.64]		[10.30]	[10.02]
Adj. R^2	0.117	0.123	0.123	0.134	0.171	0.172	0.132	0.153	0.153

Panel C: Fama-MacBeth Regressions

Subsample	Middle Decile			Decile 1			Decile 10		
Variable\Model	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
ΔCF (× 100)	0.29	0.27	0.27	0.49	0.52	0.62	0.33	0.30	0.32
	[4.86]	[4.88]	[4.94]	[0.97]	[1.11]	[1.22]	[2.20]	[2.09]	[2.24]
HF	-0.03	0.04	0.07	-1.45	-1.14	-1.40	0.43	0.34	0.30
	[-1.12]	[1.54]	[3.28]	[-4.56]	[-3.88]	[-2.53]	[5.32]	[4.61]	[2.30]
IO	0.13	0.03	0.04	0.51	0.00	0.08	0.72	0.37	0.38
	[6.46]	[2.01]	[2.48]	[6.15]	[0.04]	[0.92]	[13.43]	[6.76]	[6.73]
$Q_1 \cdot$HF			-0.18			-0.22			-2.64
			[-4.51]			[-0.70]			[-1.05]
$Q_5 \cdot$HF			0.01			-6.12			0.16
			[0.12]			[-0.66]			[0.94]
Leverage		0.12	0.12		0.01	0.01		0.19	0.18
		[6.82]	[6.91]		[0.07]	[0.14]		[7.20]	[7.00]
ILLIQ		-0.01	-0.01		-0.12	-0.15		-0.02	-0.02
		[-2.54]	[-3.14]		[-6.15]	[-7.76]		[-1.81]	[-1.91]
Size		0.01	0.01		-0.05	-0.08		0.08	0.08
		[2.13]	[2.34]		[-2.04]	[-3.21]		[5.63]	[5.49]

Table 2: Regressions of Matched Samples using Same Firms

The table reports regressions results of treatment and those of control groups. The treatment groups are the firm-quarters that belong to the extreme volatility deciles. The control groups include firm-quarters of the same firms in the treatment groups, when those firm-quarters do not belong to the extreme deciles. Specifically, firm-quarters from t-2 to t+2, excluding t, are included in the matched samples, where t is the quarter in which the firm belongs to the extreme decile. The dependent variable is the changes in the log of idiosyncratic volatility, and the independent variables are $\Delta CF_{i,t}$, the changes in the log of idiosyncratic cash-flow volatility, $HF_{i,t-1}$, the level of hedge-fund ownership at the end of quarter t-1, $IO_{i,t-1}$, the non-hedge-fund institutional ownership at the end of quarter t-1, $ILLIQ_{i,t-1}$, the Amihud (2002) illiquidity in quarter t-1, firm leverage in quarter t-1, size at the end of t-1, and the dummy variables, $Q^q_{i,t-1}$, that equal one if a stock belongs to illiquidity Quintile q (q=1 for liquid firms and q=5 for illiquid firms) and zero otherwise. Idiosyncratic cash-flow volatility is estimated following Irvine and Pontiff (2010). Hedge-fund ownership is the percentage holdings of institutions which are identified as hedge funds from a list of hedge fund names obtained from Lipper/TASS. Institutional holding data based on 13F filings are available through CDA/Spectrum database of Thompson Financials. Size is the log of market capitalization. The bottom row reports the t-statistics for the hypothesis that the coefficient on hedge-fund ownership is equal for the treatment and the control group (HF_T - HF_C = 0). Standard errors are clustered within each firm, and the time (quarter) fixed effect is included for each regression. The t-statistics are reported in square brackets. The sample period is 1994–2008.

Panel A: Summary Statistics

Subsample	Decile 1						Decile 10					
Group	Treatment		Control		Mean Difference		Treatment		Control		Mean Difference	
Variable	Mean	Std	Mean	Std	Difference	t value	Mean	Std	Mean	Std	Difference	t value
N	12,035		17,150				23,527		31,186			
ΔCF	0.07	3.21	0.00	3.17	0.06	[1.60]	0.20	3.45	0.15	3.40	0.05	[1.60]
HF	0.09	0.09	0.10	0.10	-0.01	[-10.57]	0.07	0.10	0.10	0.11	-0.02	[-24.67]
IO	0.27	0.21	0.29	0.22	-0.02	[-6.89]	0.14	0.18	0.19	0.21	-0.05	[-28.34]
Leverage	0.63	0.22	0.64	0.23	-0.01	[-3.52]	0.47	0.25	0.45	0.25	0.02	[8.81]
ILLIQ	-18.82	2.60	-18.41	2.88	-0.41	[-12.51]	-14.63	2.93	-15.78	2.85	1.15	[46.34]
Size	13.93	1.84	13.65	1.97	0.28	[12.09]	10.84	1.48	11.52	1.47	-0.68	[-53.34]
Lagged Decile	1.86	1.40	2.50	1.74	-0.63	[-32.96]	9.06	1.33	8.47	1.67	0.60	[44.87]

Panel B: Regression Results

Subsample	Decile 1						Decile 10					
Group	Treatment			Control			Treatment			Control		
Variable\Model	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
Intercept	-0.25	-1.52	-1.57	0.25	0.25	0.26	0.22	-0.83	-0.87	-0.37	-0.62	-0.66
	[-7.72]	[-16.63]	[-16.00]	[7.83]	[5.06]	[4.68]	[5.60]	[-12.92]	[-13.03]	[-11.02]	[-13.36]	[-13.66]
ΔCF (× 100)	0.00	0.00	0.00	0.01	0.01	0.01	0.00	0.00	0.00	0.01	0.01	0.01
	[1.47]	[1.50]	[1.47]	[2.97]	[2.93]	[2.92]	[2.44]	[2.23]	[2.26]	[4.41]	[4.23]	[4.22]
HF	-0.86	-0.72	-0.56	-0.05	-0.16	-0.15	0.43	0.32	0.17	0.23	0.22	0.16
	[-5.90]	[-4.81]	[-3.42]	[-0.84]	[-2.32]	[-2.08]	[5.52]	[4.23]	[1.81]	[5.30]	[5.20]	[3.24]
IO	0.43	0.05	0.06	-0.06	-0.09	-0.09	0.63	0.26	0.29	0.11	0.04	0.06
	[7.94]	[0.82]	[1.13]	[-2.35]	[-2.85]	[-2.85]	[14.16]	[5.69]	[6.15]	[4.87]	[1.70]	[2.32]
$Q_1 \cdot HF$			-0.38			0.00			-0.05			-0.12
			[-1.97]			[0.06]			[-0.34]			[-1.40]
$Q_5 \cdot HF$			-0.76			-0.10			0.33			0.22
			[-1.00]			[-0.42]			[2.79]			[2.92]
Leverage		-0.12	-0.11		0.09	0.09		0.19	0.20		0.10	0.11
		[-2.38]	[-2.28]		[4.07]	[4.05]		[8.85]	[8.85]		[7.90]	[8.04]
ILLIQ		-0.11	-0.11		-0.07	-0.07		-0.01	-0.01		0.00	0.00
		[-8.00]	[-8.22]		[-10.23]	[-9.93]		[-2.57]	[-3.32]		[0.11]	[-0.84]
Size		-0.05	-0.05		-0.09	-0.09		0.08	0.08		0.02	0.02
		[-2.68]	[-2.64]		[-10.73]	[-10.60]		[10.30]	[10.02]		[3.42]	[3.24]
t-Test: HF_T - HF_C = 0	-6.85	-4.60	-3.08				3.42	1.62	0.14			
Adj. R^2	0.134	0.171	0.172	0.091	0.098	0.098	0.132	0.153	0.153	0.090	0.092	0.092

Table 3: Regressions of Matched Samples using Propensity Scores

The table reports regressions results of treatment and control groups. The treatment groups are the firm-quarters that belong to the extreme volatility deciles. The control groups are the propensity-score-matched samples. Propensity score is the probability of falling in the extreme deciles estimated from the logistic regressions, where the dependent variable is the indicator variable that takes one if the firm-quarter belong to the extreme deciles and zero otherwise. The independent variables include $\Delta CF_{i,t}$, the changes in the log of idiosyncratic cash-flow volatility, $HF_{i,t-1}$, the level of hedge-fund ownership at the end of quarter t-1, $IO_{i,t-1}$, the non-hedge-fund institutional ownership at the end of quarter t-1, $ILLIQ_{i,t-1}$, the Amihud (2002) illiquidity in quarter t-1, firm leverage in quarter t-1, and size at the end of t-1, as well as the idiosyncratic volatility decile affiliation in quarter t-1. Each observation in the treatment groups is paired with the firm-quarter that has the same probability to create the matched sample, using the 6 to 2 digit matching technique. Specifically, observations with the same 6-digit probability are paired first. Then, from the remaining unmatched observations, observations with the same 5-digit probability are paired. Repeating this way, observations are matched up to a 2-digit probability. Unmatched observations in the treatment groups are excluded from the treatment samples. Idiosyncratic cash-flow volatility is estimated following Irvine and Pontiff (2010). Hedge-fund ownership is the percentage holdings of institutions which are identified as hedge funds from a list of hedge fund names obtained from Lipper/TASS. Institutional holding data based on 13F filing are available through CDA/Spectrum database of Thompson Financials. Size is the log of market capitalization. The bottom row reports the t-statistics for the hypothesis that the coefficient on hedge-fund ownership is equal for the treatment and the control group (HF_T - HF_C = 0). Standard errors are clustered within each firm, and the time (quarter) fixed-effect is included for each regression. The t-statistics are reported in square brackets. The sample period is 1994–2008.

Panel A: Summary Statistics

Subsample	Decile 1						Decile 10					
Group	Treatment		Control		Mean Difference		Treatment		Control		Mean Difference	
Variable	Mean	Std	Mean	Std	Difference	t value	Mean	Std	Mean	Std	Difference	t value
N	11,203		11,203				20,171		20,171			
ΔCF	0.08	3.20	0.04	3.17	0.04	[0.87]	0.14	3.45	0.17	3.40	-0.03	[-0.85]
HF	0.10	0.09	0.09	0.09	0.00	[2.59]	0.08	0.10	0.08	0.10	0.00	[2.74]
IO	0.28	0.21	0.28	0.22	0.01	[3.28]	0.15	0.19	0.15	0.18	0.00	[2.18]
Leverage	0.64	0.22	0.64	0.23	0.00	[-0.81]	0.46	0.25	0.46	0.25	0.00	[-1.31]
ILLIQ	-18.80	2.63	-18.59	2.81	-0.20	[-5.60]	-15.03	2.88	-14.96	2.62	-0.07	[-2.40]
Size	13.92	1.86	13.77	1.98	0.15	[5.66]	11.11	1.41	11.05	1.35	0.06	[4.21]
Lagged Decile	1.93	1.43	1.93	1.43	0.00	[-0.11]	8.91	1.38	8.88	1.37	0.03	[2.41]
Probability	0.28	0.16	0.28	0.16	0.00	[0.01]	0.31	0.18	0.31	0.18	0.00	[0.01]

Panel B: Regression Results

Subsample	Decile 1						Decile 10					
Group	Treatment			Control			Treatment			Control		
Model	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
Intercept	-0.33	-1.54	-1.60	0.48	1.03	1.12	0.31	-0.44	-0.46	-0.45	-0.60	-0.60
	[-9.07]	[-15.84]	[-15.15]	[13.22]	[16.15]	[15.35]	[6.78]	[-5.77]	[-5.59]	[-16.68]	[-11.06]	[-10.48]
ΔCF (× 100)	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
	[1.85]	[1.83]	[1.79]	[-0.03]	[-0.10]	[-0.06]	[3.03]	[2.63]	[2.65]	[3.07]	[3.11]	[3.11]
HF	-0.74	-0.63	-0.47	0.08	-0.13	-0.22	0.30	0.24	0.13	0.17	0.15	0.18
	[-5.04]	[-4.20]	[-2.85]	[0.81]	[-1.39]	[-2.04]	[3.70]	[3.09]	[1.30]	[2.70]	[2.36]	[2.41]
IO	0.53	0.14	0.15	-0.30	-0.10	-0.12	0.55	0.29	0.30	0.16	0.08	0.08
	[9.53]	[2.33]	[2.63]	[-7.88]	[-2.42]	[-3.01]	[11.82]	[6.03]	[6.16]	[4.57]	[2.20]	[2.11]
$Q_1 \cdot HF$			-0.39			0.34			0.23			-0.13
			[-1.95]			[2.92]			[1.41]			[-0.91]
$Q_5 \cdot HF$			-0.77			-0.29			0.26			-0.08
			[-1.00]			[-0.79]			[2.04]			[-0.76]
Leverage		-0.09	-0.08		0.08	0.07		0.25	0.25		-0.03	-0.03
		[-1.73]	[-1.62]		[2.47]	[2.28]		[10.09]	[10.09]		[-1.52]	[-1.54]
ILLIQ		-0.10	-0.10		-0.03	-0.02		-0.02	-0.02		-0.01	-0.01
		[-7.01]	[-7.16]		[-3.56]	[-2.88]		[-3.85]	[-4.31]		[-2.03]	[-1.69]
Size		-0.04	-0.04		-0.09	-0.09		0.04	0.04		0.01	0.01
		[-2.08]	[-2.03]		[-8.03]	[-7.91]		[4.06]	[3.66]		[0.72]	[0.87]
t-Test: HF_T - HF_C = 0	-6.62	-3.93	-1.85				1.86	1.36	-0.64			
Adj. R^2	0.136	0.168	0.169	0.126	0.144	0.145	0.129	0.142	0.142	0.113	0.114	0.114

Table 4: Changes in Idiosyncratic Volatility Following the Lehman Bankruptcy

The table reports the results of cross-sectional regressions of the changes in the log idiosyncratic volatility following the Lehman bankruptcy. The independent variables are the fraction of the stock owned by hedge funds that used Lehman as their prime broker, the non-Lehman hedge-fund ownership, the non-hedge-fund institutional ownership, firm leverage, illiquidity, and size. The pre-crisis idiosyncratic volatility and illiquidity are estimated during the period 07/01/2008–08/31/2008 and the post-crisis idiosyncratic volatility is estimated during the period 09/15/2008–11/30/2008. Hedge-fund and institutional ownership are obtained from the 13F filings in June 2008. Leverage and size are measured at 06/30/2008. The dummy variable Q_1 (Q_5) equals one if a stock belongs to the lowest (highest) quintile of illiquidity during the pre-crisis period and zero otherwise. Standard errors are clustered at Fama-French 48 industry level and the t-statistics are reported in square brackets.

Variable\Model	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	1.25	1.40	0.78	1.15	0.38	0.81
	[16.88]	[21.29]	[2.99]	[4.42]	[1.37]	[2.96]
Lehman HF	1.45	1.29	1.35	1.29	1.49	1.44
	[2.54]	[2.22]	[2.45]	[2.28]	[2.00]	[1.83]
Non-Lehman HF	-0.41	-0.35	-0.31	-0.22	-0.35	-0.29
	[-1.59]	[-1.50]	[-2.13]	[-1.50]	[-2.45]	[-2.06]
I/O	-0.09	-0.13	-0.13	-0.13	-0.14	-0.15
	[-0.99]	[-1.44]	[-2.05]	[-1.97]	[-2.32]	[-2.13]
Q_1·Lehman					-1.06	-0.95
					[-0.65]	[-0.60]
Q_5·Lehman					1.15	0.91
					[0.36]	[0.29]
Q_1·HF					-0.50	-0.32
					[-2.15]	[-1.38]
Q_5·HF					1.57	1.58
					[3.65]	[4.02]
Leverage			0.11	0.11	0.13	0.12
			[1.19]	[1.58]	[1.45]	[1.72]
ILLIQ			0.04	0.04	0.02	0.02
			[1.63]	[2.09]	[0.84]	[1.05]
Size			0.08	0.07	0.09	0.07
			[2.85]	[3.04]	[2.97]	[2.78]
Industry Fixed Effect	N	Y	N	Y	N	Y
Adj. R^2	0.005	0.040	0.013	0.045	0.020	0.050

Table 5: Hedge-Fund Shares with Restrictions

The table reports the results of panel regressions of the changes in the log of idiosyncratic volatilities on hedge-fund shares with leverage and lockup provision. HF w/o is the level of the percentage holdings of hedge funds that do use leverage or do not have a lockup provision. HF with is the level of the percentage holdings of hedge funds that use leverage or have a lockup provision. Other independent variables are $\Delta CF_{i,t}$, is the changes in the log of idiosyncratic cash-flow volatility, $IO_{i,t-1}$, the non-hedge-fund institutional ownership at the end of quarter t-1, $ILLIQ_{i,t-1}$, the Amihud (2002) illiquidity in quarter t-1, firm leverage in quarter t-1, size at the end of t-1, and the dummy variables, $Q^q_{i,t-1}$, that equal one if a stock belongs to illiquidity Quintile q (q=1 for liquid firms and q=5 for illiquid firms) and zero otherwise. Idiosyncratic cash-flow volatility is estimated following Irvine and Pontiff (2010). Hedge-fund ownership is the percentage holdings of institutions which are identified as hedge funds from a list of hedge fund names obtained from Lipper/TASS. Institutional holding data based on 13F filings are available through the CDA/Spectrum database of Thompson Financials. Size is the log of market capitalization. For panel regressions in Panel B, standard errors are clustered within each firm, and the time (quarter) fixed effect is included. The t-statistics are reported in square brackets. The sample period is 1994–2008.

Restriction	Leverage						Lockup Period					
Subsample	Decile 1			Decile 10			Decile 1			Decile 10		
Variable\Model	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
Intercept	-0.24	-1.47	-1.55	0.22	-0.83	-0.87	-0.25	-1.52	-1.59	0.22	-0.83	-0.86
	[-7.45]	[-15.96]	[-15.83]	[5.69]	[-12.90]	[-12.99]	[-7.54]	[-16.72]	[-16.17]	[5.63]	[-13.00]	[-12.98]
ΔCF (× 100)	0.37	0.37	0.35	0.42	0.37	0.38	0.36	0.37	0.36	0.41	0.37	0.38
	[1.57]	[1.56]	[1.50]	[2.48]	[2.24]	[2.28]	[1.51]	[1.56]	[1.51]	[2.47]	[2.24]	[2.27]
HF w/o	0.14	-0.22	-0.26	0.72	0.35	0.45	-1.03	-0.93	-0.65	0.43	0.32	0.11
	[0.62]	[-0.96]	[-0.87]	[4.72]	[2.52]	[2.32]	[-5.53]	[-4.68]	[-3.01]	[4.37]	[3.50]	[0.85]
HF with	-1.52	-1.07	-0.75	0.27	0.30	0.02	-0.49	-0.21	-0.39	0.43	0.30	0.38
	[-6.36]	[-4.62]	[-3.10]	[2.65]	[3.10]	[0.14]	[-1.67]	[-0.71]	[-1.04]	[2.60]	[1.90]	[1.67]
IO	0.37	0.03	0.06	0.62	0.26	0.29	0.42	0.04	0.07	0.63	0.26	0.29
	[6.55]	[0.48]	[0.97]	[13.70]	[5.76]	[6.14]	[7.72]	[0.75]	[1.28]	[13.97]	[5.77]	[6.15]
LEV		-0.12	-0.11		0.19	0.19		-0.11	-0.11		0.19	0.20
		[-2.53]	[-2.38]		[8.83]	[8.83]		[-2.33]	[-2.20]		[8.83]	[8.85]
ILLIQ		-0.11	-0.11		-0.01	-0.01		-0.11	-0.11		-0.01	-0.01
		[-7.79]	[-8.42]		[-2.60]	[-3.28]		[-7.94]	[-8.26]		[-2.61]	[-3.29]
Size		-0.05	-0.05		0.08	0.08		-0.05	-0.04		0.08	0.08
		[-2.64]	[-2.98]		[10.27]	[9.98]		[-2.58]	[-2.55]		[10.30]	[9.97]
Q_1·HF w/o			0.41			-0.37			-0.81			0.55
			[1.10]			[-0.77]			[-2.81]			[1.78]
Q_5·HF w/o			-1.05			-0.10			-1.12			0.40
			[-0.74]			[-0.38]			[-1.37]			[2.47]
Q_1·HF with			-1.37			0.20			0.60			-1.65
			[-3.29]			[0.47]			[1.18]			[-2.46]
Q_5·HF with			-0.70			0.52			-0.02			0.02
			[-0.54]			[2.92]			[-0.01]			[0.08]
Adj. R^2	0.137	0.172	0.175	0.132	0.153	0.153	0.134	0.172	0.173	0.132	0.153	0.153

Table 6: Changes in Hedge-Fund Ownership of Extreme Deciles

The table reports the results of panel regressions of the changes in the hedge-funds ownership on a dummy for idiosyncratic-volatility Decile 1, a dummy for Decile 10, and control variables. The dependent variable is the changes of the hedge-fund ownership from quarter t-1 to quarter t. D_1 (D_{10}) is a dummy variable that equals one if a stock belongs to idiosyncratic volatility Decile 1 (Decile 10) during quarter t and zero otherwise. The control variables include $HF_{i,t-1}$, the level of hedge-fund ownership at the end of quarter t-1, $IO_{i,t-1}$, the non-hedge-fund institutional ownership at the end of quarter t-1, $ILLIQ_{i,t-1}$, the Amihud (2002) illiquidity in quarter t-1, firm leverage in quarter t-1, size at the end of t-1, and the dummy variables, $Q^q_{i,t-1}$, that equal one if a stock belongs to illiquidity Quintile q (q=1 for liquid firms and q=5 for illiquid firms) and zero otherwise. Hedge-fund and institutional ownership are obtained from the 13F filings in June 2008. Standard errors are clustered within each firm, and the time (quarter) fixed effect is included for each regression. The t-statistics are reported in square brackets. The sample period is 1994–2008.

Variable\Model	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	0.013	0.018	0.013	0.017	0.014	0.016
	[23.11]	[23.30]	[22.60]	[22.50]	[24.73]	[15.01]
D_1	-0.003	-0.002	-0.003	-0.002	-0.003	-0.002
	[-11.43]	[-8.90]	[-5.07]	[-4.03]	[-4.90]	[-4.30]
D_{10}	-0.005	-0.005	-0.002	-0.002	-0.001	-0.002
	[-20.02]	[-21.52]	[-6.31]	[-8.49]	[-5.14]	[-6.69]
HF	-0.071	-0.073	-0.068	-0.070	-0.070	-0.072
	[-41.58]	[-41.99]	[-38.98]	[-39.41]	[-39.72]	[-39.91]
IO	0.015	0.016	0.015	0.015	0.016	0.016
	[25.02]	[23.68]	[24.88]	[23.38]	[23.87]	[23.45]
$D_1 \cdot HF$			-0.001	0.000	0.003	0.003
			[-0.09]	[-0.06]	[0.45]	[0.45]
$D_{10} \cdot HF$			-0.041	-0.039	-0.049	-0.048
			[-10.14]	[-9.74]	[-10.44]	[-10.20]
Q_1					-0.003	-0.003
					[-15.93]	[-10.05]
Q_5					-0.004	-0.003
					[-20.72]	[-12.38]
$D_1 \cdot HF \cdot Q_1$					-0.006	-0.006
					[-0.87]	[-0.86]
$D_1 \cdot HF \cdot Q_5$					0.041	0.038
					[3.33]	[3.17]
$D_{10} \cdot HF \cdot Q_1$					-0.060	-0.062
					[-4.38]	[-4.46]
$D_{10} \cdot HF \cdot Q_5$					0.049	0.050
					[7.80]	[8.03]
Leverage		-0.002		-0.002		-0.002
		[-8.50]		[-8.00]		[-7.45]
ILLIQ		-0.001		-0.001		0.000
		[-10.26]		[-10.22]		[-4.94]
Size		-0.001		-0.001		-0.001
		[-12.33]		[-12.07]		[-5.77]
Adj. R^2	0.077	0.078	0.078	0.079	0.081	0.082

Table 7: Time-Trend Regressions of Idiosyncratic Volatility Deciles

The table reports the results of time-series regressions of the share of each decile of idiosyncratic volatility in the aggregate idiosyncratic volatility (Equation (17)) on a time trend. The idiosyncratic volatility is estimated following Ang, Hodrick, Xing, and Zhang (2006). Specifically, for each stock-month, daily returns are regressed on the Fama-French three factors. Residuals from the regressions are squared and averaged over the month to obtain the idiosyncratic volatility. Then, stocks are ranked into deciles based on their idiosyncratic volatility. Finally, the share of each decile in a given month is calculated as the ratio of value-weighted sum of idiosyncratic volatility of the stocks in the decile to the value-weighted sum of stocks in the entire cross-section. Autocorrelations in the error terms of the regressions are corrected up to six lags using maximum-likelihood method. Probabilities of Phillips-Perron unit-root tests are reported in the last two columns. Daily returns of common stocks (share code in 10 and 11) are obtained from CRSP for the shares traded in NYSE, AMEX, and Nasdaq for the period 1963–2008. Stocks with less than $2 at the end of the previous year or less than 100 trading days during the previous year are excluded.

Decile	Intercept		Time Trend		R^2	Phillips-Perron (Prob: Tau)	
	Estimate	T-value	Estimate × 10^4	T-value		No Trend	Trend
1	0.132	[11.02]	-2.136	[-5.67]	0.866	0.091	0.001
2	0.128	[14.18]	-1.111	[-3.89]	0.650	0.173	0.001
3	0.116	[20.17]	-0.299	[-1.64]	0.315	0.185	0.001
4	0.112	[29.85]	-0.043	[-0.36]	0.136	0.124	0.001
5	0.100	[30.99]	0.212	[2.06]	0.129	0.234	0.001
6	0.091	[32.80]	0.304	[3.42]	0.167	0.184	0.001
7	0.081	[24.55]	0.499	[4.71]	0.276	0.173	0.001
8	0.072	[13.27]	0.679	[3.95]	0.446	0.092	0.001
9	0.069	[10.23]	0.874	[4.09]	0.457	0.058	0.001
10	0.092	[10.19]	1.301	[4.52]	0.388	0.011	0.001
10-1	-0.043	[-2.80]	3.570	[7.35]	0.711	0.001	0.001

Table 8: Time-Series Regressions of the Extreme Deciles of the Idiosyncratic Volatility

Panel A reports the time trend of each regression variable and Panel B reports the results of time-series regressions of the shares of the extreme deciles of the idiosyncratic volatility in the aggregate idiosyncratic volatility (d_1 and d_{10}). The independent variables are a time trend, idiosyncratic cash-flow volatility, the AUM of Long/Short-Equity hedge funds, firm leverage, illiquidity, the AUM of non-Long/Short-Equity hedge funds, the institutional ownership, the TED spread, and the interaction between the AUM of Long/Short-Equity hedge funds and the TED spread. The idiosyncratic cash-flow volatility for a firm is estimated following Irvine and Pontiff (2009). Then, the shares of the extreme deciles of the idiosyncratic cash-flow volatility are calculated as in Equation (11). The AUM of hedge funds is the assets under management at the end of previous quarter. A firm leverage is measured as total liabilities of the firm divided by its market equity. Then, the leverage of each decile in a given quarter is calculated as the ratio of value-weighted sum of the leverage of the firms in the decile to the value-weighted sum of the leverage of stocks in the entire cross-section. Illiquidity of each decile in a given quarter is calculated as the ratio of value-weighted sum of Amihud measure of illiquidity of the stocks in the decile to the value-weighted sum of Amihud measure of stocks in the entire cross-section. The institutional ownership is the total market capital owned by institutions for each decile of idiosyncratic return volatility at the end of previous quarter. The TED spread is calculated as the difference between the three-month T-bill interest rate and the three-month LIBOR at the end of previous quarter. All the variables except the time trend and TED spread are log-transformed. The t-statistics are Newey-West adjusted using 4 lags and are reported in square brackets. The sample period is from 1994–2008.

Panel A: Time Trends in Variables

Variables	Return Volatility	Cash-Flow Volatility	AUM of L/S Equity	Firm Leverage	Illiquidity	AUM of Non-L/S Equity	Institutional Ownership	TED Spread
Decile 1	-0.021	-0.007		0.003	-0.016		0.021	
	[-1.92]	[-1.04]		[0.58]	[-3.16]		[3.33]	
Decile 10	0.009	0.009		0.029	-0.005		0.061	
	[4.11]	[1.45]		[2.34]	[-1.47]		[16.64]	
All			80.353			74.360		572.466
			[35.27]			[45.02]		[0.85]

Panel B: Time-Series Regression Result

Model	Variables	Linear Trend	Cash-Flow Volatility	AUM of L/S Equity	Firm Leverage	Illiquidity	AUM of Non-L/S Equity	Institutional Ownership	TED Spread	LSE × TED	R^2 / Adj. R^2
1	d1	-0.014	0.869								0.48
		[-2.07]	[3.85]								0.47
	d10	0.007	0.242								0.39
		[4.06]	[3.80]								0.37
	d10-d1	0.021	0.541								0.47
		[2.54]	[4.68]								0.45
2	d1	0.257		-3.461							0.45
		[3.32]		[-3.56]							0.44
	d10	-0.004		0.156							0.18
		[-0.14]		[0.47]							0.15
	d10-d1	-0.261		3.617							0.53
		[-3.63]		[3.97]							0.52
3	d1	0.169	0.631	-2.323							0.60
		[2.84]	[3.77]	[-3.10]							0.58
	d10	0.004	0.268	0.045							0.40
		[0.20]	[4.51]	[0.20]							0.36
	d10-d1	-0.196	0.384	2.765							0.63
		[-2.88]	[4.63]	[3.19]							0.61
4	d1	-0.018	0.705		0.832						0.58
		[-1.96]	[3.06]		[1.60]						0.55
	d10	0.004	0.187		0.125						0.46
		[1.74]	[3.27]		[2.82]						0.43
	d10-d1	0.017	0.469		0.210						0.50
		[1.96]	[3.90]		[1.15]						0.48
5	d1	0.022		-0.794		-0.196	-0.126	1.272			0.95
		[1.33]		[-3.21]		[-2.18]	[-0.49]	[13.74]			0.95
	d10	-0.009		-0.416		0.430	0.363	0.436			0.51
		[-0.36]		[-1.57]		[3.65]	[1.30]	[4.63]			0.46
	d10-d1	-0.029		0.710		0.005	-0.444	0.871			0.93
		[-0.86]		[1.29]		[0.08]	[-1.42]	[8.65]			0.93
6	d1	0.020	0.028	-0.808	-0.036	-0.180	-0.077	1.261			0.95
		[1.27]	[0.54]	[-3.09]	[-0.33]	[-1.76]	[-0.29]	[12.25]			0.95
	d10	0.001	0.115	-0.534	0.117	0.188	0.373	0.323			0.59
		[0.04]	[1.97]	[-1.95]	[2.43]	[1.23]	[1.35]	[4.05]			0.54
	d10-d1	-0.028	0.062	0.874	-0.065	0.072	-0.611	0.844			0.93
		[-0.86]	[1.40]	[1.82]	[-1.50]	[0.73]	[-2.03]	[8.55]			0.93
7	d1	0.167	0.588	-2.530					-0.082	0.003	0.62
		[3.06]	[3.45]	[-3.77]					[-1.41]	[1.47]	0.58
	d10	-0.007	0.216	-0.013					-0.082	0.003	0.53
		[-0.43]	[3.28]	[-0.07]					[-3.45]	[3.47]	0.48
	d10-d1	-0.202	0.351	2.919					0.017	-0.001	0.65
		[-3.05]	[3.86]	[3.54]					[0.31]	[-0.39]	0.62
8	d1	0.021		-0.911		-0.112	0.017	1.244	-0.007	0.000	0.95
		[1.37]		[-3.53]		[-1.00]	[0.07]	[12.53]	[-0.31]	[0.37]	0.95
	d10	-0.016		-0.344		0.333	0.325	0.348	-0.050	0.002	0.55
		[-0.62]		[-1.31]		[2.52]	[1.35]	[3.76]	[-2.07]	[2.08]	0.48
	d10-d1	-0.024		0.898		0.111	-0.625	0.845	0.028	-0.001	0.94
		[-0.81]		[1.75]		[1.01]	[-1.96]	[8.53]	[1.14]	[-1.23]	0.93
9	d1	0.019	0.022	-0.876	0.139	-0.063	-0.013	1.194	-0.014	0.001	0.95
		[1.39]	[0.42]	[-3.22]	[0.75]	[-0.53]	[-0.04]	[10.98]	[-0.69]	[0.82]	0.95
	d10	-0.001	0.096	-0.509	0.162	0.080	0.342	0.228	-0.040	0.001	0.64
		[-0.05]	[1.45]	[-1.94]	[2.53]	[0.70]	[1.43]	[3.05]	[-2.21]	[2.16]	0.58
	d10-d1	-0.019	0.052	0.885	-0.002	0.125	-0.657	0.818	0.033	-0.001	0.94
		[-0.64]	[1.29]	[1.81]	[-0.04]	[1.15]	[-2.07]	[7.96]	[1.26]	[-1.34]	0.93

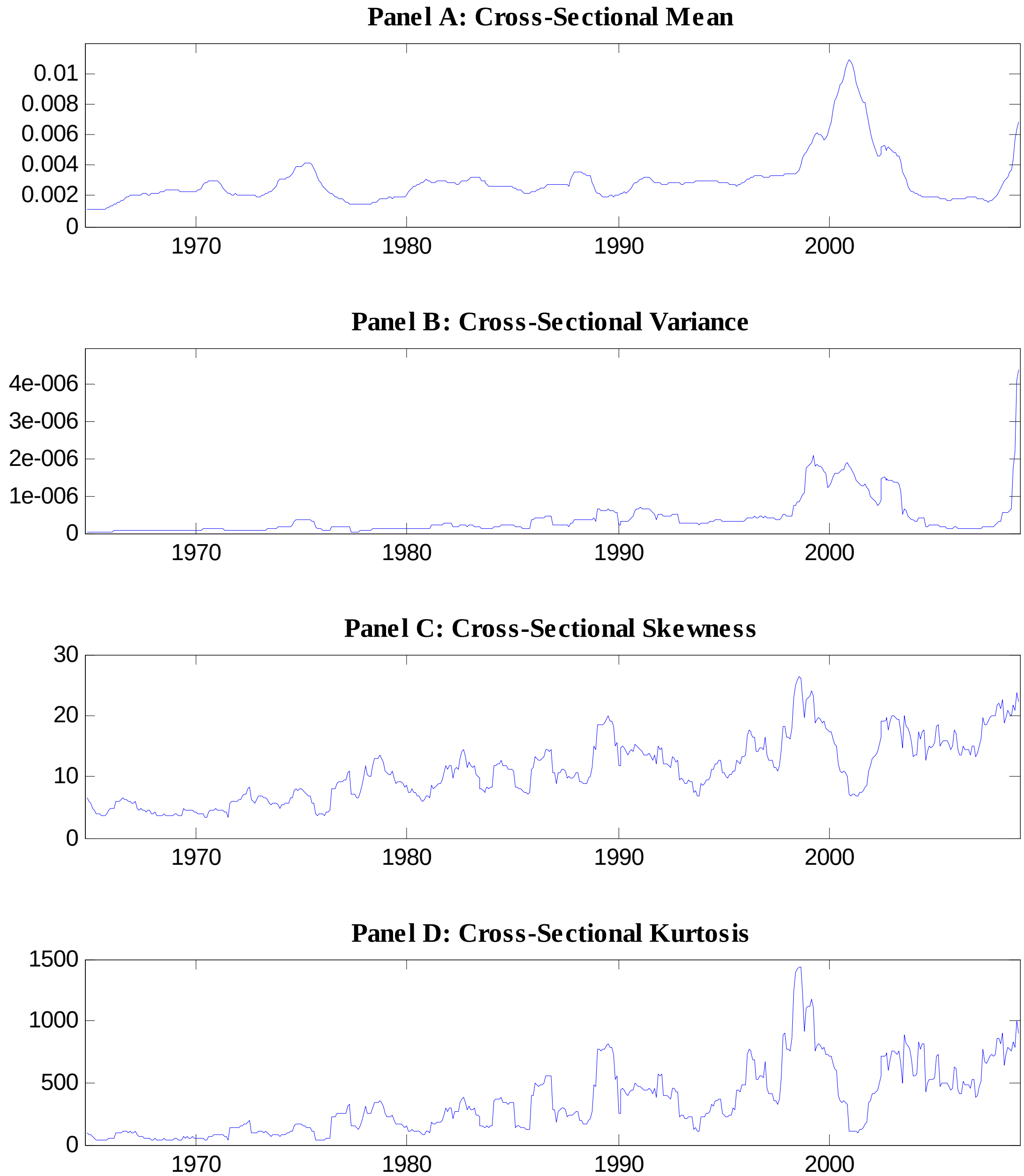
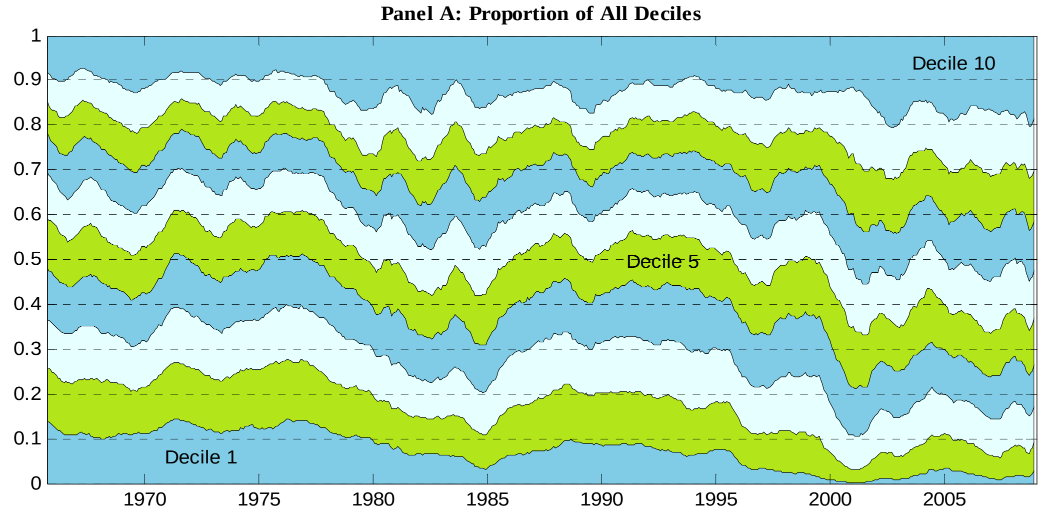


Figure 1. Time trends of the cross-sectional moments of idiosyncratic volatility. The figure plots the time series of 12-month backward moving average of the cross-sectional moments of monthly idiosyncratic volatility. Panel A, B, C and D show value-weighted cross-sectional mean, variance, skewness, and kurtosis of monthly idiosyncratic volatility, respectively. The idiosyncratic volatility is estimated following Ang, Hodrick, Xing, and Zhang (2006). Specifically, for each stock-month, daily returns are regressed on the Fama-French three factors. Residuals from the regressions are squared and averaged over the month to obtain the idiosyncratic volatility. Daily returns of common stocks (share code in 10 and 11) are obtained from CRSP for the shares traded in NYSE, AMEX, and Nasdaq for the period 1963−2008. Stocks with less than $2 at the end of the previous year or less than 100 trading days during the previous year are excluded.



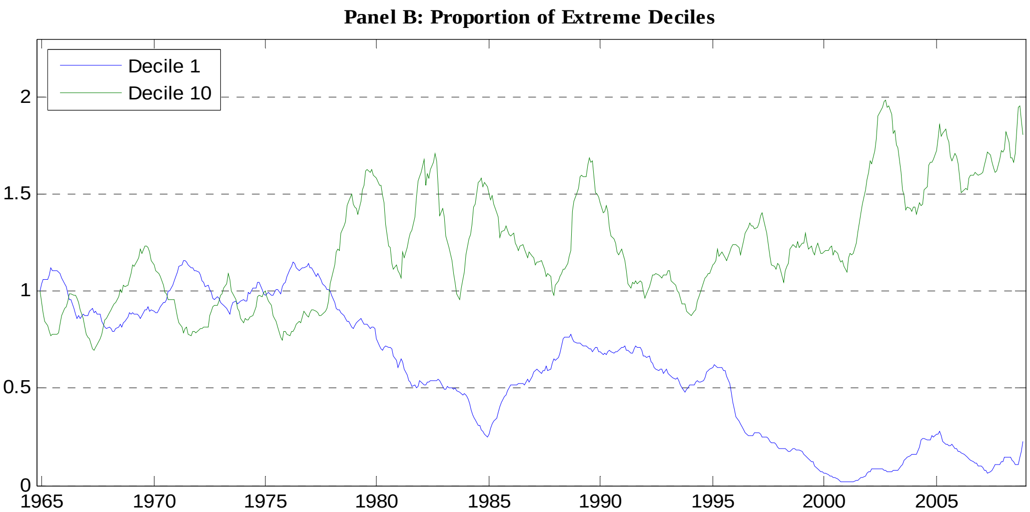


Figure 2. Time trend of the share of each idiosyncratic-volatility decile in the aggregate idiosyncratic volatility. Panel A shows the time series of the share of each decile of the idiosyncratic volatility in the aggregate idiosyncratic volatility (Equation (7)). Panel B shows the shares of the 1st and the 10th deciles (d_1 and d_{10}). A 12-month backward moving average is used to obtain a smoothed time series in both panels. In Panel B, each time series is normalized through dividing by its beginning-of-the-sample value. The share of a decile in the aggregate idiosyncratic volatility is calculated as follows. For each stock-month, daily returns are regressed on the Fama-French three factors. Residuals from the regressions are squared and averaged over the month to obtain idiosyncratic volatility, following Ang, Hodrick, Xing, and Zhang (2006). Then, stocks are ranked into deciles based on their idiosyncratic volatility. Finally, the share of each decile in a given month is calculated as the ratio of value-weighted sum of idiosyncratic volatility of the stocks in the decile to the value-weighted sum of stocks in the entire cross-section. Daily returns of common stocks (share code in 10 and 11) are obtained from CRSP for the shares traded in NYSE, AMEX, and Nasdaq for the period 1963−2008. Stocks with less than $2 at the end of the previous year or less than 100 trading days during the previous year are excluded.

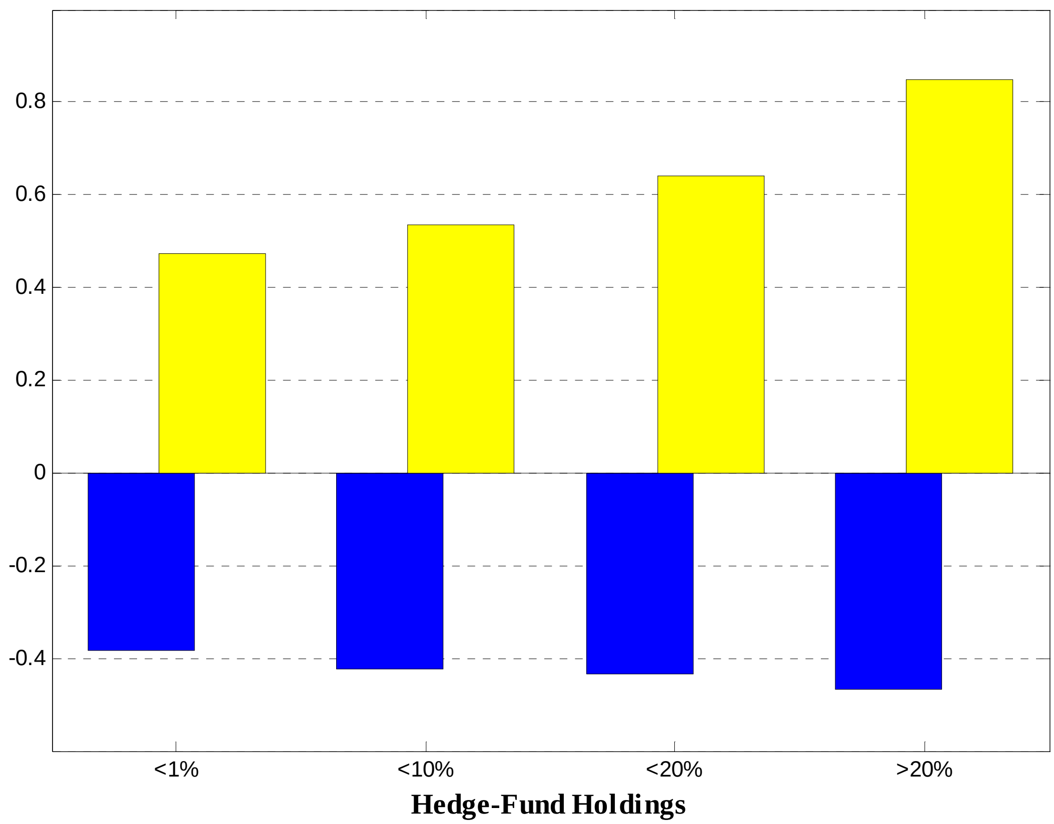


Figure 3. Average changes in idiosyncratic volatility based on hedge-fund holdings. The figure plots the average changes in the log of quarterly idiosyncratic volatility of stocks in the extreme idiosyncratic-volatility deciles. Blue bars show the average changes of idiosyncratic volatility of stocks in the lowest idiosyncratic-volatility decile, while red bars show those of stocks in the highest idiosyncratic-volatility decile. Stocks are ranked into deciles based on their idiosyncratic volatility, then are divided into four groups based on the ownership percentage held by hedge funds. The sample period is 1994–2008.

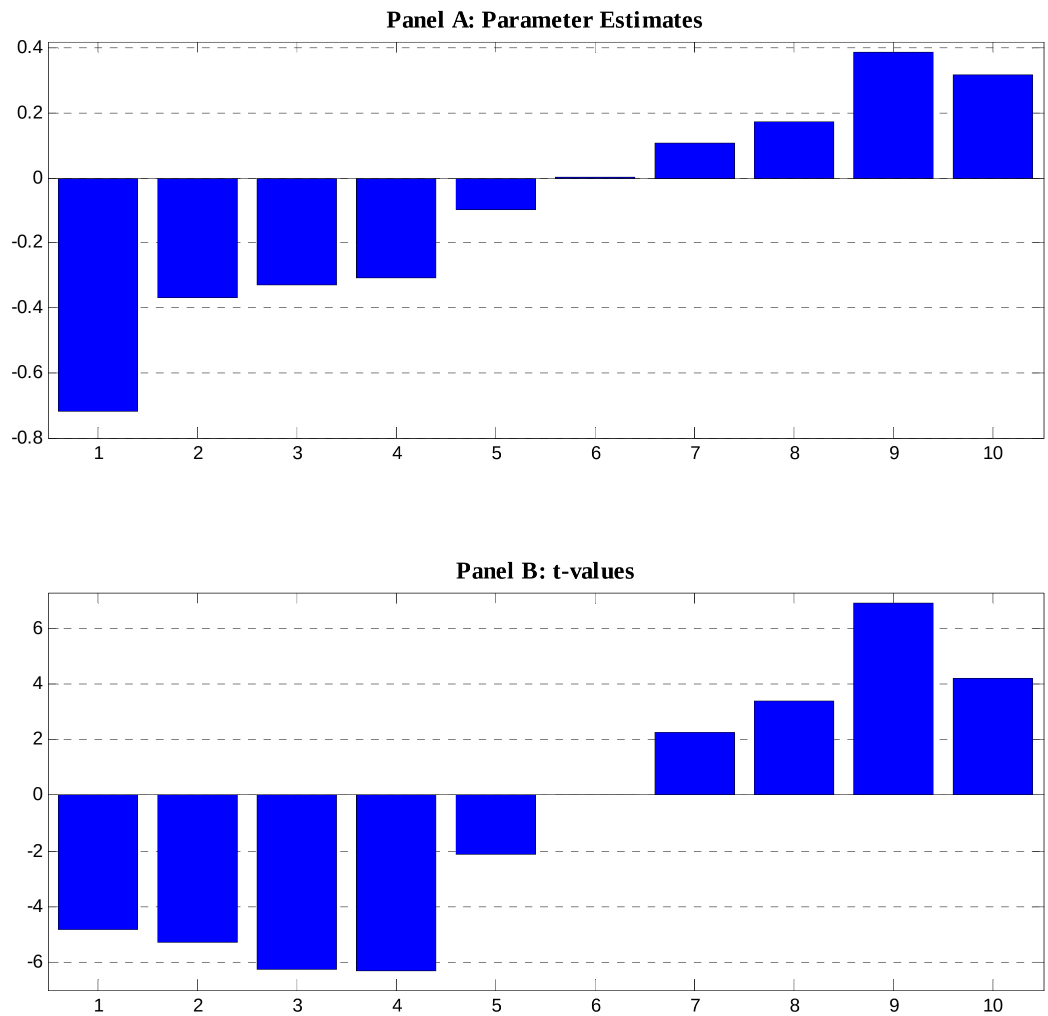
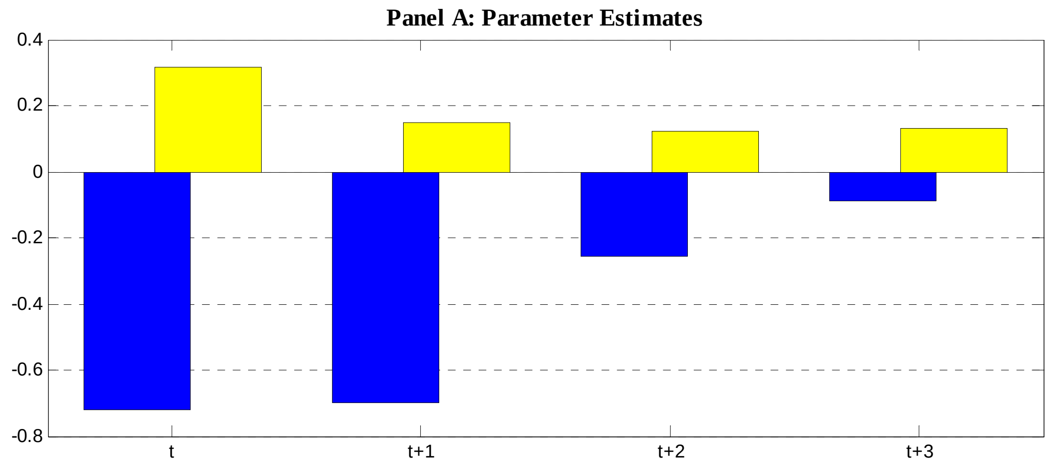


Figure 4. Regression results for decile subsamples. The figure plots the summary results of panel regressions for subsamples of decile 1 to decile 10. The dependent variable is the changes in the log of idiosyncratic volatility, and the independent variables are $\Delta CF_{i,t}$, the changes in the log of idiosyncratic cash-flow volatility, $HF_{i,t-1}$, the level of hedge-fund ownership at the end of quarter *t-1*, $IO_{i,t-1}$, the non-hedge-fund institutional ownership at the end of quarter *t-1*, $ILLIQ_{i,t-1}$, the Amihud (2002) illiquidity in quarter *t-1*, firm leverage in quarter *t-1*, and size at the end of *t-1*. The coefficients on *HF* and their *t*-values are reported. The sample period is 1994–2008.



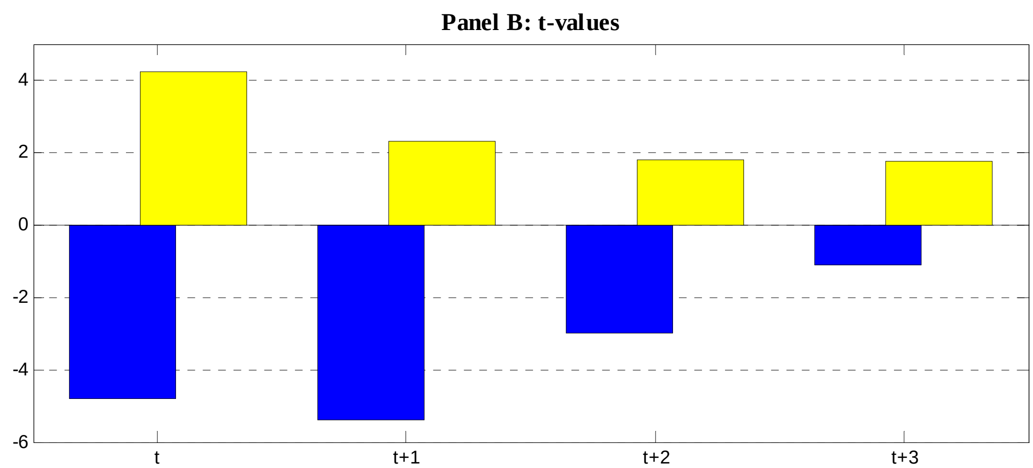


Figure 5. Changes in long-horizon volatility. The figure plots the average log changes of long-horizon idiosyncratic volatility, estimated over the expanding windows of quarter *t* to *t+j* (for *j* = 0 to 3), from the idiosyncratic volatility at *t-1* for the stocks in the extreme idiosyncratic-volatility deciles. Blue bars show the average changes of idiosyncratic volatility of stocks in the lowest idiosyncratic-volatility decile, while red bars show those of stocks in the highest idiosyncratic-volatility decile. The log changes are measured as the log of the ratio of the volatility during the period from time *t* to *t+j* to the volatility at time *t-1*. The sample period is 1994–2008.