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ABSTRACT

Idiosyncratic Return Volatility in the Cross-Section of Stocks*

This paper uncovers the changes in the cross-sectional distribution of idiosyncratic volatility of stocks over the period 1963--2008. The contribution of the top decile to the total market idiosyncratic volatility increased, while the contribution of the bottom decile decreased. We introduce a simple theoretical model showing that larger capital of Long/Short-Equity funds further exacerbates large idiosyncratic shocks but attenuates small idiosyncratic shocks. This effect is stronger for more illiquid stocks. Time-series and cross-sectional results are consistent with the predictions of the model. The results are robust to industry affiliation, stock liquidity, firm size, firm leverage, as well as sign of price change. These findings highlight the roll of hedge funds and other institutional investors in explaining the dynamics of extreme realizations in the cross-section of returns.

JEL Classification: G11 and G12
Keywords: hedge funds, idiosyncratic risk and limits to arbitrage

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1. Introduction

Before the seminal paper of Campbell, Lettau, Malkiel, and Xu (2001, hereafter CLMX), firm-level risk had been largely ignored by the finance literature, perhaps because standard models of asset pricing imply that only systematic risk is priced. However, as CLMX emphasize, idiosyncratic risk is important for several theoretical and practical reasons. It is a source of additional risk of an undiversified portfolio (Merton (1987)) and understanding its nature contributes to finding the appropriate level of diversification. It is also valuable for constructing event studies since the significance of abnormal returns is affected by the volatility of stocks relative to their benchmarks. More importantly for our purposes, idiosyncratic risk is a relevant risk measure for financial institutions attempting to exploit the relative mispricing of individual assets.

In any given point of time, stocks display a cross-sectional distribution of their realized idiosyncratic shocks. Focusing on the mean of this distribution, CLMX document a deterministic upward time trend in idiosyncratic risk of US equities over the period 1962–1997. A subsequent literature (e.g., Gaspar and Massa (2006), Brandt, Brav, Graham, and Kumar (2008), and Irvine and Pontiff (2009)) analyze the determinants of the trend and its robustness for extended time periods. In contrast, we focus on extreme realizations in the cross-sectional distribution of idiosyncratic risk over time. Our paper contributes to the literature in the following ways. First, we document that the cross-sectional distribution of idiosyncratic volatility of US stocks has been increasingly skewed over time. In particular, the share of the top decile of idiosyncratic volatility in the entire cross-section has increased from 10% to 19% between 1963 and 2008, while the share of the bottom decile decreased from 13% to 3% during the same period. Second, we propose an explanation for this observation with the guidance of a simple theoretical model. Specifically, we argue that the trading activity of Long/Short-Equity funds amplifies large idiosyncratic shocks and reduces small idiosyncractic shocks. Thus, the increasing total capital of these institutions over time has a significant role in our observed patterns. Finally, we present both time-series and cross-sectional evidence in support of our explanation.

Although most works in the literature focus on the time pattern of the average idiosyncratic risk, we argue that knowing the frequency and size of extreme realizations of idiosyncratic risk in the cross-section of stocks is even more critical for some financial market participants. For example, consider a Long/Short-Equity fund specializing in the relative mispricing of stocks. Given the significant fixed cost in identifying mispriced assets, the trading desk most likely specializes in a limited number of assets at any given point in time. Hence, the idiosyncratic risk of these assets is highly relevant to risk management of the institution. Also, most institutional traders are subject to loss limits in some form or another.[1] Consequently, following extremely large realizations of idiosyncratic shocks to assets held, these institutions are forced to sell, causing large losses. Furthermore, as demonstrated by a number of recent works, such fire sales tend to exacerbate mispricing.[2] Thus, while the activity of these funds typically decreases the equilibrium size of idiosyncratic shocks, it can also amplify the particularly large realization of these shocks.

Our theoretical model, based on Shleifer and Vishny (1997), formalizes this idea. In particular, it illustrates that the change of the distribution of idiosyncratic shocks stems from two distinct sources: the changing distribution of the underlying cash flows and the evolving trading patterns of financial institutions. We assume two types of institutional investors; long-term traders holding assets to collect their cash flows and managers of Long/Short-Equity funds aiming to exploit temporary mispricing due to idiosyncratic risk. As funds are subject to endogenous funding constraints, they have to liquidate their positions following large losses. We show that while idiosyncratic shocks to returns are increasing in the underlying cash-flow shocks, larger capital of Long/Short-Equity funds further increases large idiosyncratic shocks but decreases small idiosyncratic shocks. We also show that the effect of hedge funds must be stronger for less liquid stocks.

Our main empirical finding is that the cross-sectional distribution of idiosyncratic volatility of US stocks has been increasingly skewed over time. For our empirical tests, we follow Ang, Hodrick, Xing, and Zhang (2006, hereafter AHXZ) to estimate idiosyncratic risk of a stock for each month. Specifically, idiosyncratic volatility is measured from the standard deviation of residuals from Fama-French three-factor regression of daily excess returns (Fama and French (1993)). We order the stocks into deciles based on their estimated idiosyncratic risk in a given month, notwithstanding the composition of these deciles may change from month to month. We then measure the contribution of the top and bottom deciles to the aggregate idiosyncratic shock during the same month. We

[1] These loss limits might be generated explicitly, for example, in the form of internal or external value-at-risk (VAR) constraints, or implicitly, by the expected or realized fund-flow response to poor performance. See also the related theoretical (e.g., Shleifer and Vishny (1997), Xiong (2001), Danielsson, Shin, and Zigrand (2004), Brunnermeier and Pedersen (2009), and Kondor (2009)) and empirical (e.g., Coval and Stafford (2007)) literature.

[2] See Gromb and Vayanos (2002), Lorenzoni (2008), Diamond and Rajan (2010), and Brunnermeier and Sannikov (2010). On the empirical side, Brunnermeier and Nagel (2004) show that hedge funds decreased their holdings significanlty before the internet bubble collapsed. Ben-David, Franzoni, and Moussawi (2010) find that hedge funds were more likely to sell high-volatility stocks and liquid stocks in fire sales during the financial crisis of 2007-2008.

show that the contribution of the top decile is increasing over time while the contribution of the bottom decile is decreasing over time. We show that this pattern holds regardless of the size and the liquidity of firms and is robust to industries. We also do not find significant cohort effects of positive or negative idiosyncratic shocks. To show that our results are not driven by the increasing number of stocks over time, we confirm this pattern in a random sample of stocks redrawn each month, as well as in a sample containing only the firms in the S&P 500 index in each particular month.

We perform both time-series and cross-sectional analyses to provide evidence connecting the observed time trends to our theoretical model. We study whether cash-flow volatility and proxies of the trading activity of various financial institutions can explain the diverging trends of the top and bottom deciles of idiosyncratic return volatility. We begin the analysis by running time-series regressions of the shares of extreme deciles in the aggregate idiosyncratic volatility on a deterministic time trend, the cash-flow volatility, the assets under management (AUM) of Long/Short-Equity funds, and various controls. We find that the upward trend in the top decile is explained by firms' cash-flow volatility. We also find evidence that the decreasing trend in the bottom decile is due to the AUM of Long/Short-Equity funds. We repeat our analysis for the subsamples sorted by firm illiquidity. Consistent with the theoretical model, the effect of Long/Short-Equity trading is stronger for less liquid stocks. For stocks in the least liquid quintile, AUM of Long/Short-Equity has a significantly positive effect on the top decile but a significantly negative effect on the bottom decile.

Our firm-level panel approach also provides supporting evidence for our hypotheses. We study whether the changes of idiosyncratic volatility of a given stock in a given month can be explained by changes in its cash-flow volatility and its hedge-fund ownership, as extracted from hedge-fund quarterly 13F filings with the Securities and Exchange Commission (SEC). We find that the idiosyncratic volatility of firms with a relatively high hedge-fund ownership tend to increase if they belong to the top decile and decrease if they belong to the bottom decile. This effect is even stronger for less liquid stocks. In contrast, an increase in cash-flow volatility increases idiosyncratic risk regardless of which decile the firm belongs. All these results are consistent with our model.

This paper is mostly related to the examination on the time trend of aggregate idiosyncratic return volatility started by CLMX and followed by a long series of works, such as Brandt, Brav, Graham, and Kumar (2008), Irvine and Pontiff (2009), and Bekaert, Hodrick, and Zhang (2010).

Many studies search for the causes of this upward time trend. Some papers relate the trend to the fundamentals of firms' business environment. For example, Irvine and Pontiff (2009) attribute the upward trend to the increased level of fundamental cash-flow volatility, which in turn is caused by more intense competition in the US economy. Gaspar and Massa (2006) establish a link between idiosyncratic volatility and firms' competitive environment, such as market power and the concentration level of the industry. Other papers relate the time trend to the changes in trading activities of market participants. For example, Xu and Malkiel (2003) show that idiosyncratic volatilities of individual firms are positively associated with institutional ownership (see also Kamara, Lou, and Sadka (2008)). Brandt, Brav, Graham, and Kumar (2008) document that the time trend in idiosyncratic volatility since 1990 is mostly associated with trading activities of retail investors. Yet, there are much evidence that the upward trend is reversed when the sample period is extended over 2000 (see e.g., Bekaert, Hodrick, and Zhang (2005) and Brandt, Brav, Graham, and Kumar (2009)).

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. While the existence of the time trend documented in CLMX has been questioned in the extended sample and some papers document that the trend is largely due to small illiquid stocks, neither of these caveats apply to our work. First, in examining the trend of the extreme deciles, we divide the deciles by the cross-sectional mean to eliminate the potential trend in the aggregate idiosyncratic volatiliy. In addition, our results are based on a sample period up to 2008 and the main finding is robust to a universe of large stocks. Another stream of research on idiosyncratic volatility emerges from AHXZ who examine the relation between idiosyncratic volatility and expected return in the cross-section. Our research is similar in that we examine the cross-sectional distribution of idiosyncratic volatilities, but it is different in that we are interested in the time trend of the cross-sectional distribution rather than the risk-return tradeoff.

Our analysis also adds to the literature that provides systematic evidence on whether arbitragers 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 for both amplification and reduction of shocks depending on their size. The paper is also related to the literature connecting 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 experienced a particularly high shock in the previous period.

The structure of the paper is as follows. In the next section, we develop a theoretical model which motivates our empirical tests. In section 3, we describe our sample and estimation methods. In section 4, after we confirm the finding of previous literature, we present the time trend of idiosyncratic volatility in the cross-section and conduct several robustness checks. In section 5, we examine the relationship between the observed time trend and potential determinants of this trend. In section 6, we conclude.

2. A Model of limited arbitrage, capital share of hedge funds, and the cross-section of idiosyncratic volatility

We use a slightly modified version of Shleifer and Vishny (1997) model on limited arbitrage. Consider a market with a large number of assets. The cash flow of each asset has a systematic component and a mean reverting idiosyncratic shock. There are two types of agents participating in the market. **Long-term traders** hold assets for the cash flows, so their demand for each asset is positively related to the cash flow of the asset and negatively related to its price. **Managers** of Long/Short-Equity funds aim to benefit from the mean reversion in idiosyncratic risk. Thus, focusing on a small number of assets, they decompose the systematic and the idiosyncratic part in cash flows and estimate the dynamics of the idiosyncratic risk. Then, they hold a long-short position of the particular assets and a well-diversified portfolio to achieve a zero exposure on the systematic component. Similar to Shleifer and Vishny (1997), we assume that the size of managers position is limited by their capital and the level of their capital is positively related to past trading profits. Our main objective is to derive the equilibrium relation between the dynamics of the idiosyncratic component of returns and the cash flows, the capital of managers, and the liquidity of the assets. In particular, the model illustrates that idiosyncratic shocks to returns are increasing in the underlying cash-flow shocks, while larger amounts of capital under management of Long/Short-Equity funds further increase large idiosyncratic shocks but decrease small idiosyncratic shocks. Furthermore, all these effects are larger in magnitude for less liquid stocks.

In particular, consider a group of managers who analyze the cash-flow characteristics of stock i. Suppose they find that the cash-flow dynamics of this asset in the next three periods is described by

$$\theta_{t+u(i)} - \tilde{S}_{u(i)}, \tag{1}$$

where $\theta_{t+u(i)}$ is the systematic component and $\tilde{S}_{u(i)}$ is the idiosyncratic component. The index $u(i)$ denotes that idiosyncratic shock to asset i can be in one of three phases, $u = 1, 2, 3$. In Phase 1, $\tilde{S}_1 = S$. In Phase 2, $\tilde{S}_2 = 0$ or $\tilde{S}_2 = \lambda \tilde{S}_1$ with probability q and $(1-q)$, respectively. We assume $\lambda > 1$, thus the shock either intensifies in absolute terms or disappears. In Phase 3, $\tilde{S}_3 = 0$. (We denote a random variable by tilde and its realization by the same character without tilde.) We assume that cash flows are paid at the end of the respective period, but known by the beginning of each period. The demand of long-term traders for the asset is

$$\kappa \frac{\theta_{t+u(i)} - \tilde{S}_{u(i)}}{\tilde{p}_{u(i)}}, \tag{2}$$

where $\frac{1}{\kappa} \geq 1$ parametrizes the sensitivity of long-term traders demand on prices.[3]

Each manager's portfolio consists of a position in the particular asset to gain from the short-term convergence of the price of a particular asset and a hedging position invested in a well-diversified portfolio in such a way that managers do not take on systematic risk. Suppose that the value of the representative manager position in asset i is $D_{u(i)}$. Then the market clearing conditions in each phase is given by

$$\kappa \frac{\theta_{t+u(i)} - \tilde{S}_{u(i)}}{\tilde{p}_{u(i)}} + \frac{D_{u(i)}}{\tilde{p}_{u(i)}} = 1. \tag{3}$$

Since

$$\frac{\kappa \left(\theta_{t+u(i)} - \tilde{S}_{u(i)}\right)}{1 - \frac{D_{u(i)}}{\tilde{p}_{u(i)}}} = \tilde{p}_{u(i)}, \tag{4}$$

κ measures the price effect of a unit trade by managers. If κ is small, a change in $\frac{D_u}{\tilde{p}_u^1}$ has a little effect on the price, while for a large κ, the price effect is also large. Therefore, κ can be interpreted

[3] To microfound this assumption, one can imagine that the cash flows in period t become public information at the beginning of the period. Then the value of the discounted future cash flows of the asset is an increasing function of current cash flows. Thus, any microfoundation for which long-term traders buy more of the asset if its fundamental value increases, and buy less of it if its price increases, would support this assumption. For such microfoundation, the parameter $\frac{1}{\kappa}$ would be positively related to the risk-aversion of long-term traders.

as the illiquidity of the particular asset. The other part of managers' long-short portfolio is a short position in a well-diversified portfolio, which exactly offsets the systematic component of returns. Given that this part implies a relatively small position in a large number of assets, we assume that this hedging part does not affect the prices of the components of this portfolio. Thus, the cash flow of each unit of this portfolio is

$$\theta_{t+u(i)}, \tag{5}$$

its price is

$$\kappa\theta_{t+u(i)}, \tag{6}$$

and the manager holds the same number of units of this portfolio as asset i.

Managers are risk neutral, and the value of their position in the asset cannot exceed F_u in phase u , that is, $D_u \leq F_u$. The value F_1 can be thought of as a position limit, which is proportional to the funds' capital in phase 1. Similar to Shleifer and Vishny (1997), while F_1 is exogenous, F_2 is endogenous. The second phase position limit depends on past profits as

$$F_2\left(\tilde{S}_2\right) = \max(0, a\Pi_1\left(D_1, \tilde{p}_1, \tilde{p}_2\right) + F_1), \tag{7}$$

where $\Pi_1\left(D_1, \tilde{p}_1, \tilde{p}_2\right)$ is the net profit or loss to the manager by the second phase, given her position D_1 and the prices $\tilde{p}_1$ and $\tilde{p}_2$.[4] We assume that $\kappa S > F_1$, that is, managers do not have sufficient capital to fully eliminate the idiosyncratic shock in Phase 1. In the Appendix we show that the following proposition holds.

Proposition 1. *There is an a^* and q^* such that if $a > a^*$ and $q > q^*$ then the equilibrium is characterized as follows.*

1. *In the first phase, managers invest fully, $D_1 = F_1$.*

2. *In the second and third phases, managers liquidate their position and do not hold any assets.*

[4] The literature includes various reasons for why hedge funds cannot assume arbitrarily large positions and why their effective position limits depend positively on past profitability. For example, Shleifer and Vishny (1997) use capital flows from investors, Gromb and Vayanos (2002) and Brunnermeier and Pedersen (2009) use margin constraints, and Xiong (2001) uses the wealth effect of risk-averse arbitrageurs to draw similar conclusion.

3. Prices are given as follows

$$
\begin{aligned}
p_1 &= \kappa\left(\theta_{t+1} - S\right) + F_1 && (8)\\
p_2\left(\tilde{S}_2 = \lambda S\right) &= \kappa\left(\theta_{t+2} - \lambda S\right) && (9)\\
p_2\left(\tilde{S}_2 = 0\right) &= \kappa\theta_{t+2} && (10)\\
p_3 &= \kappa\theta_{t+3}. && (11)
\end{aligned}
$$

Proof. In the Appendix. ■

The parameter restriction q ensures that the worsening of the shock has a sufficiently low chance that managers fully invest in Phase 1. The restriction on a ensures that a worsening shock in Phase 2 fully wipes out the capital of managers taking maximal position in Phase 1. Thus, managers do not hold any assets regardless of the shock in the second phase, because either the trading opportunity disappears or their capital is wiped out.

Let us turn to the analysis of the cross-sectional distribution of idiosyncratic volatility. Consider the expression

$$((p_{u+1} - p_u) - \kappa\left(\theta_{t+u+1} - \theta_{t+u}\right))^2 \qquad (12)$$

as the model variant of our measure of idiosyncratic volatility. This is the return in a given period minus the part of the return which is due to the systematic component. In line with the concept of idiosyncratic risk, we assume that even if each asset goes through the same three phases, they are not all in the same phase at any particular time-point. In particular, consider a large number of assets. Then each point in time a group consisting one third of all the assets is in Phase 1, a group of the same size is in Phase 2, and the last group is in Phase 3. Then, using equations (8)-(11), our model implies the following cross-sectional distribution of idiosyncratic volatility at any given point in time.

fraction of stocks	realized IV	which assets belong to the fraction?
$q\frac{1}{3}$	0	Phase 3 assets with $S_2 = 0$
$\frac{1}{3} + q\frac{1}{3}$	$(\kappa S - F_1)^2$	Phase 2 assets with $S_2 = 0$ and all Phase 1 assets
$(1-q)\frac{1}{3}$	$(\kappa\lambda S - (\kappa S - F_1))^2$	Phase 2 assets with $S_2 = \lambda S$
$(1-q)\frac{1}{3}$	$(\kappa\lambda S)^2$	Phase 3 assets with $S_2 = \lambda S$

Under our parameter conditions, the realized shocks increase from the top to the bottom row of this table as

$$0 < (\kappa S - F_1)^2 < (\kappa(\lambda - 1) S + F_1)^2 < (\kappa \lambda S)^2 .$$

To translate our model to our empirical specification, we think of the fraction of stocks in the first and second rows of the table as the group representing the bottom quintile of the cross-sectional distribution, while the fraction of stocks in the third and fourth row as the top quintile of the cross-sectional distribution. Then, the following proposition states the model equivalent of our tested hypotheses.

Proposition 2. *If $a > a^*$ and $q > q^*$, the following statements hold*

1. *The absolute size of the idiosyncratic return shock increases in each quintile in the size of the cash-flow shock. That is,*

$$\frac{\partial (\kappa S - F_1)^2}{\partial S}, \frac{\partial (\kappa(\lambda - 1) S + F_1)^2}{\partial S}, \frac{\partial (\kappa \lambda S)^2}{\partial S} > 0.$$

2. *The average of the absolute size of idiosyncratic return shock is increasing in first period capital, F_1, in the top quintile and decreasing in the bottom quintile. That is,*

$$\frac{\partial (\kappa S - F_1)^2}{\partial F_1} < 0, \frac{\partial (\kappa(\lambda - 1) S + F_1)^2}{\partial F_1} + \frac{\partial (\kappa \lambda S)^2}{\partial F_1} > 0$$

3. *If illiquidity κ increases, the absolute size of each effect in the previous two statements increase. That is*

$$\begin{aligned} \frac{\partial\left(\frac{\partial(\kappa S - F_1)^2}{\partial S}\right)}{\partial \kappa}, \frac{\partial\left(\frac{\partial(\kappa(\lambda-1)S+F_1)^2}{\partial S}\right)}{\partial \kappa}, \frac{\partial\left(\frac{\partial(\kappa\lambda S)^2}{\partial S}\right)}{\partial \kappa} &> 0 \\ \frac{\partial\left(\left|\frac{\partial(\kappa S - F_1)^2}{\partial F_1}\right|\right)}{\partial \kappa}, \frac{\partial\left(\frac{\partial(\kappa(\lambda-1)S+F_1)^2}{\partial F_1}\right)}{\partial \kappa} + \frac{\partial\left(\frac{\partial(\kappa\lambda S)^2}{\partial F_1}\right)}{\partial \kappa} &> 0 \end{aligned}$$

Proof. In the Appendix. ■

Figure 1 illustrates our results. We plot the realized idiosycnratic volatility of a particular stock under different scenarios in each phase u. If managers do not trade at all, the realization would follow the solid line and the dash-dotted line depending on whether the shock disappears ($S_2 = 0$) or worsens ($S_2 = \lambda S$). If managers have capital F_1 in Phase 1, the realization follows the dotted line and the dashed line if $S_2 = 0$ and $S_2 = \lambda S$, respectively. It is apperent that the large shocks are realized when $S_2 = \lambda S$, while the small shocks correspond to the case when

$S_2 = 0$. Thus, as we pointed out, we think of the first group of shocks as the top-quintile shocks and label them by T on the figure, while the second group of shocks correspond to the bottom-quintile shocks and are labeled by B. It is apparent that if F_1 is larger, then shocks in the bottom quintile decrease. The intuition is that larger capital increases managers' total position against the temporary shock. However, a larger F_1 also increases the average shock in the top quintile as the size of the liquidated positions due to reaching the loss limits also increases. This increases realized return volatility. Nevertheless, each shock is positively related to S, the fundamental cash-flow shock, and κ, the illiquidity of the asset.

3. Data and methodology

In this section, we explain the estimation method of the subject variables of our empirical tests. We follow AHXZ and Irvine and Pontiff (2009) in estimating idiosyncratic return volatility and idiosyncratic cash-flow volatility for an individual firm, respectively.[5] We then develop a measure that describes the extreme realizations of these variables in the cross-sectional distribution.

A. Idiosyncratic return volatility and its cross-sectional distribution

Following AHXZ, we estimate idiosyncratic volatility relative to the Fama-French three-factor model. We examine both monthly and quarterly idiosyncratic volatility using daily return data.[6] Specifically, for period t and stock i, we estimate the following regression model

$$r_{i,s} = \alpha_i + \beta_{i,MKT} MKT_s + \beta_{i,SMB} SMB_s + \beta_{i,HML} HML_s + \varepsilon_{i,s}, \tag{13}$$

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

[5] Some studies question the method by which idiosyncratic volatility is estimated in the literature. For example, Garcia, Mantilla-Garcia, and Martellini (2011) use the cross-sectional variance (CSV) of stock returns to estimate the aggregate idiosyncratic risk and find that the CSV predicts well the aggregate return. Fu (2009) argues that idiosyncratic volatility estimated using an E-GARCH model performs better in explaining the risk-return tradeoff. Although those papers provide sound evidence, our focus is not on the method of estimating idiosyncratic volatility. Also, Fu (2009) and Huang, Liu, Rhee, and Zhang (2010) point out that contemporaneous idiosyncratic risk measured from standard deviation has a positive relation with expected return, further validating the use of the measure proposed in AHXZ.

[6] We use monthly series of idiosyncratic volatility for the graphical analysis as well as for the time-trend regressions (Tables 1 and 2). We use quarterly series for other regression analyses (Table 3, 4, and 5) since the explanatory variables in these regressions are available at the quarterly frequency. The quarterly series display similar time trends as the monthly series.

of the regression over the number of trading days in period t, $D_{i,t}$:

$$IV_{i,t} = \frac{1}{D_{i,t}} \sum_{s \in t} \varepsilon_{i,s}^2. \tag{14}$$

Note that our estimation method of idiosyncratic volatility is somewhat different than that applied in CLMX, 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 from CRSP and daily risk-free rate and Fama-French factors from Kenneth French's website.[7] 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 AHXZ, 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. Hereafter, we refer to this sample as the CRSP sample.

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:

$$M_t = \sum_i w_{i,t} IV_{i,t} \tag{15}$$

$$V_t = \sum_i w_{i,t} (IV_{i,t} - M_t)^2 \tag{16}$$

$$S_t = \frac{1}{N_t} \sum w_{i,t}^{\frac{3}{2}} \Big(\frac{IV_{i,t} - M_t}{\sqrt{V_t / N_t}} \Big)^3 \tag{17}$$

$$K_t = \frac{1}{N_t} \sum w_{i,t}^{2} \Big(\frac{IV_{i,t} - M_t}{\sqrt{V_t / N_t}} \Big)^4 - 3, \tag{18}$$

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.

[7] We thank Ken French for providing the factors on his website: http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/

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:[8]

$$d_{k,t} = \sum_{i \in k} w_{i,t} IV_{i,t} / M_t. \tag{19}$$

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.

B. 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.[9] 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 follow Vuolteenaho (2002). Specifically, 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 regression at

[8] 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.

[9] 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.

the Fama-French 48 industry level (Fama and French (1997)):[10]

$$dE_{i,t} = \alpha + \beta_1 dE_{i,t-1} + \beta_2 dE_{i,t-2} + \beta_3 dE_{i,t-3} + \beta_4 dE_{i,t-4} + \epsilon_{i,t}. \tag{20}$$

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

$$\epsilon_{m,t} = \frac{1}{N_t} \sum \epsilon_{i,t}. \tag{21}$$

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

$$IV_{i,t}^{CF} = (\epsilon_{i,t} - \epsilon_{m,t})^2. \tag{22}$$

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

$$d_{k,t}^{CF} = \sum_{i \in k} w_{i,t} IV_{i,t}^{CF} / \sum_{j} w_{j,t} IV_{j,t}^{CF}. \tag{23}$$

Quarterly EPS and book equity data are obtained from the intersection of Compustat and the CRSP sample.[11] The sample firms are required to have at least four consecutive quarters 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 outlier in the regression. The sample period for the pooled regression in (20) is from January 1972 to December 2008 due to the availability of book-equity data.

[10] 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 (20). 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 (20). 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.

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

4. Extreme realizations in idiosyncratic return volatility

A. Diverging time trends

CLMX document the increasing trend of idiosyncratic volatility during the period 1962–1997, while other papers in the literature show that the trend reverses by 2007 (see, e.g., Brandt, Brav, Graham, and Kumar (2009) and Bekaert, Hodrick, and Zhang (2010)). We start our analysis by confirming prior findings while extending the sample period to 2008. Figure 2 plots the 12-month moving average of the cross-sectional mean of idiosyncratic volatility (annualized). The top panel displays the time trend up to 1997, confirming the result of CLMX. The graph exhibits the increasing trend of aggregate idiosyncratic volatility, tripling over the sample period. The bottom panel also confirms the result of Brandt, Brav, Graham, and Kumar (2009) and others that the level of the aggregate idiosyncratic volatility 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. Figure 3 plots the time series of other statistical properties of the cross-sectional distribution. Panels A, B, and C 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 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 (19), 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 4 shows the time trend of our measure of each decile share. Panel A plots all deciles, while Panel B focuses on 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.

The natural question that is raised from observing Figure 4 is whether the time trends are stochastic. We formally 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:

$$d_{k,t} = \alpha + \gamma d_{k,t-1} + u_t \tag{24}$$

$$d_{k,t} = \alpha + \delta t + \gamma d_{k,t-1} + u_t. \tag{25}$$

The last two columns of Table 1 report the p-values of the Phillips-Perron tests. For the test that uses a constant term alone (Equation (24)), we reject a unit root for d_{10} at the 5% level, and d_1, d_8, and d_9 at the 10% level, while for other deciles, we cannot reject a unit root. However, for the difference $d_{10} - d_1$, we significantly reject a unit-root process. For the test that includes a time-trend term (Equation (25)), we reject 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.

Following the rejections of stochastic time trends, we test for deterministic time trends. Specifically, we run the following regression model with autocorrelated errors

$$\begin{aligned} d_{k,t} &= \alpha + \delta t + \nu_t \\ \nu_t &= \sum_{j=1}^{m} \rho_j \nu_{t-j} + \varepsilon_t. \end{aligned} \tag{26}$$

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 shown in Table 1. 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.

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 most negative for Decile 1 and 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 CLMX and other studies do not affect our results. Since the trend in each decile is monotonic in volatility rankings, 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. Robustness of the trend

So far the paper studies the entire cross-section of firms, regardless of industry affiliation and other characteristics. To highlight the robustness of our results we perform the following robustness tests: (a) we test whether the trends exist in various industries and across different firm characteristics; (b) we test firms' affiliations to the extreme deciles in event time. If firms' affiliations are persistent, it is likely that certain characteristics of the firms in the extreme deciles are associated with the observed time trends; (c) over the sample period, many relatively small firms have been listed. To alleviate concerns that the trends are due to the increasing number of small firms, we control for the number of firms and their size in performing our trend analyses; and (d) we test whether the trends are driven by the either the positive or negative idiosyncratic shocks. All the results support the view that our main findings are not explained by a specific group of firms.

First, we examine whether the established time trends remain after controlling for some firm characteristics. We sort stocks into quintiles by a given control variable, and then examine the time trends of d_1 and d_{10} within each quintile. We use illiquidity and size as control variables. We estimate the illiquidity of firm i during year y using the Amihud (2002) measure

$$ILLIQ_{i,y} = \frac{1}{D_{i,y}} \sum_{s \in y} \frac{|R_{i,s}|}{P_{i,s} Vol_{i,s}}, \tag{27}$$

where $D_{i,y}$ is number of trading days in year y, $R_{i,s}$ is the raw return on day s, and P and Vol are stock price and trading volume, respectively. To form illiquidity quintiles, we sort firms by their illiquidity measured during the prior calendar year. Size is firm's market capitalization at the end of the previous month. We plot the idiosyncratic volatility time trends among the illiquidity and size quintiles in Figure 5. The trends are apparent in the different illiquidity and size quintiles.

Next, we directly test whether firms' affiliations to an idiosyncratic volatility decile change in event time. If affiliations significantly change, then it is the extreme realizations to random firms rather than to the same firms that drives the uncovered trends, that is, firms in extreme idiosyncratic volatility deciles in a particular month are likely to have different characteristics from firms in the extreme deciles during the following month. The following event-study analysis is performed. Extreme decile portfolios of idiosyncratic volatility (Deciles 1 and 10) are constructed each month. These portfolios are held for 60 months post-formation, and are also traced back for 24 months pre-formation. We calculate two statistics for these portfolios: (1) we estimate the share of the portfolios' idiosyncratic volatility in the aggregate idiosyncratic volatility. This is analogous to d_1 and d_{10}, but we are holding constant the individual stocks in the portfolios for the event-time period; (2) we calculate the average decile affiliation of the stocks in each portfolio in event time. By definition, at the formation month of the portfolios ($t = 0$), the average decile affiliation is 1 for stocks in Decile 1, and 10 for stocks in Decile 10. We are interested in the persistence of the average decile affiliation post- and pre-portfolio formation. For the sample period from July 1963 through December 2008, we construct 455 extreme decile portfolios.

Figure 6 plots the results of the event study. Panel A reports the time-series averages of portfolios' share in the aggregate idiosyncratic volatility in event time. By construction, the average shares of the extreme portfolios at $t = 0$ are equivalent to the time-series averages of d_1 and d_{10}. The average share of Decile 10 at $t = 0$ is above 10% and that of Decile 1 is below 10%, which is also confirmed from Figure 4. Shortly before and after portfolio formation, the shares of the extreme deciles display a significant reversal, after which the series gradually converge to a long-term mean value. Specifically, the share of Decile 10 shows a sudden increase at time 0, quickly reverting back to its pre-formation level and gradually decreasing over time, while the share of Decile 1 exhibits the opposite pattern. Thus, stocks in the extreme deciles at the formation period exhibit different statistical properties of idiosyncratic volatility outside of the decile formation period.

In Panel B, we examine the evolution of the average decile affiliation of the stocks in the extreme portfolios in event time. At $t = 0$, the average decile is either 1 or 10. As in Panel A, we observe a sudden positive spike or a drop during the portfolio formation. This indicates that stocks in Decile 1 and Decile 10 in a given month are quite different from stocks in those decile during the following months and the previous months. The temporary changes imply that an affiliation to an extreme decile is relatively short-lived. Nevertheless, there is evidence of persistence in the volatility of individual stocks. On average, stocks in Decile 10 remain in relatively high deciles (about Decile 7) before and after formation, while stocks in Decile 1 remain in relatively low deciles (about Decile 3).

Next, we study the idiosyncratic volatility patterns across different industries. Stocks are classified into 48 industries following Fama and French (1997). We exclude eight industries with less than 20 firms on average during the sample period. We sort firms in each industry into idiosyncratic volatility deciles and run the regression (26) with d_1, d_{10}, and $d_{10} - d_1$ as the left-hand-side variables. Table 2 reports the regression results. Industries are descendingly ordered in the table according to the t-statistics corresponding to the time-trend coefficients of $d_{10} - d_1$. Overall, 26 industries show a positive coefficient in $d_{10} - d_1$, implying that the diverging time trends in the extreme deciles are prevalent among most industries. There are 14 industries that show a negative (i.e., converging) time trend. Among industries with a positive time trend, 13 industries are statistically significant at the 5% level, while three industries are statistically significant among negative-trend industries. Electronic equipment, Automobiles, Telecommunications, Trading, and Computers are examples of industries that display a particularly strong diverging trend, while Pharmaceutical, Precious metal, and Aircraft show a strong converging trend.

The explanatory power of the diverging trends is mostly due to the trend in d_1. Out of 13 industries with a significant diverging trend, 11 industries exhibit a significant negative trend in d_1, while only seven industries have a significant positive trend in d_{10}. In general, the regression R^2 is higher when d_1 is used as a dependent variable. As we see in the next section, the downward trend in d_1 is related to hedge-fund trading activity while the upward trend in d_{10} is associated with both hedge-fund activity and the increase in cash-flow volatility. Irvine and Pontiff (2009) argue that the increase in cash-flow volatility is attributed to the increasingly intense economy-wide competition. Our result seems to be consistent with this idea, because, for example, the industries Telecommunication, Trading (Finance), Computers, and Real Estate display positive trends in d_{10}, both in terms of statistical significance and economic magnitude. Firms in these industries are more likely to face more competition than firms in other industries. Overall, Table 2 shows that the time trends in the cross-sectional distribution of idiosyncratic volatility vary considerably among industries. However, the diverging time trend is observed in the majority of the industries, and the magnitude of the time trend for the industries with a diverging trend is much higher than that of converging-trend industries.

Over the sample period, the number of firms has more than tripled. The sample size at the beginning of 1964 is 1,562, while there are 4,966 firms at the end of 2008. The sample reaches its highest size during the late 1990s, with more than 6,800 firms, but it gradually decreases after the internet bubble in early 2000s and the financial crisis in 2008. Also, many relatively small firms are listed over the sample period. To evaluate whether these changes in the sample affect our results, we study the trends in idiosyncratic volatility in two subsamples. The first subsample consists of 1,000 firms randomly selected every month during the sample period. This method controls the number of firms in this subsample. The second subsample consists of S&P 500—this controls for both the number of firms and their market capitalization. Figure 7 shows that the time trends in idiosyncratic volatility exist in both subsamples. The time trend is even stronger in the subsample of S&P 500 firms. Since S&P 500 index is typically composed of 500 large firms, the implication is that the time trends in idiosyncratic volatiliy are not driven by newly listed, smaller firms.

Finally, we study whether the time trends stem from either the positive or negative idiosyncratic shocks. By construction, the daily idiosyncratic shocks during the estimation period sum to zero per firm. If a small number of large negative (positive) shocks are extremely large compared to the average negative (positive) shocks, then the diverging time trend may be mostly due to the diverging trend in the realization of negative (positive) shocks. To investigate this issue, we divide daily idiosyncratic shocks into positive and negative groups. To obtain enough observations of positive or negative shocks for a stock in a given month, we run the regression (13) per firm per year instead of per firm per month. Then, we average the squared positive and negative shocks separately over each month to obtain the monthly averages of positive and negative idiosyncratic shocks. Figure 8 plots the time trends of the positive and negative shocks of their corresponding top and bottom deciles. The figure confirms that the trends are robust to shocks of both signs.

Thus, we conclude that both large positive and large negative shocks have increased over the sample period, while small positive and small negative shocks have decreased over the same period, relative to their respective averages.

5. Fundamentals or trading activity?

In the previous section, we examine the cross-section of idiosyncratic return volatility and establish the diverging time trends in the extreme deciles. In this section, we study some potential determinants of these time trends. The literature suggests that the time trend in the aggregate idiosyncratic volatility can be attributed to two different sources: the volatility of firm fundamentals, such as cash flows, and trading activities of market participants. For example, Xu and Malkiel (2003) show that the idiosyncratic volatility of individual stocks is positively related with both institutional ownership and expected earnings growth. Brandt, Brav, Graham, and Kumar (2009) document that the increasing trend during pre-1990 period and the reversal by 2007 are associated with the trading patterns of retail investors. Irvine and Pontiff (2009) show that the time trend in idiosyncratic return volatility is mirrored by a similar trend in idiosyncratic cash-flow volatility.

Thus, in this section, we test whether the time trends in the extreme deciles of idiosyncratic volatility are due to changes in firm fundamentals or changes in trading activity. To evaluate the possibility that our results are explained by the changes in fundamentals, we investigate the connection between the observed trends in the extreme deciles and the corresponding trends in the cash-flow volatility of the firms in the deciles. To evaluate the possibility that our results are explained by the changes in the trading process, we investigate the trading activities of several different types of institutions: Long/Short-Equity hedge funds, non-Long/Short-Equity hedge funds, and institutional investors excluding hedge funds. Based on our theoretical model in Section 2, we expect a positive relation between idiosyncratic cash-flow volatility and idiosyncratic return volatility, while the AUM of Long/Short-Equity managers is expected to induce opposite effects on the top and bottom deciles. We argue that an increase in the capital of Long/Short-Equity managers leads small shocks to become smaller and large shocks to become larger. We also argue that the Long/Short-Equity effect is stronger for less liquid stocks.

We begin the analysis by running time-series regressions of the shares of extreme deciles in the aggregate volatility on the cash-flow volatility in the deciles, the AUMs of Long/Short-Equity hedge funds, and various controls. We then continue to investigate whether the effect of each determinant of the time trend is stronger for the group of highly illiquid stocks, by examining the trends of the extreme deciles of idiosyncratic volatility in the illiquidity quintiles. Finally, a panel-regression analysis using individual stocks provides more direct evidence. Consistent with the predictions of our model, the regression results suggest that while fundamental factors positively affect idiosyncratic volatility, hedge-fund ownership reduces the volatility of low-volatility stocks yet increases that of high-volatility stocks.

A. Determinants of the time trend

To investigate the potential determinants of the diverging time trends in the extreme deciles of idiosyncratic volatility, we run the following time-series regression

$$d_{k,t} = \alpha + \delta t + \beta_1 d_{k,t}^{CF} + \beta_2 LSE_{t-1} + \gamma' \mathbf{X}_{t-1} + \varepsilon_t, \tag{28}$$

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 is the natural logarithm of the total AUM of Long/Short-Equity funds in a given period, and $\mathbf{X}$ is the vector of control variables. Fund AUMs are obtained from Lipper/TASS database, and are used as proxies for the trading activities of hedge funds. 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-Equity funds, and other institutional investors. As only a small fraction of total institutional ownership is due to hedge funds, we use total institutional ownership as proxy for the trading activity of institution other than hedge funds. Institutional ownership is measured as the percentage of 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. The decile total value is further divided by the total market capitalization of the decile. Institutional ownership data are obtained from the CDA/Spectrum database provided by Thompson Reuters. Due to the availability of hedge fund data, the sample period for the regression 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 independent variables throughout different specifications. By adding the time trend, both dependent and independent variables are effectively detrended. Therefore, Equation (28) 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. We run the regression using the full sample, as well as separately using the stocks in each illiquidity quintile. The reported t-statistics are Newey-West adjusted.

i. Full sample

Table 3 reports the regression results for the full sample. 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 3 for the period 1964–2008 also hold for the more recent period 1994–2008. The t-statistics of the time trends for d_1 and d_{10} are -1.92 and 3.42, respectively. The cash-flow volatility and illiquidity for Decile 1 display a significantly negative trend, while the trends in those variables for Decile 10 are insignificant. Hedge-fund AUM 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 six 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 theoretical predictions. Its coefficient for d_1 is significantly negative, while it is positive, albeit insignificant, for d_{10}. Also, the inclusion 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, to the extent that LSE represents the trading activity of hedge funds in equities, the evidence suggests that 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, we find that different variables are important in explaining the patterns of d_1 and d_{10}. For d_1, only LSE is important, while only cash-flow volatility is important for d_{10}. 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 trend 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. The effects of these two variables are robust to different model specifications. In the final model, we include both cash-flow volatility and LSE, as well as all of the control variables. Other than LSE and cash-flow volatility, leverage is significantly positive for d_{10} and institutional ownership is significantly positive for d_1. Therefore, fundamental variables, such as cash-flow and leverage, are important for stocks with high-idiosyncratic volatility, while the trading activities of different types of institutions affect stocks with low-idiosyncratic volatility.

Nevertheless, a comparison of Models 4 and 6 highlights that the variables that proxy for institutional trading are still important for understanding the time trend of d_{10}, because the inclusion of variables unrelated to the trading process is not sufficient for eliminating the significance of this time trend. However, the inclusion of the variables that proxy for institutional trading, although displaying insignificant coefficients, eliminate the time trend in d_{10}. We conclude that our time-series results on the full sample provide evidence that the trend in the bottom decile is related to the activity of financial institutions, while the trend in the top decile is mostly associated with the changes in the distribution of the underlying cash flows.

ii. Illiquidity quintiles

Our model predicts that the effects of the increasing trading activity of hedge funds are amplified with the illiquidity of the stock. Therefore, we divide the sample into illiquidity quintiles and run the regression (28) within each illiquidity quintile. Table 4 reports the results for Quintile 1 (most liquid stocks) and Quintile 5 (least liquid stocks) for the sample period 1994–2008. Quintiles are formed based on stocks' illiquidity measured during the previous calendar year. Within each illiquidity quintile, we further form deciles of idiosyncratic volatility and calculate our measure of the relative share of each decile, d_k, in the cross-section of firms that belong to that quintile.

The first model in each panel reports the results of time-trend regressions within illiquidity quintiles. The time trend for d_1 is significantly negative in Quintile 5, with a t-statistic of -6.67, while the trend is not significant for Quintile 1. In contrast, the time trend of d_{10} is significantly positive for both quintiles, with t-statistics of 2.94 and 3.99 for Quintiles 1 and 5, respectively. The second model in each panel reports the results of a regression model that includes idiosyncratic cash-flow volatility and LSE as explanatory variables. The inclusion of these variables eliminates the diverging time trends for both quintiles of illiquidity. The coefficients of cash-flow volatility are positive for both d_1 and d_{10} in both quintiles of illiquidity (albeit some are not statistically significant). As for the coefficients of LSE, they appear significantly negative for d_1 in both illiquidity quintiles, while for d_{10} the coefficient of LSE is insignificant in Quintile 1 and significantly positive in Quintile 5 (at the 10% level). These results suggest that Long/Short-Equity funds behave as liquidity providers for relative small idiosyncratic shocks regardless of a firm's liquidity, while they behave as liquidity demanders for illiquid stocks with high-idiosyncratic volatility.

The third model of each panel includes all the control variables. The results are generally consistent with those of the second model. Nevertheless, the effect of LSE on d_{10} appears more signficant in illiquidity Quintile 5, further emphasizing that Long/Short-Equity funds trading activity both amplifies large shocks and reduces small shocks for less liquid stocks.

Consistent with our theoretical prediction, we find some evidence that the effects of Long/Short-Equity funds' trading activity are stronger for less liquid stocks. This effect may stem from two different sources. The trading effects may be larger because of the larger price impact (measured as κ in our model) of trading illiquid assets, or because Long/Short-Equity funds focus on the mispricing of less liquid stocks. Both explanations are consistent with our empirical results. These findings contribute to the debate on whether hedge funds act as liquidity providers or liquidity demanders (see, e.g., Getmansky, Lo, and Makarov (2004), Boyson, Stahel, and Stulz (2010), Sadka (2010), and Jylha, Rinne, and Suominen (2011)). Our evidence suggest that the answer depends both on the size of the idiosyncratic shock and the illiquidity of the particular asset.

B. Panel regression results

In the previous subsection, we perform time-series analyses at the decile level. In this part, we perform individual-firm-level analyses to obtain a more direct link between idiosyncratic volatility and the determinants of the time trends. Specifically, we are interested in finding the manner through which the trading activity of Long/Short-Equity fund and the cash-flow volatility affect the idiosyncratic volatility of individual firms and whether it depends on the liquidity level of the stocks.

For this analysis, 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. Note, that in contrast to the time-series analysis above that separates Long/Short-Equity and non-Long/Short-Equity funds, here we compute for each firm its total share ownership across all available hedge funds, regardless of investment style. The reason is sample size: we are only able to match several hunderd Long/Short-Equity funds. The implied assumption, which we believe to be reasonable, is that the trading activity of non-Long/Short-Equity funds in the equity portion of their portfolios is similar to that of Long/Short-Equity funds.

We run the following panel regression

$$\Delta IV_{i,t} = \alpha + \sum_{j \in \{1,10,Other\}} \beta^{j\prime} D^j_{i,t} \mathbf{X_1}_{i,t} + \sum_{q \in \{1,5\}} \sum_{j \in \{1,10,Other\}} \delta^{q,j} Q^q_{i,t} D^j_{i,t} HF_{i,t} + \gamma' \mathbf{X_2}_{i,t} + \varepsilon_t, \quad (29)$$

where $\Delta IV_{i,t}$ is the change in idiosyncratic volatility of firm i at time t, $\mathbf{X_1}$ includes the model variables, the changes in cash-flow volatility (at time t) and the level of hedge-fund ownership (at the end of period $t-1$), HF, $\mathbf{X_2}$ includes the control variables, non-hedge-fund institutional ownership (at the end of period $t-1$), firm leverage (at the end of period $t-1$), illiquidity (at time t), $ILLIQ$, and size (at the end of period $t-1$), and the dummy variables $D^j_{i,t}$ equal one for firms that belong to Decile j (for j = 1, 10, or other) and zero otherwise, and the dummy variables $Q^q_{i,t}$ equal one if a stock belongs to illiquidity Quintile q ($q = 1$ for liquid firms and $q = 5$ for illiquid firms) and zero otherwise. We use first differences of idiosyncratic return volatility and idiosyncratic cash-flow volatility to eliminate the potential time trends. We also interact non-hedge-fund institutional ownership with the decile dummies, $D^j_{i,t}$. To allow for linear effects of illiquidity, we also consider the following model

$$\Delta IV_{i,t} = \alpha + \sum_{j \in \{1,10,Other\}} \beta^{j\prime} D^j_{i,t} \mathbf{X_1}_{i,t} + \sum_{j \in \{1,10,Other\}} \delta^j D^j_{i,t} HF_{i,t} ILLIQ_{i,t} + \gamma' \mathbf{X_2}_{i,t} + \varepsilon_t. \quad (30)$$

Each of the models in Equations (29) and (30) is run with and without year fixed effects. We are interested in the coefficient estimates of the interaction terms and the liquidity effects, that is, the βs and δs. Table 5 reports the results. Models (1) and (2) are basic regression models that exclude any illiquidity effect. Models (3) and (4) estimate Equation (29), while Models (5) and (6) estimate Equation (30).

The regression results are consistent both with our theoretical predictions as well as the time-series results above. First, our model predicts that cash-flow shocks increase the idiosyncratic return volatility. The results confirm this prediction; cash-flow volatility is positive (and for most models significant) for all the idiosyncratic volatility deciles and for all regression specifications. For Decile 10, cash-flow volatility is significant at conventional levels, and significant for other deciles at least at the 10% level. In the time-series regressions, the significance of cash-flow volatility for Decile 1 disappears when other variables are included. However, Table 5 shows that at the individual-stock level, cash-flow volatility affects idiosyncratic volatility significantly for all deciles.

Second, also consistent with our model, hedge-fund ownership induces different effects on stocks with high and low idiosyncratic volatility. 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 stocks in the extreme deciles is much stronger in terms of economic magnitude. Once again, this result suggests that Long/Short-Equity hedge-fund trading activities reduce the volatility of low-volatility stock and increase volatility of high-volatility stocks.

Finally, the effects of hedge-fund ownership are stronger for highly illiquid firms. In Models (3) and (4), the interaction term of hedge-fund ownership with D_1 and Q_5 is significantly negative, while the interaction term of hedge-fund ownership with D_{10} and Q_5 is significantly positive. In contrast, in Quintile 1, the hedge-fund ownership effect is weaker compared to stocks with an average level of illiquidity. For example, the interaction term of hedge-fund ownership with D_{10} and Q_1 is significantly negative. Yet, the total effect is still positive for the stocks in idiosyncratic-volatility Decile 10 and illiquidity Quintile 1. For example, the total effect in Model (3) is 1.934 ($= 3.015 - 1.081$). Models (5) and (6) also confirm this finding. The interaction term of hedge-fund ownership with D_1 and illiquidity is significantly negative, while the interaction term of hedge-fund ownership with D_{10} and illiquidity is significantly positive.

Additionally, non-hedge-fund institutional ownership generally exhibits a positive effect on idiosyncratic volatility. The coefficients for the middle deciles and Decile 10 are positive and significant throughout the different specifications, yet the coefficient for Decile 1 is insignificant. 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)).

To summarize, the panel regressions confirm our earlier findings that Long/Short-Equity funds trade in a manner that reduces the volatility of low-idiosyncratic-volatility stocks, and increases the volatility of high-idiosyncratic-volatility stocks. This effect is stronger for more illiquid stocks.

6. Conclusion

Most studies of idiosyncratic volatility focus on the time trend of its aggregate level. Though we also study the time trend of idiosyncratic volatility, our approach has a couple of distinguishing features. First, we examine the cross-sectional distribution of idiosyncratic volatility. Thus, we examine the shape of cross-sectional distribution, including higher moments and tail behavior of the distribution, while prior literature focuses on the cross-sectional mean alone. Second, we develop a simple theoretical model which examines the dynamics of extreme realizations in the cross-section of returns and explains the role of idiosyncratic cash-flow volatility and institutional trading on the cross-section of idiosyncratic volatility. Our empirical tests are motivated and guided by this theoretical model.

Our main results are as follows. First, from our sample period, 1963–2008, we conclude that high-idiosyncratic volatility stocks have become more volatile over time, while low-idiosyncratic volatility stocks have become less volatile, relative to the aggregate idiosyncratic volatility. 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, using time-series and panel regressions for a shorter sample period, 1994–2008, we provide evidence that the time trends of top and bottom deciles are related to idiosyncratic cash-flow volatility and the trading activity of Long/Short-Equity hedge funds. Consistent with our theoretical predictions, the cash-flow volatility has a positive effect on idiosyncratic volatility of both the top and bottom deciles, while an increasing capital of Long/Short-Equity funds exacerbates idiosyncratic volatility of the top decile but attenuates that of the bottom decile. Finally, the hedge-fund effects are stronger for stocks with high levels of illiquidity. Therefore, hedge funds appear to provide liquidity for low-volatility stocks and demand liquidity for high-volatility stocks.

Appendix

A. Proof of Proposition 1

It is easy to see that in Phase 2 managers will not hold any position, so the price of the asset is given by

$$\kappa\theta_{t+3} = p_3.$$

Managers also do not hold assets by the end of Phase 2, if $\tilde{S}_2 = 0$. In this case, the price of the asset in Phase 2 is also

$$\kappa\theta_{t+2},$$

and

$$\begin{aligned}\Pi_1\left(D_1, p_1, \kappa\theta_t\right) &= \frac{D_1}{p_1}\left(\kappa\theta_{t+2} + \theta_{t+1} - S - p_1\right) - \frac{D_1}{p_1}\left(\kappa\theta_{t+2} + \theta_{t+1} - \kappa\theta_{t+1}\right) \\ &= D_1\frac{\kappa\theta_{t+1} - S - p_1}{p_1},\end{aligned}$$

where the two terms are the profits from the long and short position, respectively. If $\tilde{S}_2 = \lambda S$ and a manager chooses to hold a position D_2 in Phase 2, then her trading profit is given by

$$\begin{aligned}&\frac{D_1}{p_1}\left(p_2 + \theta_{t+1} - S - p_1\right) - \frac{D_1}{p_1}\left(\kappa\theta_{t+2} + \theta_{t+1} - \kappa\theta_{t+1}\right) + \\ &\qquad + \frac{D_2}{p_2}\left(\theta_{t+2} - \lambda S + \kappa\theta_{t+3} - p_2\right) - \frac{D_2}{p_2}\left(\theta_{t+2} + \kappa\theta_{t+3} - \kappa\theta_{t+2}\right) \\ &\qquad\qquad = D_1\frac{p_2 - \kappa\theta_{t+2} + \kappa\theta_{t+1} - S - p_1}{p_1} + D_2\frac{\kappa\theta_{t+2} - p_2 - S\lambda}{p_2},\end{aligned}$$

where $p_2 = \tilde{p}_2\left(\lambda S\right)$.

Thus, arbitrageurs solve the problem

$$\begin{aligned}&\max_{D_1,D_2} q\left(D_1\frac{\kappa\theta_{t+1} - S - p_1}{p_1}\right) + (1-q)\left(D_1\frac{p_2 - \kappa\theta_{t+2} + \kappa\theta_{t+1} - S - p_1}{p_1} + D_2\frac{\kappa\theta_{t+2} - p_2 - S\lambda}{p_2}\right) \\ &\text{s.t. } D_1 \le F_1 \\ &\qquad D_2 \le F_2\left(\lambda S\right) = aD_1\frac{\kappa\theta_{t+1} - S - p_1}{p_1} + F_1 \qquad \text{(A1)}\end{aligned}$$

We solve for the equilibrium backwards. It is easy to see that if $\tilde{S}_2 = \lambda S$, managers take a maximal position which implies

$$p_2 = \kappa\left(\theta_{t+2} - \lambda S\right) + F_2.$$

Also, from problem (A1), there must be a q^* that if $q > q^*$ managers take a maximal position in the first period as well. In this case,

$$\kappa\left(\theta_{t+1} - S\right) + F_1 = p_1,$$

and

$$F_2\left(\lambda\tilde{S}_1\right) = \max(0, a\Pi_1\left(D_1, \tilde{p}_1, \tilde{p}_2\right) + F_1) = \max(0, F_1\left(1 - a\frac{F_1 + S\left(1-\kappa\right)}{\kappa\left(\theta_{t+1} - S\right) + F_1}\right)).$$

Let us make two assumptions on the parameters which significantly simplify the derivation of our results. First, suppose that $q > q^*$. Second, suppose that a is sufficiently large so that

$$F_2\left(\lambda\tilde{S}_1\right) = 0.$$

That is, if the absolute level of the idiosyncratic shock increases in the second phase, the losses of managers invested fully in the first phase wipe out all their capital for the second phase. Thus,

$$p_2 = \kappa\left(\theta_{t+2} - \lambda S\right).$$

B. Proof of Proposition 2

Observe that

$$\begin{aligned}
\frac{\partial\left(\kappa S - F_1\right)^2}{\partial S} &= 2\kappa S > 0. \\
\frac{\partial\left(\kappa\left(\lambda-1\right)S + F_1\right)^2}{\partial S} &= 2\kappa\left(\lambda-1\right)\left(\left(\kappa\left(\lambda-1\right)S + F_1\right)\right) > 0 \\
\frac{\partial\left(\kappa\lambda S\right)^2}{\partial S} &= 2S\kappa^2\lambda^2 > 0,
\end{aligned}$$

and

$$\begin{aligned}
\frac{\partial\left(\kappa S - F_1\right)^2}{\partial F_1} &< 0, \\
\frac{\partial\left(\kappa\left(\lambda-1\right)S + F_1\right)^2}{\partial F_1} + \frac{\partial\left(\kappa\lambda S\right)^2}{\partial F_1} &= \frac{\partial\left(\kappa\left(\lambda-1\right)S + F_1\right)^2}{\partial F_1} = 2\left(\kappa\left(\lambda-1\right)S + F_1\right) > 0.
\end{aligned}$$

The third statement is a straight-forward consequence of these results.

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Table 1: Time-Trend Regressions of Idiosyncratic Volatility Deciles

The table reports the results of time-series regressions of the proportion of each decile of idiosyncratic volatility to the total idiosyncratic volatility on a time trend. Idiosyncratic volatilities are estimated following Ang, Hodrick, Xing, and Zhang (2006). Specifically, for each stock-month, daily returns are regressed on Fama-French three factors. Residuals from the regressions are squared and averaged over the month to measure idiosyncratic volatility. The relative proportion of each idiosyncratic volatility decile in a given month is calculated as the ratio of the value-weighted sum of the idiosyncratic volatilities of the stocks in the decile to the value-weighted sum of stocks in the entire cross-section. Autocorrelation in the error terms of the regressions are corrected up to six lags using maximum likelihood. 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 2: Time-Trend Regressions of the Extreme Deciles in Individual Industries

The table reports the results of time-series regressions of the shares of the extreme deciles in the total idiosyncratic volatility of an individual industry on a time trend. Dependent variables are the share of Decile 1, Decile 10, and Decile 10 minus Decile 1 of the idiosyncratic volatility in each industry. The value of each decile of an industry in a given month is calculated as the ratio of the value-weighted sum of the idiosyncratic volatilities of the stocks in the decile to the value-weighted sum of the idiosyncratic volatilities of stocks in the entire cross-section of the industry. Industry classification is according to Fama and French (1997). Industries with less than 20 firms per month on average are excluded. Autocorrelation in the error terms of the regressions are corrected up to six lags using maximum likelihood. The table is sorted by the T-values of the time trend of Decile 10 minus Decile 1. 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.

Industry \ Dependent Variable	d10 - d1			d1			d10			Avg. No of
	Est × 10^4	T-value	R^2	Est × 10^4	T-value	R^2	Est × 10^4	T-value	R^2	Firms
1. Electronic Equipment	4.450	9.62	0.351	-3.600	-10.82	0.484	0.837	3.42	0.043	165
2. Automobiles and Trucks	5.340	8.95	0.344	-5.040	-9.82	0.456	0.302	0.87	0.082	60
3. Telecommunications	5.960	6.96	0.321	-4.580	-9.02	0.265	1.370	3.82	0.139	79
4. Trading (Finance)	4.590	5.56	0.432	-0.970	-3.87	0.545	3.430	6.78	0.317	559
5. Computers	5.230	4.48	0.386	-4.300	-4.88	0.384	1.020	3.26	0.113	89
6. Chemicals	1.810	3.55	0.125	-1.490	-4.28	0.244	0.362	1.29	0.026	74
7. Shipping Containers	2.220	2.95	0.143	-2.210	-4.36	0.138	0.055	0.13	0.075	23
8. Consumer Goods	1.550	2.88	0.075	-1.440	-3.36	0.097	0.141	0.61	0.017	79
9. Textiles	1.620	2.82	0.090	-0.570	-3.68	0.141	1.060	2.18	0.060	34
10. Insurance	1.870	2.52	0.137	-0.032	-0.11	0.266	1.200	1.98	0.097	75
11. Machinery	1.160	2.27	0.134	-0.630	-2.23	0.320	0.562	1.91	0.045	125
12. Steel Works, Etc	1.340	2.11	0.168	-0.670	-4.29	0.141	0.687	1.80	0.068	67
13. Real Estate	1.650	2.06	0.152	-0.054	-0.58	0.093	1.660	2.40	0.147	38
14. Healthcare	1.630	1.89	0.116	-0.029	-0.09	0.100	1.600	2.17	0.091	66
15. Nonmetallic Mining	0.724	1.71	0.089	-0.960	-5.09	0.247	-0.220	-0.55	0.075	26
16. Business Supplies	0.799	1.59	0.075	0.664	2.12	0.166	1.460	5.45	0.077	39
17. Transportation	0.572	1.26	0.080	0.178	0.84	0.237	0.722	1.94	0.080	88
18. Banking	0.777	1.20	0.191	0.293	0.72	0.371	1.050	2.08	0.167	202
19. Utilities	1.330	1.00	0.417	-0.310	-2.41	0.385	0.998	1.09	0.351	150
20. Measuring and Control Equip	0.701	1.00	0.076	0.271	0.56	0.096	1.040	3.57	0.032	57
21. Recreational Products	0.556	0.66	0.132	-1.380	-5.14	0.108	-0.710	-1.10	0.146	36
22. Entertainment	0.489	0.53	0.105	0.752	1.31	0.155	1.170	2.56	0.063	36
23. Retail	0.338	0.46	0.201	-0.270	-0.52	0.252	0.068	0.21	0.095	180
24. Others	0.795	0.36	0.163	-1.330	-1.44	0.179	-0.360	-0.35	0.057	43
25. Apparel	0.168	0.35	0.048	-0.300	-1.53	0.087	-0.100	-0.31	0.031	52
26. Construction	0.098	0.11	0.173	0.264	1.17	0.272	0.473	0.66	0.147	41
27. Electrical Equipment	-0.140	-0.25	0.079	0.188	0.34	0.209	0.052	0.14	0.044	74
28. Personal Services	-0.270	-0.35	0.055	-0.110	-0.55	0.088	-0.370	-0.61	0.038	31
29. Construction Materials	-0.150	-0.40	0.037	-0.220	-1.01	0.220	-0.390	-1.07	0.032	108
30. Priting and Publishing	-0.270	-0.48	0.067	0.524	3.34	0.113	0.251	0.50	0.055	37
31. Restaurants, Hotel, Motel	-0.950	-1.01	0.210	0.432	1.20	0.182	-0.440	-0.62	0.176	68
32. Rubber and Plastic Products	-1.050	-1.40	0.092	0.103	0.52	0.128	-0.940	-1.39	0.070	26
33. Wholesales	-0.490	-1.48	0.029	0.510	3.07	0.170	0.004	0.01	0.018	116
34. Petroleum and Natural Gas	-0.750	-1.56	0.112	0.422	1.64	0.086	-0.310	-1.10	0.090	144
35. Food Products	-0.760	-1.61	0.065	0.734	2.97	0.229	-0.079	-0.28	0.008	60
36. Business Services	-0.950	-1.61	0.114	1.220	7.89	0.298	0.252	0.54	0.088	280
37. Medical Equipment	-1.260	-1.66	0.118	2.380	3.37	0.220	1.100	3.03	0.120	71
38. Pharmaceutical Products	-4.040	-3.06	0.395	4.380	6.14	0.655	0.700	1.29	0.147	108
39. Precious Metals	-2.010	-4.27	0.139	0.769	3.60	0.114	-1.230	-3.19	0.103	21
40. Aircraft	-1.590	-4.47	0.064	0.060	0.19	0.139	-1.550	-5.43	0.074	22

Table 3: 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 on a time trend, cash-flow volatility, AUM of Long/Short-Equity hedge funds, and various controls, including firm leverage, illiquidity, AUM of non-Long/Short-Equity hedge funds, and institutional ownership. Cash-flow volatility is estimated following Irvine and Pontiff (2009). Specifically, for each firm-quarter, cash-flow innovation (dE) is calculated as $dE_{i,t} = (E_{i,t} - E_{i,t-4})/B_{i,t-1}$. Using the cash-flow innovations, we estimate the pooled cross-sectional time-series regression at each industry level: $dE_{i,t} = \alpha + \beta_1\, dE_{i,t-1} + \beta_2\, dE_{i,t-2} + \beta_3\, dE_{i,t-3} + \beta_4\, dE_{i,t-4} + \varepsilon_{i,t}$. For each quarter, the squared difference between the residual of a firm and the cross-sectional average of the residuals in the quarter is the idiosyncratic cash-flow volatility of the firm. Then each idiosyncratic cash-flow volatility is divided into deciles based on the firm's idiosyncratic return volatility. And the shares of the extreme deciles of the idiosyncratic cash-flow volatility are calculated as the ratio of the value-weighted sum of the idiosyncratic cash-flow volatilities of the stocks in the decile to the value-weighted sum of stocks in the entire cross-section. AUM is natural logarithm of assets under management of hedge funds at the end of previous quarter. Leverage for an individual firm is measured as its total liabilities divided by its market equity. Then 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. Institutional ownership is the percentage owned by institutions for each decile at the end of previous quarter. T-statistics are calculated with Newey-West standard error using 4 lags and reported in brackets. The sample period is from January 1994 to December 2008.

Panel A: Time Trends in Variables

Variables	Return Volatility	Cash-Flow Volatility	AUM of L/S Equity	Firm Leverage	Illiquidity	AUM excl L/S Equity	Institutional Ownership
Decile 1	-0.810	-1.690		1.919	-0.250		3.631
	[-1.92]	[-2.01]		[1.03]	[-2.89]		[10.99]
Decile 10	1.113	0.711		0.485	-0.990		6.325
	[3.32]	[1.41]		[1.81]	[-1.07]		[9.63]
All			80.353			74.360	
			[35.27]			[45.02]	

Panel B: Time-Series Regression Result

Model	Variables	Linear Trend (Est × 1000)	Cash-Flow Volatility (Est × 100)	AUM of L/S Equity (Est × 100)	Firm Leverage (Est × 100)	Illiquidity (Est × 100)	AUM excl L/S Equity (Est × 100)	Institutional Ownership (Est × 100)	R^2 / Adj. R^2
1	d1	-0.620	11.362						0.335
		[-1.51]	[2.26]						0.311
	d10	0.799	44.130						0.570
		[4.45]	[7.80]						0.555
	d10-d1	1.404	21.551						0.490
		[3.94]	[2.49]						0.472
2	d1	5.396		-7.613					0.402
		[3.76]		[-3.98]					0.380
	d10	-2.050		3.909					0.167
		[-0.54]		[0.85]					0.137
	d10-d1	-7.440		11.522					0.388
		[-2.01]		[2.46]					0.366
3	d1	4.731	6.100	-6.715					0.427
		[3.66]	[1.25]	[-3.71]					0.396
	d10	0.090	43.885	0.909					0.566
		[0.04]	[6.82]	[0.36]					0.543
	d10-d1	-4.260	20.168	7.174					0.513
		[-1.64]	[1.88]	[2.22]					0.487
4	d1	-0.780	9.335		6.546				0.408
		[-1.48]	[1.60]		[1.28]				0.377
	d10	0.466	35.679		81.284				0.627
		[2.74]	[9.09]		[5.60]				0.607
	d10-d1	1.600	18.611		8.767				0.526
		[4.45]	[2.09]		[2.40]				0.501
5	d1	3.445		-6.054		-76.017	-0.953	26.786	0.578
		[2.12]		[-4.38]		[-1.23]	[-0.58]	[3.81]	0.538
	d10	-1.830		4.015		16.908	-0.363	1.483	0.225
		[-0.41]		[0.96]		[2.15]	[-0.08]	[0.17]	0.151
	d10-d1	-5.330		11.632		7.138	-2.704	-3.322	0.401
		[-1.22]		[2.38]		[1.04]	[-0.76]	[-0.37]	0.345
6	d1	3.165	2.489	-4.890	2.525	-66.819	-1.823	26.452	0.589
		[1.70]	[0.62]	[-2.23]	[0.60]	[-1.06]	[-0.85]	[3.50]	0.532
	d10	-0.820	35.714	-0.049	81.532	2.120	1.956	-1.221	0.626
		[-0.29]	[9.18]	[-0.02]	[3.99]	[0.27]	[0.73]	[-0.30]	0.574
	d10-d1	-3.330	19.661	5.538	4.828	5.238	0.664	0.281	0.529
		[-0.99]	[1.78]	[1.39]	[1.12]	[0.66]	[0.21]	[0.05]	0.464

Table 4: Time-Series Regressions of the Extreme Deciles of the Idiosyncratic Volatility in Illiquidity-Quintile Subsamples

The table presents the results of time-series regressions in illiquidity-quintile subsamples. In each illiquidity-quintile subsample, the shares of the extreme deciles of the idiosyncratic volatility are regressed on a time trend, cash-flow volatility, AUMs of Long/Short-Equity hedge funds, and various controls, including firm leverage, illiquidity, AUM of non-Long/Short-Equity hedge funds, and institutional ownership. Each illiquidity-quintile subsample is constructed based on the Amihud (2002) measure of illiquidity during previous calendar year. Then within an illiquidity-quintile subsample, stocks are divided into deciles based on their idiosyncratic volatility. Finally, the shares of the extremes decile of the idiosyncratic volatility in a given quarter are calculated as the ratio of value-weighted sum of the idiosyncratic volatility of the stocks in the decile to the value-weighted sum of stocks in the entire cross-section of the illiquidity-quintile subsample. Similarly, each idiosyncratic cash-flow volatility is divided into deciles based on the firm's idiosyncratic return volatility decile in the illiquidity-quintile subsample. And the shares of the extreme deciles of the idiosyncratic cash-flow volatility within the illiquidity-quintile subsample are computed as the ratio of the value-weighted sum of the idiosyncratic cash-flow volatilities of the stocks in the decile to the value-weighted sum of stocks in the entire cross-section of the illiquidity-quintile subsample. AUM is natural logarithm of assets under management of hedge funds at the end of previous quarter. Leverage for an individual firm is measured as its total liabilities divided by its market equity. Then for each illiquidity-quintile subsample, leverage of each decile in a given quarter is computed 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. For each illiquidity-quintile subsample, 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. Institutional ownership is the percentage owned by institutions for each decile of an illiquidity-quintile subsample at the end of previous quarter. T-statistics are calculated with Newey-West standard errors using 4 lags and reported in the brackets. The sample period is from January 1994 to December 2008.

Illiquidity Quintile	Model	Variables	Linear Trend (Est × 1000)	Cash-Flow Volatility (Est × 100)	AUM of L/S Equity (Est × 100)	Firm Leverage (Est × 100)	Illiquidity (Est × 100)	AUM excl L/S Equity (Est × 100)	Institutional Ownership (Est × 100)	R^2 / Adj. R^2
1	1	d1	0.162							0.040
			[0.84]							0.023
		d10	1.288							0.148
			[2.94]							0.134
		d10-d1	1.126							0.111
			[2.92]							0.096
	2	d1	3.007	9.546	-3.449					0.425
			[4.47]	[4.70]	[-4.04]					0.394
		d10	0.432	9.203	0.683					0.193
			[0.12]	[1.50]	[0.16]					0.149
		d10-d1	-2.560	9.963	4.080					0.195
			[-0.70]	[1.71]	[0.93]					0.151
	3	d1	1.239	9.747	-2.825	0.791	14.353	1.890	-1.115	0.493
			[1.37]	[2.99]	[-3.05]	[0.30]	[1.62]	[2.00]	[-0.30]	0.423
		d10	-3.150	6.954	-0.281	84.976	-9.565	5.405	-11.532	0.390
			[-0.66]	[1.23]	[-0.08]	[5.47]	[-0.64]	[1.20]	[-1.20]	0.306
		d10-d1	-1.910	7.491	-1.805	16.137	-0.228	5.995	-9.641	0.286
			[-0.38]	[1.35]	[-0.45]	[2.41]	[-0.01]	[1.38]	[-1.21]	0.188
5	1	d1	-0.460							0.638
			[-6.67]							0.632
		d10	1.844							0.265
			[3.99]							0.252
		d10-d1	2.307							0.338
			[4.60]							0.326
	2	d1	0.862	3.830	-1.630					0.746
			[2.23]	[1.75]	[-3.39]					0.732
		d10	-4.260	4.929	7.534					0.312
			[-1.19]	[0.62]	[1.71]					0.274
		d10-d1	-5.110	9.466	9.078					0.408
			[-1.37]	[1.27]	[1.96]					0.376
	3	d1	0.190	2.559	-1.097	0.386	13.877	0.469	1.293	0.791
			[0.32]	[1.86]	[-1.97]	[0.16]	[2.48]	[0.87]	[0.63]	0.762
		d10	4.410	3.405	7.937	6.752	-28.017	-11.967	-17.823	0.432
			[0.97]	[0.44]	[2.25]	[0.07]	[-1.40]	[-2.29]	[-1.01]	0.355
		d10-d1	3.288	7.076	10.941	2.193	-24.964	-13.224	-9.087	0.505
			[0.72]	[0.98]	[2.78]	[0.14]	[-1.44]	[-2.24]	[-0.66]	0.437

Table 5: Panel Regression of Idiosyncratic Volatility

The table reports the results of panel regressions of changes in idiosyncratic volatilities of individual stocks. Three different specifications are considered based on the illiquidity effect on the idiosyncratic volatility. Models (1) and (2) are basic regression models that exclude any illiquidity effect. Model (3) and (4) estimate the following regression:

$$\Delta IV_{i,t} = \alpha + \sum_{j\in\{1,10,other\}} \beta^{j\prime} D^{j}_{i,t} \mathbf{X}_{1i,t} + \sum_{q\in\{1,5\}} \sum_{j\in\{1,10,other\}} \delta^{q,j} Q^{q}_{i,t} D^{j}_{i,t} HF_{i,t} + \gamma' \mathbf{X}_{2i,t} + \varepsilon_{i,t}$$

where $\mathbf{X}_{1i,t}$ is a vector of the model variables, $\mathbf{X}_{2i,t}$ is a vector of the control variables, the dummy variables $D^{j}_{i,t}$ equal one for firms that belong to Decile j (for j=1, 10, or other) and zero otherwise, and the dummy variables $Q^{q}_{i,t}$ equal one if a stock belongs to illiquidity Quintile q (q=1 for liquid firms and q=5 for illiquid firms) and zero otherwise. The model variables include the changes in idiosyncratic cash-flow volatility, $\Delta CF_{i,t}$, and the level of hedge-fund ownership, $HF_{i,t-1}$. The control variables include non-hedge-fund institutional ownership (at the end of period t-1), firm leverage (at the end of period t-1), illiquidity (at time t), $ILLIQ_{i,t}$, and size (at the end of period t-1). Model (5) and (6) estimate the following regression:

$$\Delta IV_{i,t} = \alpha + \sum_{j\in\{1,10,other\}} \beta^{j\prime} D^{j}_{i,t} \mathbf{X}_{1i,t} + \sum_{j\in\{1,10,other\}} \delta^{j} D^{j}_{i,t} HF_{i,t} ILLIQ_{i,t} + \gamma' \mathbf{X}_{2i,t} + \varepsilon_{i,t.}$$

Idiosyncratic cash-flow volatility is estimated following Irvine and Pontiff (2010). Hedge-fund ownership is percentage holdings of institutions which are identified as hedge funds. A list of hedge fund names is obtained from Lipper/TASS. Institutional holding data is from 13F available through CDA/Spectrum database of Thompson Financials. Illiquidity is estimated quarterly following Amihud (2002). Size is the natural logarithm of market capitalization at the end of previous quarter. Standard errors are clustered within each year and T-statistics are reported in the brackets. The sample period is from January 1994 to December 2008.

Variable\Model	(1)	(2)	(3)	(4)	(5)	(6)
$D_{other}\cdot\Delta CF$	0.006	0.004	0.006	0.004	0.006	0.004
	[1.92]	[1.96]	[1.90]	[1.95]	[1.93]	[1.97]
$D_{1}\cdot\Delta CF$	0.007	0.005	0.007	0.005	0.007	0.005
	[2.03]	[1.77]	[2.10]	[1.89]	[2.07]	[1.89]
$D_{10}\cdot\Delta CF$	0.009	0.008	0.009	0.008	0.009	0.007
	[4.04]	[4.18]	[4.57]	[4.94]	[4.93]	[4.90]
$D_{other}\cdot HF$	0.248	0.142	0.264	0.160	-0.004	0.288
	[2.31]	[3.18]	[2.52]	[3.54]	[-0.01]	[0.78]
$D_{1}\cdot HF$	-4.404	-4.614	-4.171	-4.410	-8.773	-8.332
	[-11.30]	[-18.07]	[-9.73]	[-15.61]	[-12.65]	[-12.64]
$D_{10}\cdot HF$	3.389	3.288	3.015	2.897	11.170	11.538
	[16.62]	[15.08]	[10.57]	[9.52]	[18.62]	[19.14]
$D_{1}\cdot Q_{1}\cdot HF$			0.026	0.038		
			[0.15]	[0.20]		
$D_{1}\cdot Q_{5}\cdot HF$			-1.853	-1.691		
			[-7.54]	[-9.18]		
$D_{10}\cdot Q_{1}\cdot HF$			-1.081	-1.090		
			[-5.38]	[-5.43]		
$D_{10}\cdot Q_{5}\cdot HF$			2.338	2.418		
			[7.28]	[7.47]		
$D_{other}\cdot HF\cdot ILLIQ$					-0.015	0.007
					[-0.75]	[0.35]
$D_{1}\cdot HF\cdot ILLIQ$					-0.240	-0.205
					[-5.34]	[-5.30]
$D_{10}\cdot HF\cdot ILLIQ$					0.465	0.492
					[9.30]	[9.81]
$D_{other}\cdot I/O$	0.230	0.177	0.222	0.162	0.219	0.168
	[3.76]	[5.87]	[3.56]	[5.72]	[3.41]	[5.50]
$D_{1}\cdot I/O$	-0.153	-0.161	-0.167	-0.175	-0.176	-0.183
	[-1.36]	[-1.37]	[-1.33]	[-1.33]	[-1.32]	[-1.32]
$D_{10}\cdot I/O$	1.564	1.517	1.779	1.729	1.949	1.911
	[9.63]	[10.05]	[8.78]	[9.01]	[8.56]	[8.71]
Leverage	0.001	0.001	0.001	0.001	0.001	0.001
	[0.98]	[1.23]	[0.96]	[1.11]	[0.89]	[1.04]
ILLIQ	0.064	0.057	0.067	0.066	0.062	0.051
	[3.58]	[4.19]	[3.64]	[4.06]	[3.43]	[4.10]
Size	0.074	0.064	0.074	0.061	0.072	0.061
	[3.04]	[3.40]	[2.80]	[3.22]	[2.94]	[3.26]
Year Fixed Effect	N	Y	N	Y	N	Y
Q_1 & Q_5 Dummies	N	N	Y	Y	N	N
R^2	0.362	0.397	0.364	0.401	0.364	0.399

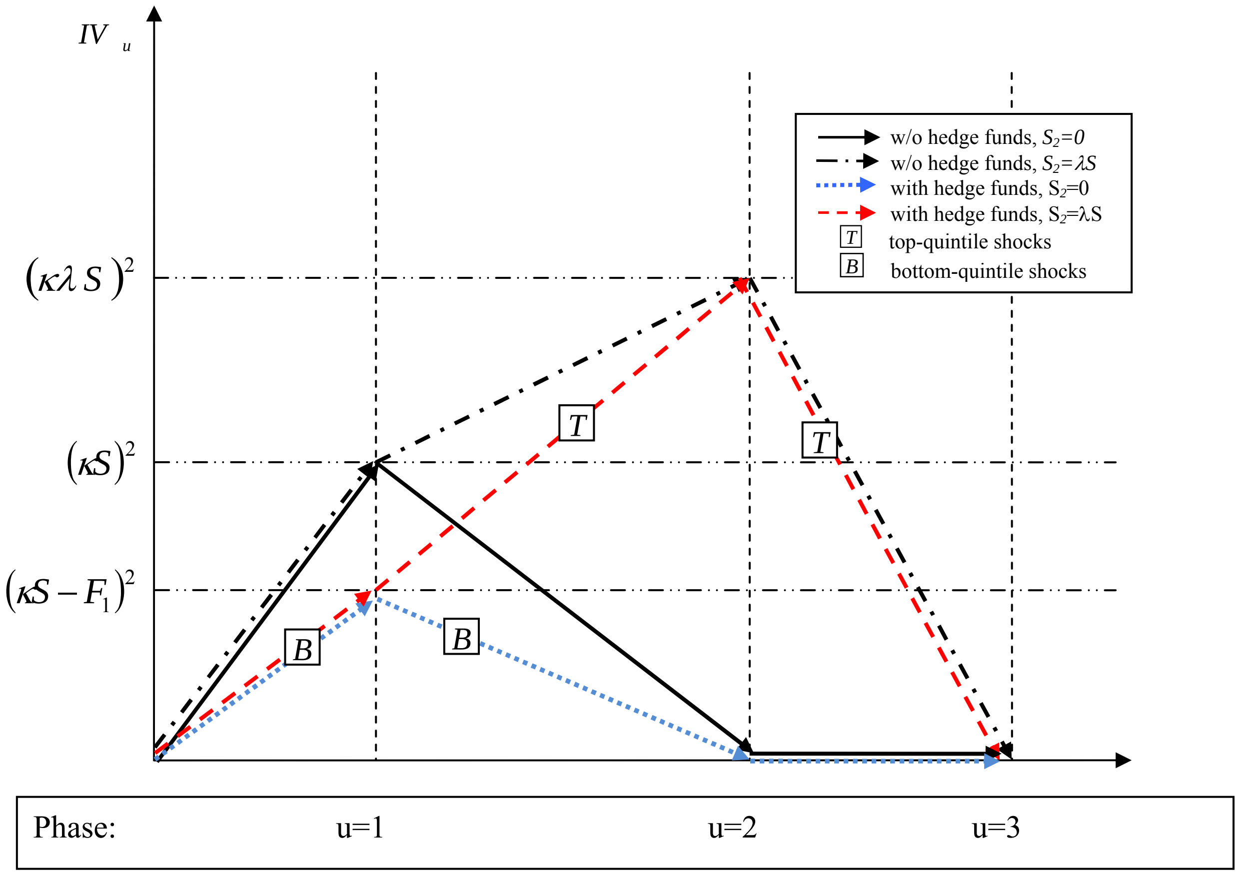
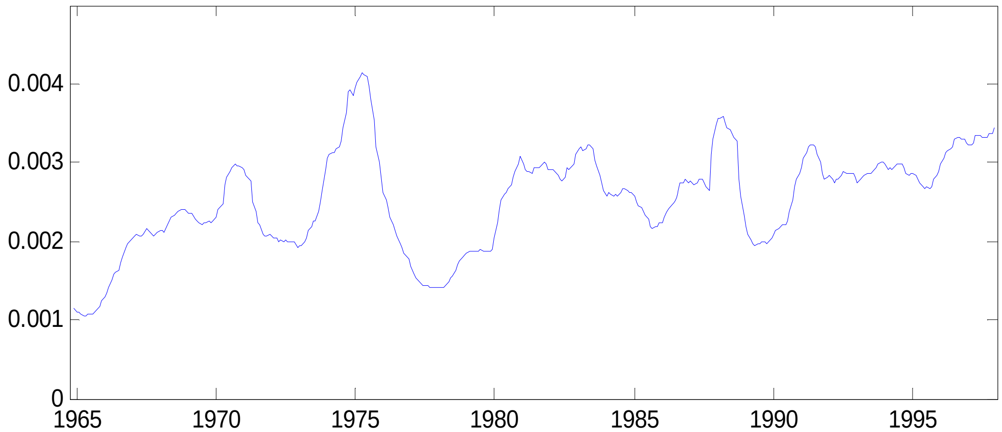


Figure 1. Dynamics of the idiosyncratic risk. The figure illustrates the evolution of idiosyncratic shock of a stock under various scenarios. F_1 is the initial capital of Long/Short-Equity manager, κ is the price impact of trading one unit of the stock, and S is the cash-flow shock to the stock in Phase one. In Phase two, the shock either increases to λS or disappears. Under the scenario that Long/Short-Equity managers do not trade, solid arrows and dash-dotted arrows represent the dynamics of idiosyncratic volatility when the shock disappears by Phase two and when it increases, respectively. When Long/Short-Equity managers trade, dotted arrows and dashed arrows represent the dynamics of idiosyncratic shock when the shock disappears by Phase two and when it increases, respectively. Shocks denoted by *B* represent bottom-quintile shocks, while shocks denoted by *T* represent top-quintile shocks of the cross-section. As initial capital increases, bottom-quintile shocks decrease and top-quintile shocks increase. Also, the magnitude of a shock is increasing function of S and κ.

Panel A: Cross-Sectional Mean (to 1997: CLMX)



Panel B: Cross-Sectional Mean (Extended)

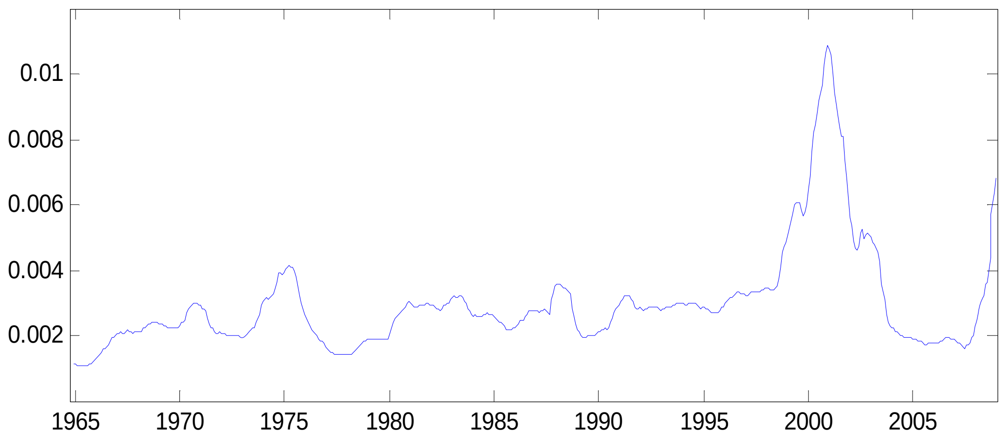


Figure 2. Time trend of the cross-sectional mean of idiosyncratic volatilities. The figure plots the time series of 12-month backward moving average of the cross-sectional mean of annualized monthly aggregate idiosyncratic volatility. The top panel shows the time-series up to 1997, to compare with the result of Campbell, Lettau, Malkiel, and Xu (2001). The bottom panel extends the sample period to 2008. The idiosyncratic volatility is estimated following Ang, Hodrick, Xing, and Zhang (2006). Specifically, for each stock-month, daily returns are regressed on Fama-French three factors. Residuals from the regressions are squared and averaged over the month to measure 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.

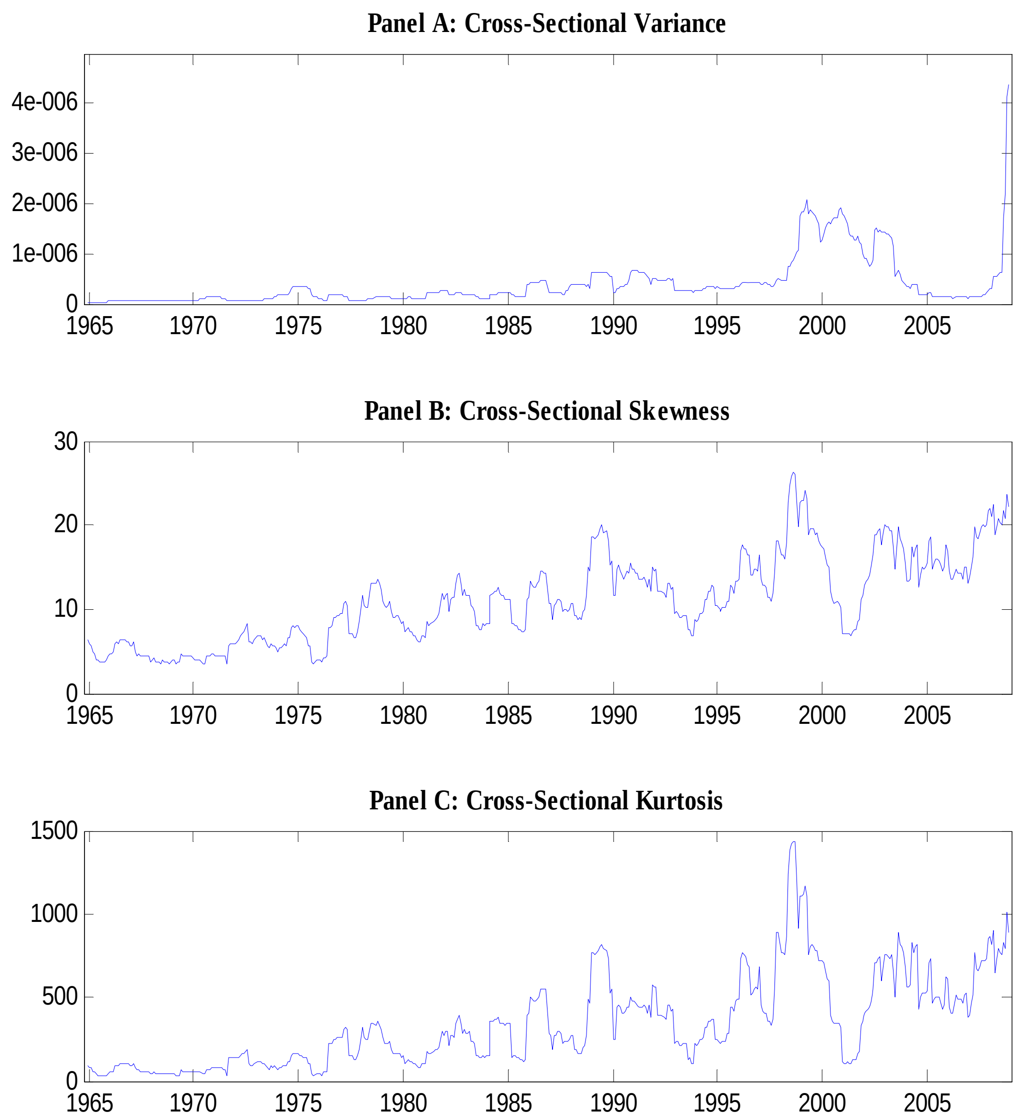
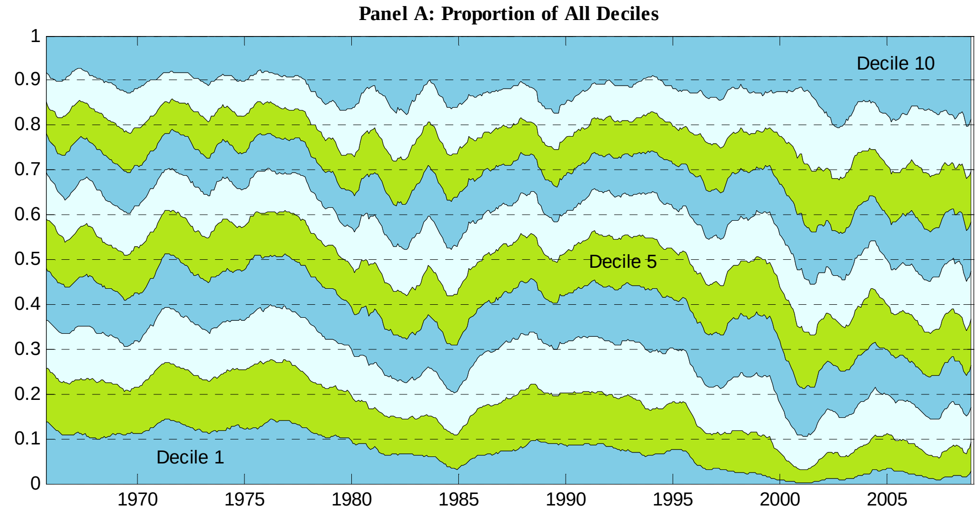


Figure 3. Time trends of the higher cross-sectional moments of idiosyncratic volatilities. The figure plots the time series of 12-month backward moving average of the cross-sectional moments of monthly idiosyncratic volatilities. Panel A, B, and C show value-weighted cross-sectional variance, skewness, and kurtosis of monthly idiosyncratic volatilities, respectively. The idiosyncratic volatility is estimated following Ang, Hodrick, Xing, and Zhang (2006). Specifically, for each stock-month, daily returns are regressed on Fama-French three factors. Residuals from the regressions are squared and averaged over the month to measure 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.



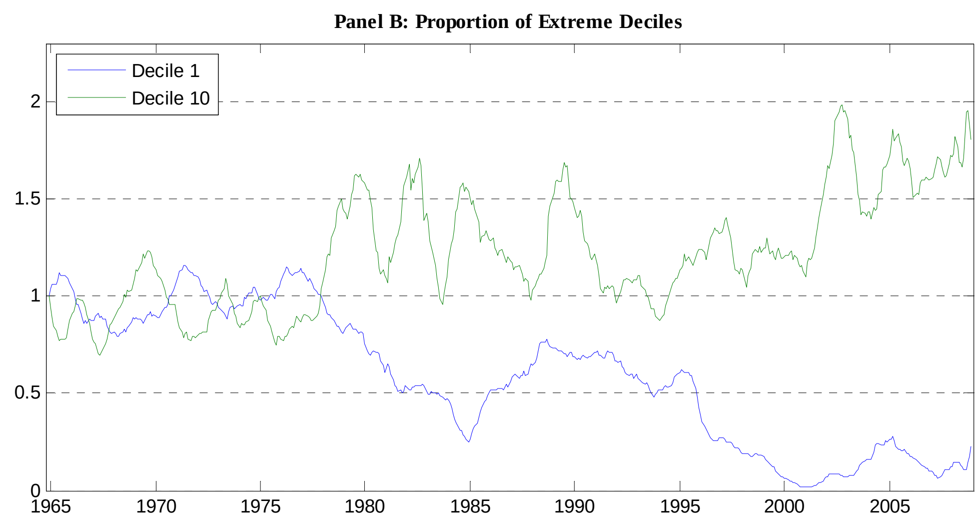


Figure 4. Time trend of the share of each idiosyncratic volatility decile in the aggregate idiosyncratic volatility. Panel A shows the time series of the share of each decile of the idiosyncratic volatility in the aggregate idiosyncratic volatility of the cross-section. Panel B shows the shares of the 1^{st} (low volatility) and the 10^{th} (high volatility) deciles. 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 Fama-French three factors. Residuals from the regressions are squared and averaged over the month to measure idiosyncratic volatility, following Ang, Hodrick, Xing, and Zhang (2006). Then stocks are ranked into deciles based on their idiosyncratic volatilities. 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.

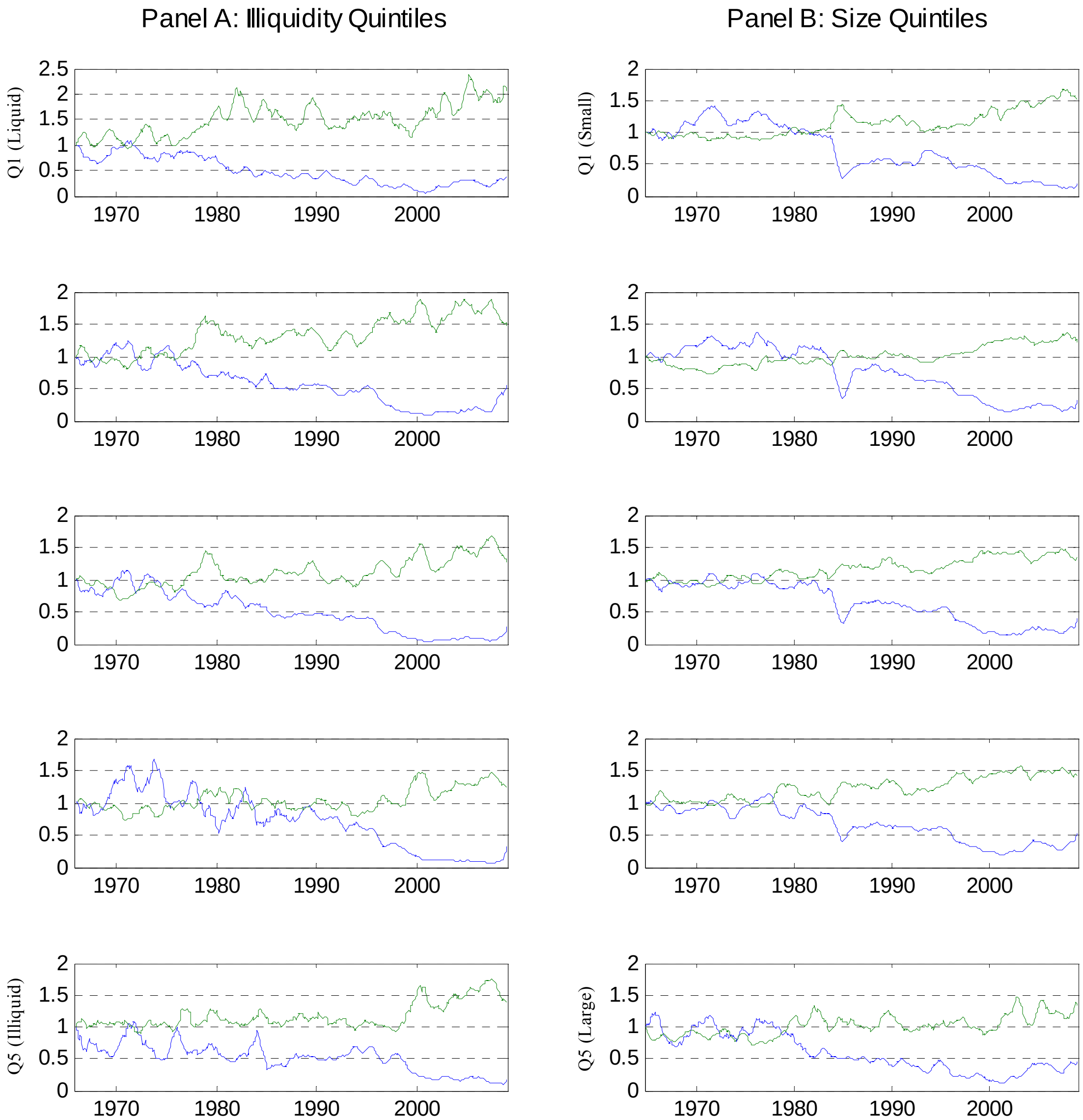


Figure 5. Time trends of the extreme deciles of the idiosyncratic volatility in illiquidity and size quintiles. The figure plots the shares of the 1st (low volatility) and the 10th (high volatility) deciles of the idiosyncratic volatility in illiquidity and size quintiles. A 12-month backward moving average is used and each time series is normalized through dividing by its beginning-of-the-sample value. The first row shows illiquidity and size Quintile 1 and the last row shows Quintile 5. Illiquidity Quintile 1 (Quintile 5) is the group of most (least) liquid stocks and size Quintile 1 (Quintile 5) is the group of stocks with smallest (largest) market capitalization. Illiquidity and size quintiles are constructed based on the yearly measure of illiquidity of previous calendar year or market capitalization of previous month. For each stock-month, daily returns are regressed on Fama-French three factors. Residuals from the regressions are squared and averaged over the month to measure idiosyncratic volatility, following Ang, Hodrick, Xing, and Zhang (2006). Then within a quintile, stocks are divided into deciles based on their idiosyncratic volatilities. Finally, the shares of the extremes deciles of the idiosyncratic volatility in a given month are computed as the ratio of value-weighted sum of the idiosyncratic volatility of the stocks in the decile to the value-weighted sum of stocks in the entire cross-section of the quintile. 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.

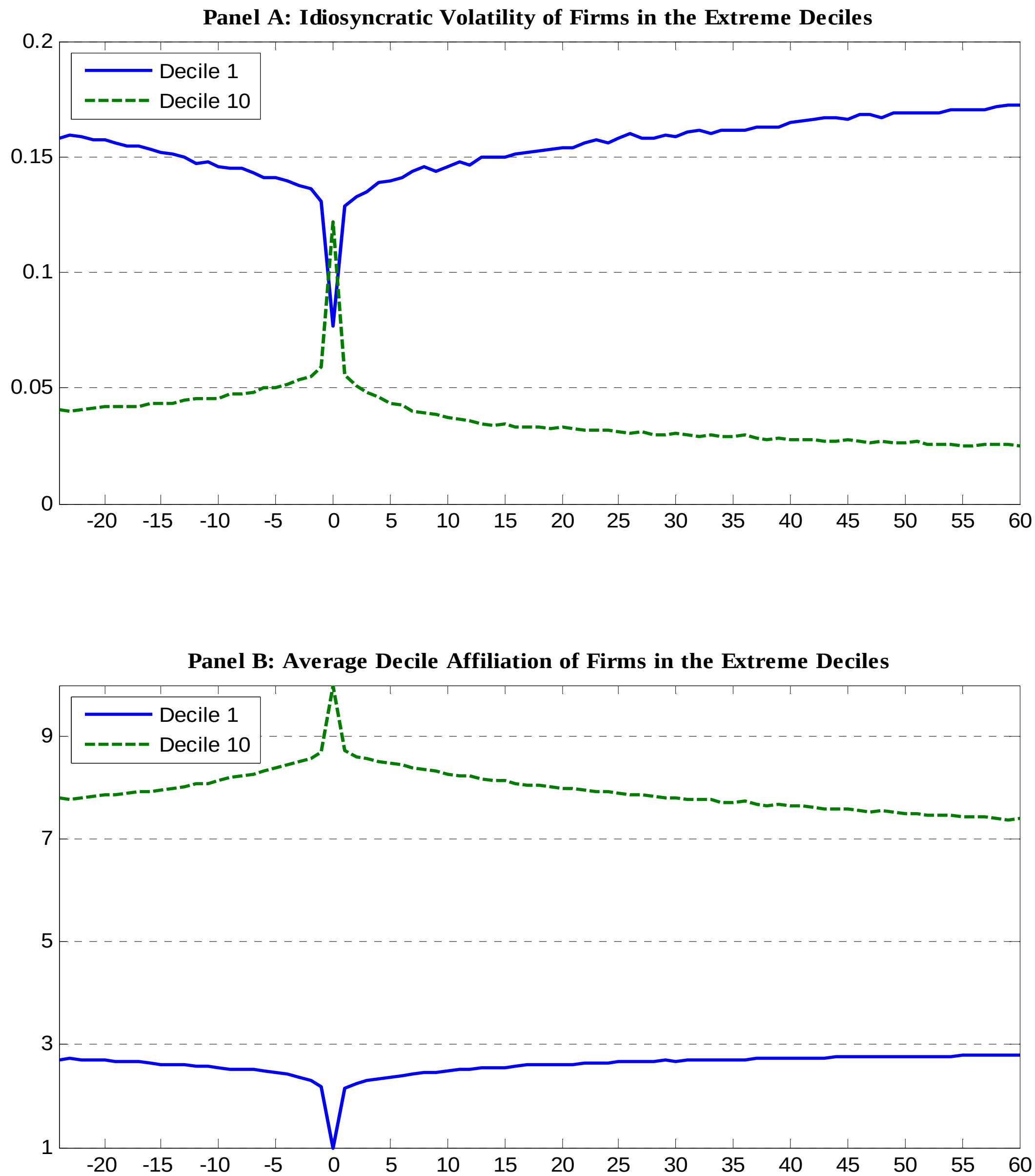
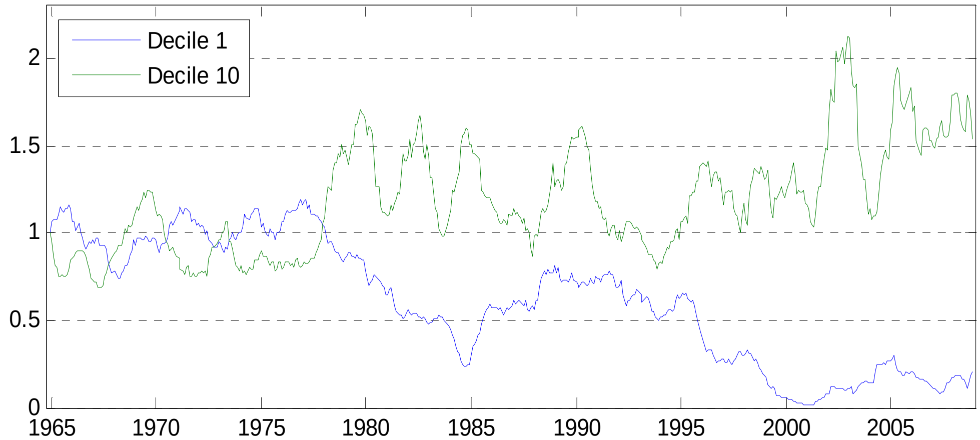


Figure 6. Time trends of the extreme decile portfolios during event time. Panel A reports the time-series averages of the extreme decile portfolios' share in the aggregate idiosyncratic volatility in event time. Panel B plots the average decile affiliation of the stocks in the extreme portfolios in event time. Stocks are ranked into deciles based on their idiosyncratic volatilities, and Decile 1 and Decile 10 portfolios are constructed each month (*t*=0). The portfolios are held for 60 months post-formation and are also traced back for 24 months pre-formation. The share of each extreme decile portfolio in a given month during the event time is calculated as the ratio of value-weighted sum of idiosyncratic volatility of the stocks in the portfolio to the value-weighted sum of stocks in the entire cross-section. For the sample period from July 1963 to December 2008, 455 extreme decile portfolios are constructed and the averages of the portfolios are plotted. 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.

Panel A: Random Sample of 1000 firms



Panel B: S&P 500

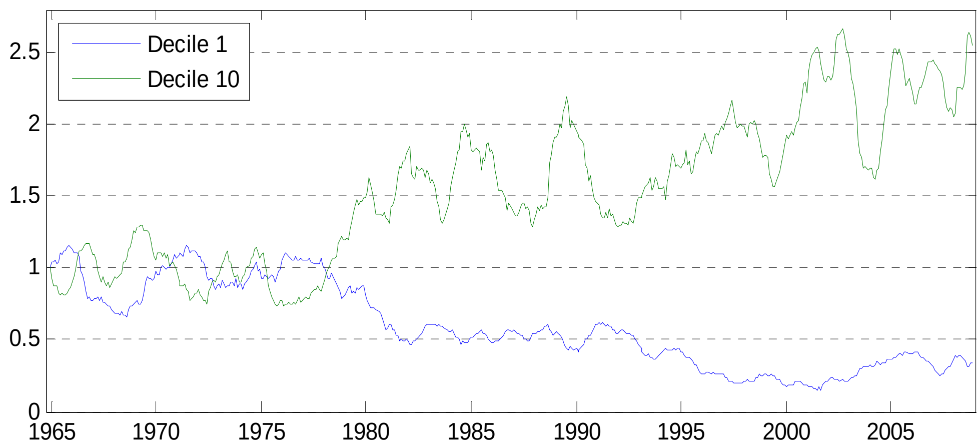
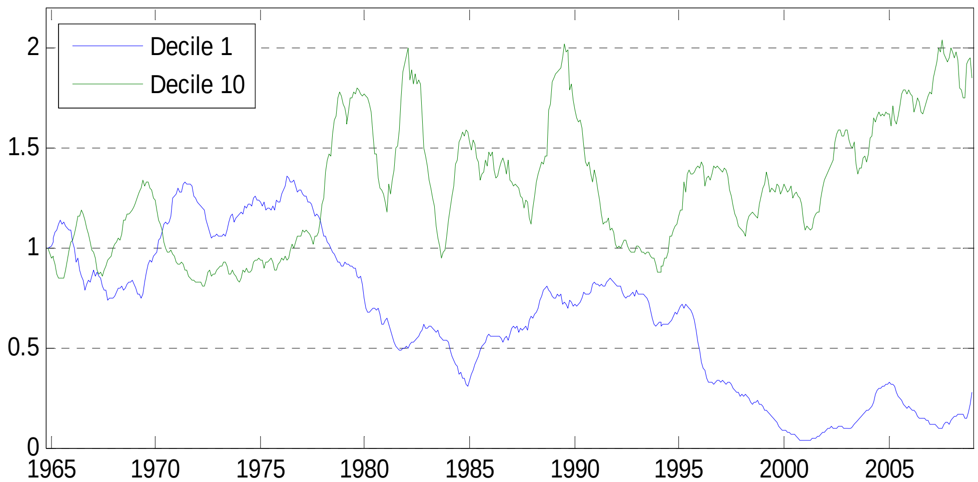


Figure 7. Time trends of the extreme deciles of idiosyncratic volatility in a sample of random firms and the S&P 500 index. The figure plots the shares of the 1st (low volatility) and the 10th (high volatility) deciles of the idiosyncratic volatility in the aggregate idiosyncratic volatility of subsamples. Panel A shows the time trends in the sample that consists of 1,000 firms randomly selected every month during the sample period. Panel B plots the time trends in the sample that consists of firms in S&P 500 index. A 12-month backward moving average is used and each time series is normalized through dividing by its beginning-of-the-sample value. For each stock-month, daily returns are regressed on Fama-French three factors. Residuals from the regressions are squared and averaged over the month to measure idiosyncratic volatility, following Ang, Hodrick, Xing, and Zhang (2006). The share of each decile in a given month is calculated as the ratio of the value-weighted sum of idiosyncratic volatilities of the stocks in the decile to the value-weighted sum of stocks in the entire cross-section of the subsamples. The sample period is from July 1963 to December 2008.

Panel A: Positive Shocks



Panel B: Negative Shocks

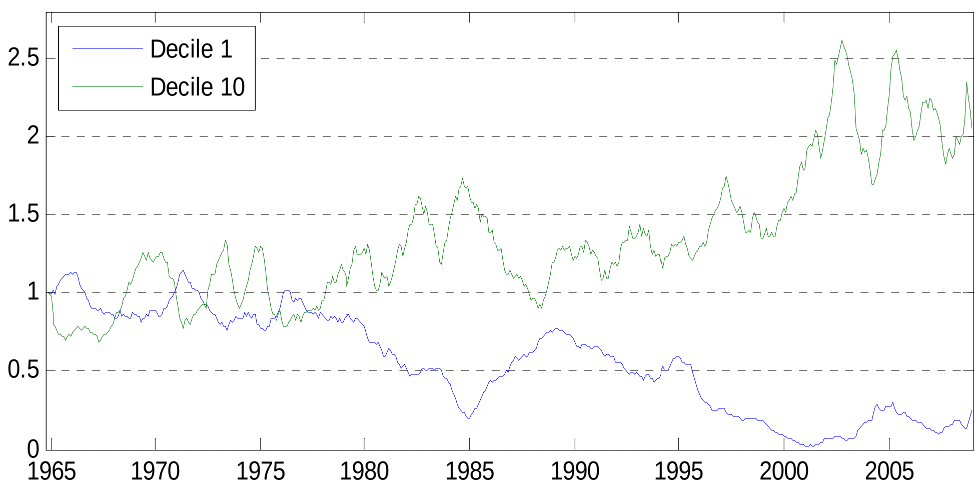


Figure 8. Time trends of the extreme deciles of positive and negative idiosyncratic shocks. The top (bottom) panel plots the time-series of the shares of the extreme deciles of positive (negative) idiosyncratic shocks in the aggregate positive (negative) shocks. A 12-month backward moving average is used and each time series is normalized through dividing by its beginning-of-the-sample value. For each stock-year, daily returns are regressed on Fama-French three factors. Residuals from the regressions are divided into positive and negative groups. Within each group, residuals are squared and averaged over a month to estimate the positive (negative) idiosyncratic shocks for the month. 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.