Idiosyncratic Return Volatility in the Cross-Section of Stocks

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Abstract
This paper uncovers the time trends of idiosyncratic volatility in the cross-section of stocks over the period 1963-2008. High idiosyncratic volatility stocks have become more volatile over time while low idiosyncratic volatility stocks have become less volatile, relative to total market idiosyncratic volatility. The trends are robust to industry, liquidity, and size, as well as sign of price change. We test whether patterns in idiosyncratic cash flow volatility, hedge fund assets under management, and overall institutional ownership can explain the effect. The upward trend in high idiosyncratic volatility can be explained by the increase in idiosyncratic cash flow volatility, while the downward trend in low idiosyncratic volatility can be attributed to Long/Short-Equity hedge fund activity. There is some evidence that Long/Short-Equity funds act as liquidity demanders while non-Long/Short-Equity funds and other institutions act as liquidity providers.

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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, probably because standard models of asset pricing imply that only systematic risk is priced. However, as CLMX emphasized, idiosyncratic risk is important for several theoretical and practical reasons. It is source of additional risk of an undiversified portfolio (Merton (1987)) and understanding its nature helps to find the right level of diversification. Also, it is important for constructing event studies since the significance of abnormal return is affected by volatility of stocks relative to 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.

CLMX document that there is a deterministic time trend of upward slope in idiosyncratic risk of US equity market from 1962 to 1997, while the aggregate market volatility does not display the upward time trend during the period. Many researchers search for the causes of the time trend. Some papers relate the trend with 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) find the link between the idiosyncratic volatility and firms’ competitive environment, such as market power and the concentration level of the industry. Other papers relate the time trend with the changes in trading activities of market participants. Xu and Malkiel (2003) show that idiosyncratic volatilities of individual firms are positively associated with institutional ownership. 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. After all, there are much evidence that the upward trend is reversed when the sample period is extended over 2000. (For example, Bekaert, Hodrick, and Zhang (2005) and Brandt, Brav, Graham, and Kumar (2009))

Although the bulk of the literature is focusing 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 might be even more critical for the participants of financial markets. For example, consider a trading desk specializing on the relative mispricing of individual assets. Given the significant fixed cost in finding mispriced assets, the trading desk most likely specializes on a limited number of assets at any given point in time. Hence, the idiosyncratic risk of these assets matters. Also,
most institutional traders are subject to loss constraints in some form or another. Con-sequently, following extremely large realizations of idiosyncratic shocks to assets held, these institutions are forced to sell causing large losses. Furthermore, as a number of recent work demonstrate, such fire sales might result in the amplification of mispricing of assets imposing a significant negative externality on other market participants. This is why we focus on the exploration of distribution of these extreme realizations of idiosyncratic risk in the cross-section of stocks.

First, we develop a simple theoretical model which examines the effect of institutional trading on the cross-section of idiosyncratic volatilities. We assume two types of institutional investors. Long-term traders hold assets for the cash flows. Managers of long-short equity funds aims to exploit the temporary mispricing due to idiosyncratic risk. Our model illustrates that idiosyncratic shocks to returns is increasing in the underlying cash-flow shocks for every stock, while larger capital of long-short equity funds increases large idiosyncratic shocks further but decreases small idiosyncratic shocks. Furthermore all these effects are larger in magnitude in the case of less liquid stocks.

Consistent with our model, we find that the cross-sectional distribution of idiosyncratic volatilities of US stocks is increasingly skewed over time. In particular, the share of the top-decile of idiosyncratic volatilities in the entire cross-section has increased from 10% to 19% between 1963 and 2008, and the share of the bottom-decile decreased from 13% to 3% during the time period. We show that this pattern holds regardless of the size and the liquidity of firms and is robust to industries. We also find the evidence that while the upward trend in the top-decile is mirrored in cash-flow volatility, the downward trend in the bottom decile is connected to the increasing activity of long/short-equity funds during the time period.

To obtain a measure of idiosyncratic volatility for an individual firm, we follow Ang, Hodrick, Xing, and Zhang (2006, hereafter AHXZ). For each month and for each stock, daily returns are regressed on the Fama-French three factors. Residuals from the regressions are squared and averaged over the month to obtain the idiosyncratic return volatility measure. In each month we divide our sample of idiosyncratic return volatility into ten deciles. Then we calculate the share of a given decile in the total cross-sectional distribution of idiosyncratic volatilities. We show that there is significant

\footnote{These loss limits might be generated explicitly, for example in the form of internal or external 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 (2002), Danielsson, Shin, and Zigrand (2004), Brunnermeier and Pedersen (2007), Kondor (2009)) and empirical (e.g. Coval and Stafford (2007)) literature.}

\footnote{See Lorenzoni (2008), Diamond and Rajan (2010), Brunnermeier and Sannikov (2010).}
positive time trend in the share of the top decile, while there is a significant negative
time trend in the share of the bottom decile. This indicates that stocks with relatively
low idiosyncratic volatility tend to have lower idiosyncratic volatility, while stocks with
relatively high idiosyncratic volatility tend to have higher volatility, compared to the
average idiosyncratic volatility in the entire cross-section. Thus, the cross-sectional
skewness has increased over the sample period. To make sure that not the increasing
number of observations drive our results, we confirm this pattern on a random sample
of stocks redrawn in each month, and also on a sample which contains only the firms in
the S&P 500 index at that particular month.

By sorting the sample across various dimensions, we demonstrate that this pattern
is largely independent of firm characteristics, such as size and liquidity. We also do not
find any clear difference in the time trends across industries. We do not find significant
cohort effects of positive or negative idiosyncratic shocks, either.

As a first step to find the underlying cause of the time trend, we consider following
two hypotheses. First, we consider the possibility that the observed pattern is due to
fundamental changes in the economy. For this, we construct a measure of idiosyncratic
cash-flow volatility for each firm in each quarter, following Irvine and Pontiff (2009).
Then, in each quarter we measure the share of idiosyncratic cash flow volatility in
the entire cross-section for those firms whose idiosyncratic return volatility is in the
top/bottom decile in the quarter. If our observed pattern of increased skewness were
caused by changing fundamentals, then the time trends in the top/bottom decile of
idiosyncratic return volatility should be explained by the trends in our corresponding
measures of cash-flow volatility.

Second, we consider the possibility that the observed pattern is due to the changing
structure of trading in financial markets. As it is well known, the share of institutional
traders in the total market capitalization has been sharply increasing over time. In
particular, the capital share of professional traders specializing in the mispricing of
individual assets has also increased over time. Theoretically, this can influence the
distribution of idiosyncratic risks in several ways. As professional traders might have
larger human and financial capital to find and exploit mispricings, the increasing share
of institutional traders might decrease the average realization of idiosyncratic shocks.
However, institutional traders are often faced with loss limits implying that following
extreme realizations of return shocks, they might be forced to liquidate at the worst
state of the world. These fire-sales might amplify the extreme realizations of mispricings.
Thus, it is possible that while their trading activity decreases relatively small shocks, it
also increases relatively large shocks. To proxy the share of professional traders in the
sector specializing in the relative mispricing of assets, we use the time-series of asset under management of long/short-equity funds. To proxy the other institutional trading activities, we use asset under management of total hedge fund excluding long/short-equity and total institutional ownership.

To explore the explanatory power of these two hypothesis, we run time-series regressions of our measure of the share of top and bottom decile idiosyncratic return volatilities in the total on the linear trend, the cash flow volatility measure, and proxies for trading activities of institutions. Interestingly, we find that the trends in the top and bottom decile are explained by different hypotheses. In particular, we find that the share of bottom decile firms has decreased due to the increasing capital of long/short-equity funds but not because of a corresponding change in the cash-flow volatility. However, the share of top decile firms has increased due to a mirroring pattern in the cash-flow volatility of the top decile firms but not because of the change in the increasing capital of long/short-equity funds.

With the regression results and given our motivational example of trading desk above, we are interested in whether extreme realizations are predictable and which firms are more likely to be affected by the extreme realizations. For this, we repeat our investigation for predicted idiosyncratic risk instead of the realized idiosyncratic risk. To estimate predicted volatility, we regress idiosyncratic volatilities on the past observations of various firm characteristics, firm fixed effects, and time fixed effects. We show that our pattern is not present in the predictable component of past volatility.

Finally, we ask whether it is same firms that have been more (or less) volatile compared to the average. To answer this question, we perform an event study by constructing extreme decile portfolios and holding the components of the portfolios constant for the event-time period. We find that stocks in the extreme decile this period tend to be in different deciles next period. Thus, it is not the volatilities of same firms but the relative magnitude of extreme realization that have been larger (or smaller).

Our paper is most related to the exploration of idiosyncratic return volatility on financial markets started by CLMX and followed by a long series of works, such as Bakaert, Hodrick, and Zhang (2010) and Brandt, Brav, Graham, and Kumar (2008), Irvine and Pontiff (2009). However, while those papers focus on the time trend of average idiosyncratic volatility, we are concerned about the dynamics of extreme realizations in the cross-section. The existence of the time trend that CLMX document has been questioned when the sample period is extended. And some papers document that the trend is largely due to small illiquid stocks. But neither of these caveats arising with
respect to the results in CLMX apply to our work. In particular, our result is from the sample up to 2008 and the main finding is especially strong for large stocks.

Another stream of researches on idiosyncratic volatility comes from AHXZ (2006) who examine the relation between idiosyncratic volatility and expected return in the cross-section. Our research is similar with AHXZ (2006) 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 risk-return trade-off.

The structure of the paper is as follows. In the next section, we develop a theoretical model which characterizes our main findings. In section 3, we describe our sample and estimation methods. In section 4, after we confirm the finding of Bakaert, Hodrick, and Zhang (2010) and Brandt, Brav, Graham, and Kumar (2009), we present our main results and conduct several robustness checks. In section 5, we sketch out some explanations to our observations. In section 6, we conclude.

2. Model of limited arbitrage, capital share of hedge funds and the skewness of idiosyncratic shocks

We use a slightly modified version of Shleifer-Vishny (1997) model on limited arbitrage. Consider a market with a lot of assets. The cash flow of each asset has a systematic component and a mean reverting idiosyncratic shock. There are two type of agents on the market. Long-term traders hold assets for the cash flows, so their demand for each asset is positively related to the current cash flow of the asset and negatively related to its price. Managers of long-short equity funds aims 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 gain a zero exposure on the systematic component. Similar to Shleifer-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 relationship between the dynamics of idiosyncratic component of returns and cash flows, capital of managers and the liquidity of assets. In particular, the model illustrates that idiosyncratic shocks to returns is increasing in the underlying cash-flow shocks in every quintile, while larger capital of long-short equity funds increases large idiosyncratic shocks further but decreases small
idiosyncratic shocks. Furthermore all these effects are larger in magnitude in the case of less liquid stocks.

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

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

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 is either gets larger in absolute terms in phase 2 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

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

where $\frac{1}{\kappa} \geq 1$ parametrizes the sensitivity of long-term traders demand on prices. Managers speculate on the short-term convergence of the price of one particular asset and a well diversified portfolio in the way that they do not take on systematic risk. Suppose the value of the representative managers’ position in asset $i$ is $D_{u(i)}$. Thus, the market clearing conditions in each phase is

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

Observe that as

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

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 discounted future cash-flows of the asset is an increasing function of current cash-flows. Thus, in any microfoundation where long-term traders buying more of the asset if its fundamental value goes up, and buying less if it is price goes up, would support this assumption. In such microfoundation the parameter $\frac{1}{\kappa}$ would be positively related to the risk-aversion of long-term traders.
\( \kappa \) also measures the price effect of a unit of trade. If \( \kappa \) is small, a change in \( \frac{D_u}{\tilde{p}_u} \) has a little effect on the price, while if \( \kappa \) is large, the price effect is also large. In this sense, we can interpret \( \kappa \) as the liquidity of the particular asset. The other leg of managers’ long-short position is a short position in a well diversified portfolio which exactly offsets the systematic component of returns. Given that this portfolio implies a relatively small position in a large number of assets, we assume that this hedging position does not effect the prices of the components of this portfolio. Thus, the cash flow of each unit of this portfolio is

\[
\theta_{t+u(i)}
\]

and its price is

\[
\kappa \theta_{t+u(i)}
\]

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

Managers are risk neutral, and the value of their position in the asset cannot exceed \( F_u \) in period \( u \). That is, \( D_u \leq F_u \). Think of \( F_1 \) 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 depend on past profits by

\[
F_2 (\tilde{S}_2) = \max(0, a \Pi_1 (D_1, \tilde{p}_1, \tilde{p}_2) + F_1)
\]

where \( \Pi_1 (D_1, \tilde{p}_1, \tilde{p}_2) \) is the net profit or loss the manager makes by the second phase given his position \( D_1 \) and prices.\(^4\) We assume that \( \kappa S > F_1 \), that is managers do not have sufficient capital to fully eliminate the idiosyncratic shock in period 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 phase, managers liquidate their position and do not hold any assets.

\(^4\)The literature names many reasons why hedge funds cannot take arbitrarily large positions and why their effective position limits positively depend on past profitability. For example, Shleifer and Vishny (1997) shows that capital flows from investors, Gromb and Vayanos (2002) and Brunnermeier and Pedersen (2009) shows that margin constraints while Xiong (2001) shows that wealth effect of risk-averse arbitrageurs can all lead to similar conclusion.
3. Prices are

\[
p_1 = \kappa (\theta_{t+1} - S) + F_1
\]
\[
p_2 (\tilde{S}_2 = \lambda S) = \kappa (\theta_{t+2} - \lambda S)
\]
\[
p_2 (\tilde{S}_2 = 0) = \kappa \theta_{t+2}
\]
\[
p_3 = \kappa \theta_{t+3}
\]

**Proof.** In the Appendix. ■

The parameter restriction \( q \) ensure that the worsening of the shock has a sufficiently low chance to make managers fully invest in the phase 1. The restriction on \( a \) ensures that when managers take a maximal position in phase 1 and the shock worsens then managers suffer sufficiently large losses that their capital is fully wiped out by the second phase. Thus, managers do not hold any assets regardless of the shock in the second phase, because either the trading opportunity disappeared, or their capital is wiped out.

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

\[
((p_{u+1} - p_u) - \kappa (\theta_{t+u+1} - \theta_{t+u}))^2
\]

as the model variant of our measure of idiosyncratic shock. This is the return in a given period minus the part of the return which is due to the systematic part. Consider also the following thought experiment. Think of \( 3N \) assets and corresponding \( 3N \) hedge managers with each group focusing on the corresponding asset. Also, suppose that phases 1, 2 and 3 of the model repeats infinitely in the following way. In any given \( t \), in terms of the model, \( N \) assets are in phase 1, \( N \) pairs are in phase 2 and \( N \) pairs are in phase 3. It is easy to see that all assets which are in phase 1 and \( q \) fraction of assets which are in phase 2 experience an idiosyncratic shock of

\[
(\kappa S - F_1)^2
\]

At the same time \( (1 - q) \) fraction of assets which are in phase 2 experience an idiosyncratic shock of

\[
(p_2 - p_1 - \kappa (\theta_{t+2} - \theta_{t+1}))^2 = (\kappa \lambda S - (\kappa S - F_1))^2
\]

Similarly, while \( q \) fraction of pairs in phase 3 experience no shock at all (the ones whose idiosyncratic shock disappeared in phase 2), the rest will experience a shock of

\[
(p_3 - p_2 - \kappa (\theta_{t+3} - \theta_{t+2}))^2 = (\kappa \lambda S)^2
\]
Under our parameter conditions shocks of the four groups are ranked as follows

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

Think of the pool of stocks with measured idiosyncratic risk of 0 and (9) as the bottom quintile of the cross-sectional distribution, while the pool of stocks with shocks (10) and (11) as the top quintiles 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 idiosyncratic return shock increases in each quintiles 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’s period capital, \( F_1 \), in the top quintiles and decreasing in the bottom quintiles. 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 \( \kappa \) increases, the absolute size of each effect in the previous two statements increase. That is

\[ \frac{\partial}{\partial \kappa} \left( \frac{\partial (\kappa S - F_1)^2}{\partial S} \right), \frac{\partial}{\partial \kappa} \left( \frac{\partial (\kappa (\lambda - 1) S + F_1)^2}{\partial S} \right), \frac{\partial}{\partial \kappa} \left( \frac{\partial (\kappa \lambda S)^2}{\partial S} \right) > 0 \]

\[ \frac{\partial}{\partial \kappa} \left( \frac{\partial (\kappa S - F_1)^2}{\partial F_1} \right), \frac{\partial}{\partial \kappa} \left( \frac{\partial (\kappa (\lambda - 1) S + F_1)^2}{\partial F_1} \right) + \frac{\partial}{\partial \kappa} \left( \frac{\partial (\kappa \lambda S)^2}{\partial F_1} \right) > 0 \]

**Proof.** In the Appendix.

3. Data and Methodology

A. Idiosyncratic Return Volatility and Its Cross-Sectional Distribution

Following AHXZ(2006), we estimate idiosyncratic volatility relative to Fama-French three factor model. We examine both monthly and quarterly idiosyncratic volatility.\(^5\)

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\(^5\)We use monthly time-series of idiosyncratic volatility for graphical analysis and time-trend regressions (Table 1 and Table 2). We use quarterly time-series for other time-series regression analysis (Table ...
Specifically, for period $t$ and stock $i$, we estimate following regression:

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

(12)

where $r_{i,s}$ is the excess return of stock $i$ over risk free rate at date $s$ in the period $t$. Then we define idiosyncratic volatility of stock $i$ as the average of the squared residuals of the regression over the number of trading days in the period $t$, $D_{i,t}$:

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

(13)

It is important to note that our estimation method of idiosyncratic volatility is different from that of the time-trend literature, started by CLMX (2001). While the purpose of the papers in the literature is to estimate the marketwide aggregate idiosyncratic volatility, our purpose is to investigate the cross-section of individual firms. Despite the advantage that there is no need to estimate betas for individual firms, CLMX’s decomposition is unable to produce individual idiosyncratic volatility estimates thus is not suitable for our purpose. However, we show in the next section that our estimate has similar time trend with those shown in the literature.

After we obtain idiosyncratic volatilities of individual stocks, we estimate their cross-sectional moments for a given period, using market capitalizations as weights. Specifically, we use following value weighted measures for cross-sectional mean, variance, skewness, and excess kurtosis:

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

(14)

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

(15)

$$S_t = \frac{1}{N_t} \sum_i w_{i,t}^2 \left( \frac{IV_{i,t} - M_t}{\sqrt{V_t/N_t}} \right)^3$$

(16)

$$K_t = \frac{1}{N_t} \sum_i w_{i,t}^2 \left( \frac{IV_{i,t} - M_t}{\sqrt{V_t/N_t}} \right)^4 - 3$$

(17)

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

To further examine the shape of the cross-sectional distribution of idiosyncratic volatility in a given period, we also calculate the relative contribution of each decile of

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3, 4, and 5) since all of the explanatory variables are in quarterly frequency. The quarterly time-series has very similar time trend with the monthly time-series.
idiosyncratic volatility to the entire cross-section. First, at period $t$, we rank each stock into ten groups based on its idiosyncratic volatility. Then we calculate the share of $k^{th}$ decile in the marketwise idiosyncratic volatility for the period $t$ as follows:

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

(18)

Therefore, the share of each decile sum to unity. Using this measure, we evaluate the contribution of each decile to the aggregate idiosyncratic volatility in a point in time. The measure, $d_{k,t}$, can be interpreted as the probability of a stock being in $k^{th}$ decile under the empirical distribution when the stock is randomly selected.

We use daily return data in the CRSP and daily risk free rate and Fama-French factors in Kenneth French's website.\(^6\) Only common stocks (share code 10 and 11) of firms traded on the NYSE, the AMEX, and the Nasdaq are included in the sample. To alleviate the effect of bid/ask spread on the volatility estimation, we limit our sample to the stocks with previous calendar year-end price of $2 or higher. And following Amihud (2002), we require that stock have more 100 trading days during previous calendar year. We also require that stocks have more than 15 trading days for each monthly idiosyncratic volatility estimation, following AHXZ (2006), and 25 trading days for quarterly estimation. The sample period is from July 1963 to December 2008. Hereafter, we call this sample as the CRSP sample.

B. Idiosyncratic Cash flow Volatility

In estimating idiosyncratic cash flow volatilities, we follow Irvine and Pontiff (2009) but with few modifications. Unlike idiosyncratic return volatility, we estimate idiosyncratic cash flow volatility only in quarterly frequency due to data availability.\(^7\) Quarterly idiosyncratic cash flow volatility is estimated as follow. In a given quarter $t$, 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 item (Compustat item EPSPXQ) as

\(^6\)http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/

\(^7\)Irvine and Pontiff (2009) construct monthly time-series of idiosyncratic cash flow volatility index by averaging firms of different reporting months over a three month rolling period. Since our purpose is to estimate volatilities for individual stocks, their approach is not applicable. Therefore, we create only quarterly time-series of idiosyncratic cash flow volatility. Our quarterly estimates of idiosyncratic return volatility have similar time trend with its monthly counterpart, and all other explanatory variables, such as AUMs of hedge funds, are also in quarterly frequency.
the proxy for cash flow. For book equity, we follow Vuolteenaho (2002). Specifically, we use Compustat item CEQQ and add short- and/or long-term deferred taxed (items TXDITCQ and TXPQ) if they are available.

Using the cash flow innovation, we estimate the pooled cross-sectional time-series regression at the Fama-French (1997) 48 industry level:

\[ dE_{i,t} = \alpha + \beta_1 dE_{i,t-1} + \beta_2 dE_{i,t-2} + \beta_3 dE_{i,t-3} + \beta_4 dE_{i,t-4} + \epsilon_{i,t} \]  

(19)

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 do not have to sum to zero. Therefore, from these individual shocks, we first calculate marketwise idiosyncratic cash flow shock by averaging over all the individual cash flow shocks.

\[ \epsilon_{m,t} = \frac{1}{N_t} \sum \epsilon_{i,t} \]  

(20)

Then the squared difference of firm’s cash flow shock from the marketwise cash flow shock is the firm’s idiosyncratic cash flow volatility.

\[ IV_{i,t}^{CF} = (\epsilon_{i,t} - \epsilon_{m,t})^2 \]  

(21)

Then each idiosyncratic cash flow volatility is divided into ten groups based on the firm’s idiosyncratic return volatility rank. And the share of \( k^{th} \) return volatility decile in the entire cross-section of idiosyncratic cash flow volatility is calculated using market value.

\[ d_{k,t}^{CF} = \sum_{i \in k} w_{i,t} IV_{i,t}^{CF} / \sum_{j} w_{j,t} IV_{j,t}^{CF} \]  

(22)

\footnote{Irvine and Pontiff (2009) do not scale the cash flow innovation by book equity. Instead, they use \( \Delta E_{i,t} = E_{i,t} - E_{i,t-4} \) as regression variables, in the same regression as in the equation (8), where \( E_{i,t} \) is EPS of the firm. Then they scale the regression residuals by previous end-of-quarter stock price to estimate the price impact of the cash flow innovation. They call this measure as cash flow shock and it is analogous to our regression residual, \( \epsilon_{i,t} \), from equation (8). However, firms with same earnings may have quite different EPS due to different numbers of shares outstanding. Using EPS innovation without scaling by firm’s equity in the regression may cause inaccurate estimates of residuals for outliers and for firms with low number of outstanding shares. Since our purpose is examining the shape of the top and bottom decile of idiosyncratic volatilities rather than estimating the mean value, we want to have individually sensible estimates for all the idiosyncratic cash flow volatilities if possible. We find that without scaling EPS by book equity, it is quite challenging task. Another difference of our idiosyncratic cash flow volatility measure from Irvine and Pontiff is that we use weighted average for the cross-sectional mean to be consistent with our idiosyncratic return volatility measure while they use equally weighted average.}
Quarterly EPS and book equity data are obtained from the intersection of Compustat and the CRSP sample. We require firms to have at least 4 consecutive quarters of EPS data. We also require that book equity at the end of previous quarter is not missing and is positive. We winsorize the bottom and top 0.5% of cash flow innovation \((dE)\) to avoid any potential accounting error and to alleviate the impact of outlier in the regression. The sample period for the time-series of idiosyncratic cash flow volatility is from January 1972 to December 2008 due to the availability of book equity data.

C. Definitions of Other Variables

We use assets-under-management (AUM) of hedge funds and institutional ownership as explanatory variables in the time-series regressions (Table 3, 4, and 5). We use AUMs of two different types of hedge funds. Long/Short-Equity AUM is natural logarithm of AUMs of the hedge funds characterized as Long/Short-Equity Style at the end of previous quarter. AUM excluding Long/Short-Equity is natural logarithm of AUMs of total hedge funds excluding Long/Short-Equity Style. AUM data are obtained from TASS.

Institutional ownership is the percentage owned by institutions for each decile of idiosyncratic return volatility at the end of previous quarter. First, we calculate the market capitalization owned by institutions for an individual firm. Then for each decile, we add up all the market capitalizations owned by institutions for the firms in the decile and then divide the value by the total market capitalization of the decile. Institutional ownership data are obtained from CDA/Spectrum database of Thompson Reuters. The sample period of AUMs and institutional ownership data is from January 1994 to December 2008.

We use firms’ illiquidity, size, and volatility as sort variables in the monthly time-trend analysis on \(d_{k,t}\), the share of each idiosyncratic volatility decile in the total cross-section (Figure 4, 5, and 6). We use the yearly illiquidity measure of Amihud (2002) to proxy firms’ illiquidity. Specifically, for the months in year \(y\), we use the following illiquidity measure of previous calendar year:

\[
ILLIQ_{i,y} = \frac{1}{D_{i,y-1}} \sum_{s \in y-1} \frac{|R_{i,s}|}{P_{i,s-1}Vol_{i,s}}
\]

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 CRSP 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.
where $D_{i,y-1}$ is number of trading days in year $y - 1$, $R_{i,s}$ is the raw return at day $s$, and $P$ and $Vol$ are price and volume, respectively. Size is the market capitalization at the end of previous month. And volatility is defined as the standard deviation of returns in the previous month.

4. Extreme Realizations in Idiosyncratic Return Volatility

A. Diverging Time Trend in Idiosyncratic Return Volatility

CLMX (2001) document the increasing trend of idiosyncratic volatility during the period from 1962 to 1997, while other papers in the literature show that the trend reverses by 2007 (For example, Brandt, Brav, Graham, and Kumar (2009) and Bakaert, Hodrick, and Zhang (2010)). We start our analysis by confirming their findings and extending the sample period to 2008. As mentioned in the previous section, we use AHXZ’s decomposition method instead of CLMX’s, as in equation (12) and (13). In Figure 1, we plot the cross-sectional mean of idiosyncratic volatility. The time-series of the mean is annualized (by multiplying 12) and averaged over previous 12 months. The top panel shows the time trend up to 1997, confirming the result of CLMX. The graph exhibits the increasing trend of the aggregate idiosyncratic volatility, with the level at the end of the sample period being more than three times higher than the level at the beginning. 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 pre-1990 level by 2007. However, there is big spike at the end of the sample period, which indicates the huge increase in stock market volatility during the financial crisis in 2008.

Instead of focusing on the changes in the level of cross-sectional mean, our purpose is to examine the shape of the cross-sectional distribution. Figure 2 plots the time-series of other statistical properties of cross-sectional distribution. Panel A, B, and C show the cross-sectional variance, skewness, and kurtosis, respectively. These cross-sectional moments are obtained using market capitalization as weight, as in equation from (14) to (17). We use 12 month backward moving averages in the graphs. Unlike cross-sectional mean, the time trend in higher moments are much more visible. Especially, the upward slopes in skewness and kurtosis are clearly observed. Increasing skewness indicates that firms with high volatility, compared to cross-sectional mean (and median), become more volatile. And increasing kurtosis means that more firms exhibit extreme realizations given a level of the average realization. In other words, both the number of relatively high volatility firms and that 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 ten groups based on their idiosyncratic volatility level. Then, as in equation (18), we develop the measure of 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 3 shows time trend of our measure of each decile share. Panel A plots all deciles, while panel B plots the trends of decile 1 and decile 10. The striking feature of Panel A is that the share of decile 1 has almost disappeared over time, while the share of decile 10 has more than doubled. In December 1964, \( d_1 \) is 12.5% in 12 month moving average, while it is 2.8% in December 2008. On the other hand, \( d_{10} \) is 10.3% in December 1964 and 18.6% in December 2008. Interestingly, 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. First, we normalize the time-series such that the beginning values of \( d_1 \) and \( d_{10} \) become unity. Then we plot the normalized time-series to compare the trends in the extreme deciles. Panel B shows the diverging time trend in the extreme deciles more clearly. The slopes in both deciles are strikingly prominent with opposite sign. 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 Figure 3 is whether the observed time trend is stochastic. We formally test whether the trend in \( d_k \) is stochastic, by running 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:

\[
\begin{align*}
    d_{k,t} &= \alpha + \gamma d_{k,t-1} + u_t \\
    d_{k,t} &= \alpha + \delta t + \gamma d_{k,t-1} + u_t
\end{align*}
\]

The last two columns of Table 1 report the p-values of Phillips-Perron test. For the test with only a constant term, we reject a unit-root for \( d_{10} \) at 5% level, \( d_1 \), \( d_8 \), and \( d_9 \) at 10% level. For other deciles, we cannot reject a unit-root. However, for the difference between \( d_1 \) and \( d_{10} \), we strongly reject a unit-root. For the test with a time-trend term, we strongly reject the unit-root for all deciles, including the difference between \( d_1 \) and \( d_{10} \), at any conventional level.

Following the rejections of stochastic time trend, we test whether there is a deterministic time trend. Specifically we run the following regression model with autocorrelated
errors.

\[ d_{k,t} = \alpha + \delta t + \nu_t \]  \hspace{1cm} (26)

\[ \nu_t = \sum_{j=1}^{m} \rho_j \nu_{t-j} + \varepsilon_t \]  \hspace{1cm} (27)

We correct for the autocorrelation in the error terms up to six lags \((m = 6)\). We use maximum likelihood method to estimate the model. The result of the regression is shown in Table 1. After the correction of autocorrelation, the Durbin-Watson falls in no autocorrelation region for all deciles. For decile 1 and decile 2, the time trend is significantly negative, while the trend is significantly positive for decile 5 to decile 10. In addition, time-trend coefficients increase monotonically across deciles, from \(-2.14 \times 10^{-4}\) to \(1.30 \times 10^{-4}\). Also, the trend coefficient in decile 10 is noticeably higher than those in other positive-trend deciles. For example, the trend of decile 10 is of magnitude six times bigger than that of decile 5. Also, as shown in the last row of the table, the diverging trend in the extreme deciles is strongly established. The coefficient for time trend in \(d_{10} - d_1\) is \(3.57 \times 10^{-4}\) and statistically significant with t-value of 7.35.

The result of the time-trend regression confirms that there is a deterministic trend with a downward slope in low deciles and with a upward slope in high deciles. It also shows that the time trends are monotonic in the rankings of idiosyncratic volatility. The time trend is most negative in decile 1 and most positive in decile 10. This implies that the contribution of low deciles to the aggregate idiosyncratic volatility has become smaller while the contribution of high deciles has become bigger. It is important to notice that the observed time trend in \(d_k\) is independent of the level of the aggregate idiosyncratic volatility. In estimating \(d_k\), we divide the decile idiosyncratic volatility by the cross-sectional mean. By doing this, we effectively take the trend in the level of the aggregate idiosyncratic volatility out from our \(d_k\) measure. Therefore the trends in the aggregate idiosyncratic volatility reported in CLMX and others do not affect our result. 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, \(d_{10} - d_1\). In the next section, we examine whether this trend is robust in various firm characteristics and industries.
B. Robustness of the Trend

So far we have studied the cross-sectional distribution across all industries and firm characteristics. Since the firms in our sample differ immensely in characteristics and belong to different industries, the observed time trend may be a feature of few industries or certain firm characteristics. Thus, in this section we test whether the trend exist in various industries and across different firm characteristics. As a different test along the same direction, we also test whether firms' affiliation to a decile have changed over time. If firms' affiliation do not change over time, it is likely that certain characteristics of the firms in extreme deciles are associated with the observed time trend. In other words, a given group of firms with certain characteristics are more likely to be hit by extreme shocks than others. We test this by directly inspecting the trend of firms' affiliation to a decile.

We also perform two additional robustness checks. Over the sample period, many smaller firms have been listed. Some may argue that the trend is due to this increasing number of small firms. Therefore we control the number of firms and their size in performing our trend analysis. Finally, we test whether either positive or negative idiosyncratic shock has driven the observed time trends. All our results support the view that our main findings cannot be connected to a specific group of firms. Extreme shocks become more extreme in general.

First, we examine whether the established time trend still exist after we control various firm characteristics. First, we sort stocks into five groups by the control variables. Then we examine the time trend of $d_1$ and $d_{10}$ within each group. We use illiquidity, size, and total volatility as control variables. We estimate illiquidity from daily return during previous calendar year, following Amihud (2002). Size is firm’s market capitalization at the end of previous month. Total volatility is the standard deviation of daily return during previous month. Estimation methods of these variables are described in detail in Section 2.

Figure 4, 5, and 6 plot the time-trends in illiquidity quintiles, size quintiles, and volatility quintiles, respectively. For illiquidity groups, while the trend is observed in all illiquidity quintiles, it is strongest in illiquidity quintile 1 (most liquid stocks). In illiquidity quintile 1, share of decile 10 has more than doubled during the sample period while the share of decile 1 has fallen below the half of the starting point. It is similar for size quintiles. The trend is strongest in size quintile 1 (smallest stocks), while it is

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10 Monthly Amihud measure of illiquidity is considered to be too volatile among many researchers. Thus, we use yearly measure to capture the liquidity feature of each stock.
To further analyze whether certain firm characteristics are associated with the time trend in the extreme deciles, we test directly whether firms’ affiliation to a decile have changed over time. If it has changed, then it is extreme realizations to random firms rather than to the same firms that have driven the established trend. Thus, firms in extreme deciles this month are likely to have different characteristics from firms in extreme deciles next month. We perform the following event study analysis. First, we construct extreme decile portfolios for decile 1 and decile 10 in each month. We hold these portfolios for 60 months from the formation. Also we trace back the portfolio results to 24 months prior to the formation. We calculate two statistics for the portfolios. First, 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 the individual stocks in the portfolios constant for the event-time period. Second, we calculate the average decile of the portfolio during the event-time period. By definition, at the formation of the portfolios ($t = 0$), the average decile is 1 for decile 1 portfolio and 10 for decile 10 portfolio. We are interested in how persistent the average decile is over the event-time period. For the sample period from July 1963 to December 2008, we construct 455 extreme decile portfolios.

Figure 7 shows the result of the event study. Panel A reports the average time-series of portfolios’ share in the aggregate idiosyncratic volatility during the event-time period. By construction, the average shares of extreme portfolios at $t = 0$ are equivalent to the time-series average of $d_1$ and $d_{10}$. The average share of decile 10 portfolio at $t = 0$ is above 10% and that of decile 1 portfolio is below 10%, which can be confirmed from Figure 3. Right before and after the formation, the shares of extreme portfolios display sudden reversal. After quick reversal, the series gradually converge to a long-term mean value. Specifically, the share of decile 10 portfolio show a sudden increase at time 0 but quickly revert to its previous level and gradually decrease over the period. The share of decile 1 portfolio shows the exact opposite pattern. Thus, stocks in extreme deciles at a given point in time have quite different statistical property in idiosyncratic volatility distribution at any other point in time.

In Panel B, we directly examine the average decile of the extreme portfolios during the event-time period. At $t = 0$, each portfolio reach 1 or 10. As in Panel A, we observe a sudden spike or a drop at the portfolio formation. This indicates that stocks in decile 1 and decile 10 this month are quite different from stocks in those decile next month or a month before. The sudden changes imply that extreme decile affiliation is short-lived and seems to be determined by the extremely large (or small) realization to random
firms at $t = 0$. However, volatility of individual stocks seems to be persistent. Stocks in decile 10 have been and remain in high decile, while stocks in decile 1 have continued to be in low deciles before and after. This is consistent with the regression result of Panel B in Table 5 reported in the next section. On average, stocks in decile 10 today have been and will stay in decile 7, while stocks in decile 1 today have been and will stay in decile 3.

Next, we look at industries. We run the same regression as in equation (15) and (16) at Fama-French 48 industry level with $d_1$, $d_{10}$, and $d_{10} - d_1$ as the left hand side variables. Industries with less than 20 firms on average during the sample period are excluded. Table 2 reports the regression result. The table is sorted by t-statistics of linear trend of $d_{10} - d_1$. After the exclusion of industries with less than 20 firms, there are 40 industries remained. Overall, 26 industries show a positive coefficient in $d_{10} - d_1$, implying that there is a diverging time trend in the extreme deciles within the industries. 14 industries show a negative (thus, converging) time trend. Among industries with a positive time trend, 13 industries are statistically significant at 5% level (15 at 10%), while only three industries (four at 10%) are statistically significant among negative-trend industries. Electronic equipment, Automobiles, Telecommunications, Trading, and Computers are the examples of displaying a particularly strong diverging trend, while Pharmaceutical, Precious metal, and Aircraft show a strong converging trend.

The explanatory power of the diverging trend comes more from the trend in $d_1$. Out of 13 industries with a significant diverging trend, 11 industries have a strong negative trend in $d_1$, while only 7 industries have a strong positive trend in $d_{10}$. Generally $R^2$ is higher when $d_1$ is used as a dependent variable. As we see next section, the downward trend in $d_1$ is related with hedge fund trading activities while the upward trend in $d_{10}$ is associated with the increase in the cash flow volatility. Irvine and Pontiff (2009) argue that the increase in the cash flow volatility is attributed to the more intense economy-wide competition. Our result seems to be consistent with this idea. For example, Telecommunication, Trading, Computers, and Real Estate display strong coefficient estimates both in terms of significance and magnitude. Firms in these industries are likely to face more fierce competition than firms in other industries. Overall, Table 2 shows that the time trend in the cross-sectional distribution of idiosyncratic volatility vary considerably among industries. However, the diverging time trend is observed in the majority of industries, and the magnitude of the trend estimate for the industries with positive (diverging) trend is much higher than that of negative trend industries.

Over the sample period the number of firms in our sample has almost quadrupled. The sample size at the beginning of 1964 is 1,562, while there are 4,966 firms at the end
of 2008. The sample size reached to the highest in late 1990s with more than 6,800 firms but has gradually decreased after the internet bubble in early 2000s and the financial crisis in 2008. Also during our sample period, many smaller firms has been listed. To see how these changes in the sample affect our result, we create two sub-samples and investigate the time trend in the sub-samples. First, we select only 1,000 firms randomly in each month, all firms having same probability of being selected in the random sample. Thus we control the number of firms in this sub-sample. Second, we use only S&P 500 firms to control the number of firms and their size. Figure 8 shows that the time trend exists in both sub-samples. Panel A reports the result of the random sample of 1,000 firms and Panel B shows the result of S&P 500 sub-sample. Interestingly, the trend is stronger in the S&P 500 sample. Since S&P 500 index is composed of 500 big firms, this implies it is not newly listed smaller firms that have driven the time trend.

Lastly, we study whether the established time trend comes only from either positive or negative idiosyncratic shocks. By definition, daily idiosyncratic shocks during the estimation period sum to zero. But one may wonder whether the observed time trend is concentrated only in positive or negative territory of idiosyncratic shocks. If a small number of large negative (positive) shocks have been extreme compared to the average negative (positive) shocks, then the diverging time trend is mostly due to the diverging trend in the realization of negative (positive) shocks. To investigate this, we divide daily idiosyncratic shocks into positive and negative groups. To obtain enough observations of positive or negative shocks for a stock in a month, we run the Fama-French regression in equation (12) on yearly basis instead of monthly. Then we average the squared positive and negative shocks separately over a month to obtain monthly average positive and negative idiosyncratic shock. Figure 9 plots the time trends of positive and negative shocks of extreme deciles. The figure confirms that the trend is robust to the shocks of both signs. Thus we conclude both positive and negative shocks have been larger for stocks with high idiosyncratic volatility and smaller for stocks with low idiosyncratic volatility, relative to the average.

5. Fundamentals or Trading Activities?

In the previous section, we examine the cross-section of idiosyncratic return volatilities and establish the diverging time trend in the extreme deciles. In this section, we study potential determinants of the established time trend. Specifically, we are interested in the fundamental question whether the distribution of volatilities has changed over time because of the changes in fundamentals or the changes in trading process and its effect
on prices.

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 run the following thought experiment. Suppose that prices are affected by institutions who specialize on trading against the temporary relative mispricing of a small number of assets but are subject to capital constraints. When the realized idiosyncratic shock is relatively small, these institutions absorb a part of this shock which is proportional to their level of capital. However, when the shock is unexpectedly large, they have to liquidate part of their positions to meet their constraints and amplify this shock. By modifying the Shleifer-Vishny (1997) argument on limited arbitrage, we formalize this idea in Section 2. We argue that as the capital of these institutions increase, it leads small shocks to become smaller and large shocks to become larger in the cross-section. We proxy the capital level of the institutions following these strategies by the AUMs of Long/Short-Equity hedge funds.

We begin our analysis by running time-series regression of the shares of extreme deciles in the total on the proxy for the fundamentals volatility, the AUMs of Long/Short-Equity hedge funds, and various controls. Then we continue by investigating whether the importance of each determinant of the time trend is consistent across different liquidity groups of stocks. Finally, we check whether our results are the characteristic of the predictable or the unpredictable component of idiosyncratic risk.

Interestingly, our results suggest that the trends on $d_1$ and $d_{10}$ are explained by different hypothesis. While the decreasing trend in low volatility shocks seem to be related to the increasing activity of Long/Short-Equity funds, the increasing trend in high volatility shocks seem to be explained by fundamental factors. Furthermore, our observed pattern characterizes the unpredictable component of idiosyncratic shocks.

A. Determinants of The Time Trend

In the idiosyncratic volatility literature, the time trend in the aggregate idiosyncratic volatility is attributed to two different sources: Volatility of fundamental cash flow and trading activities of market participants. For example, Xu and Malkiel (2003) show that idiosyncratic volatility of individual stocks is 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 its reversal by 2007 is associated
with the trading pattern of retail investors. Irvine and Pontiff (2009) show that the
time trend in idiosyncratic return volatility is mirrored by the trend in idiosyncratic
volatility of fundamental cash flow.

To investigate the potential determinants of the diverging time trend in the extreme
deciles of the cross-sectional distribution, we perform time-series regression of \(d_1\), \(d_{10}\),
and \(d_{10} - d_1\), on the cash-flow volatility, AUMs of Long/Short-Equity funds, and controls.
We follow Irvine and Pontiff (2009) to estimate cash flow volatility. We control for firm
leverage and illiquidity estimated following Amihud (2002). We also control for trading
activities of different types of institutions: hedge funds excluding Long/Short-Equity
and other institutional investors. Those variables are explained in detail in Section 3.

Figure 10 plots the quarterly time-series of \(d_{CF1}\) and \(d_{CF10}\), the share of the idiosyn-
cratic cash flow volatility of idiosyncratic return decile 1 and decile 10. The top panel
shows the trend of the entire sample, while the bottom panel shows that of S&P 500
firms. The sample period is from January 1972 to December 2008, due to availability of
book equity data in Compustat. One distinguishing feature of the cash flow volatility
is that it is much more volatile than the return volatility plotted in Figure 3. Unlike
time-series of return volatility, the diverging trend is not clearly observed. Figure 11
shows the quarterly time-series of AUMs of hedge funds before its log transformation.
Panel A shows the AUMs of total hedge funds and Panel B shows that of Long/Short-
Equity style. The sample period is from January 1994 to December 2008. In both series,
AUMs increase exponentially in 2000s, followed by a dramatic decrease in 2008. Despite
their similarity, they display different patterns, especially during the period from 2005
to early 2008.

With these variables of interest, we run the following time-series regression:

\[
d_{k,t} = \alpha + \delta t + \beta_1 d_{CF1,t} + \beta_2 LSE_{t-1} + \gamma X_{t-1} + \epsilon_t
\]  

We use \(d_1\), \(d_{10}\), and \(d_{10} - d_1\) as dependent variables. \(d_{CF1}^k\) is the idiosyncratic cash flow
volatility of the corresponding decile. \(LSE\) is the AUMs of Long/Short-Equity style
hedge fund. And \(X\) is the vector of controls. Due to the hedge fund data, the sample
period of the regression is from 1994 to 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 contemporaneous with \(d_k\).

Table 3 reports the regression result. We use nine different regression models. The
first model shows the time-trend regression where a linear trend is the only regressor.
We observe the diverging trend in \(d_1\) and \(d_{10}\) for the sample period of 1994 to 2008. \(t-
statistic of the linear trend for \(d_1\), \(d_{10}\), and \(d_{10} - d_1\) are -3.81, 3.26, and 4.82, respectively.
The second model reports the regression result where a linear trend and cash flow volatility are the regressors. Coefficient for cash flow volatility, $\beta$, is significant for all three dependent variables. However, inclusion of cash flow volatility does not weaken the significance of time-trend.

The third model reports the regression model where a linear trend and AUMs of Long/Short-Equity style hedge fund are independent variables. The coefficients on AUMs of Long/Short-Equity funds have the signs consistent with our model. The coefficient of LSE for $d_1$ is significantly negative while it is positive but insignificant for $d_{10}$. Also, inclusion of AUMs of LSE flips the signs of linear trend for both $d_1$ and $d_{10}$. The sign of linear trend in $d_1$ becomes significantly positive while the sign for the trend in $d_{10}$ changes to negative, though it is not statistically significant. Thus, to the extent that AUMs represent hedge funds trading activities, we find the evidence that Long/Short-Equity funds trade in the way that their trading activities reduce the volatilities of stocks with low idiosyncratic volatility while they increase the volatilities of stocks with high idiosyncratic volatility. Also, based on the sign of the coefficient for the linear trend, we conclude that without Long/Short-Equity funds trading, the observed trend in extreme deciles would have been converging rather than diverging.

Interestingly, we find that different variables are important in explaining the pattern of $d_1$ and $d_{10}$. The fourth model includes both cash-flow volatility and LSE. For $d_1$, only LSE is important. On the other hand, only cash-flow volatility is important for $d_{10}$. Thus, the diverging trend in $d_{10} - d_1$ is attributed to both cash-flow volatility and trading activity of Long/Short-Equity funds. However, the two variables contribute to the diverging trend in the opposite way. The increasing trend in $d_{10}$ is mirrored in the trend of cash-flow volatility while the decreasing trend in $d_1$ is associated with trading activities of Long/Short-Equity style funds.

In the last model, we include both cash-flow volatility and LSE and all the control variables. Controlling for trading activities, LSE becomes less significant. However, it is worthwhile to note that the coefficient for hedge funds excluding LSE is significantly negative while institutional ownership in $d_1$ is significantly positive. This suggests that it is not the trading activity of financial institutions in general, but those speculating on the relative mispricing of equities in particular that matters. This is consistent with our model.
B. Are Hedge Funds Liquidity Providers or Liquidity Demanders?

Our results in the previous part suggest that some hedge funds are liquidity providers at least as long as shocks are small. In this part, we ask the question whether this provision of liquidity is focused where it is needed the most: at stocks which are illiquid. For this purpose, we investigate whether trading activities of hedge funds display different patterns according to different liquidity groups. Specifically, we divide the sample into illiquidity quintiles and run the same regression as in equation (28) within each illiquidity quintile.

Table 4 reports the regression result of the illiquidity quintile 1 (most liquid stocks), quintile 5 (least liquid stocks), and the difference between the two quintiles. We estimate firms’ illiquidity level in the previous year, following Amihud (2002). Then within a illiquidity quintile, we calculate our measure for the relative share of each decile in the total cross-section, $d_k$. The first model of each panel shows the result of time-trend regression within illiquidity quintiles. The time trend for $d_1$ is strongly observed in illiquidity quintile 5 with t-stat of -10.12, while it is not significant for illiquidity quintile 1. In the difference between quintile 5 and quintile 1, the trend for $d_1$ is statistically significant and negative due to the strong trend in quintile 5. On the other hand, $d_{10}$ displays similar trend both in more liquid and less liquid quintile. The linear trend for $d_{10}$ is strongly positive in both quintiles with t-stat of 3.18 and 4.57, respectively.

Second model of each panel shows the result of the regression model where we include idiosyncratic cash-flow volatility and AUMs of LSE as explanatory variables. With inclusion of cash flow volatility and LSE AUMs, the diverging time trend does not exist any more in either quintile. In illiquidity quintile 1, cash-flow volatility is significant for both $d_1$ and $d_{10}$ at 10% level, while is significant for only $d_1$ in quintile 5. The result for Long/Short-Equity funds in this table is consistent with the result in Table 3, showing that for small shocks these funds are liquidity providers for both illiquid and liquid stocks. That is, the coefficient in $d_1$ is negative and significant both in quintile 1 and quintile 5. However, we also find that the effect is much stronger in more liquid stocks. The coefficient in $d_1$ in quintile 1 is -3.45 with t-stat of -4.70 while it is -1.63 with t-stat of -4.59 in quintile 5. In the difference between the quintiles (quintile 5 - quintile 1), the coefficient in $d_1$ is positive and significant, confirming this observation. Regarding the regression of $d_{10}$, the coefficients on the AUMs of LSE are insignificant in quintile 1, while it is significantly positive in quintile 5. This suggests that LSE demand liquidity by liquidating most illiquid stocks when shocks are large. Overall, the results in the second model imply that if anything, these funds provide liquidity for most liquid
stocks only when shocks are small.

In the third model of each panel, we add control variables. The result is generally consistent with the second model though it is weaker. Proxies for trading activities of different types of institutions are generally significant in Quintile 5 while they are not in Quintile 1. Also it is interesting to note that in Quintile 5, the signs of LSE are opposite to those of other institutions. Table 4 confirms that whether Long/Short-Equity funds provide liquidity to the market mainly depends (inversely) on the size of the particular liquidity shock and not on the liquidity of the particular asset.

C. Is the pattern predictable?

In this part, we check whether our results are the characteristic of the predictable or the unpredictable component of idiosyncratic risk. This is an interesting question from two aspects. First, if institutions are concerned about idiosyncratic volatility, it is important for them to predict which firms will be affected by the extreme realizations. If our pattern is from the predictable component, this should be achievable. Second, our argument that trading activity can influence idiosyncratic risk because of limited arbitrage is much more convincing if our observed pattern is from the unpredictable component. Otherwise firms could prepare for the extreme shocks to make sure that they do not have to liquidate their positions in this event. Also, if institutions traded based on their predicted volatility, we would observe same time trend in the time-series of predicted idiosyncratic volatility.

To answer this question, we sort stocks based on their expected idiosyncratic volatilities predicted from firm characteristics or from the historical volatilities. Using the expected volatility instead of realized volatility, we calculate the relative share of each decile, $d_k$. Then we run the same regressions as in Table 4. If it is firms with similar characteristics that have shown more extreme realizations over time - that is, if we can predict extreme realizations of volatilities based on firm characteristics - , we would expect that $d_1$ and $d_{10}$ portfolios sorted by expected volatility display similar time trend with that of the actual time-series of $d_1$ and $d_{10}$. Likewise, if firms’ volatilities are persistent in their rankings - that is, more (less) volatile firms are likely to be more (less) volatile next period -, $d_1$ and $d_{10}$ portfolios sorted by historical volatility would display similar time trend with that of $d_1$ and $d_{10}$.

Table 5 reports the result of this analysis. We run three different regression models as in Table 4. Model 1 include only linear trend, Model 2 include linear trend, cash flow volatility, and AUMs of hedge funds, and Model 3 add institutional ownership to other
variables. In Panel A, we use expected volatility estimated from firm characteristics. Specifically, we run the following regression to estimate expected idiosyncratic volatility:

\[ IV_{i,t} = \beta_1 Illiq_{i,t-1} + \beta_2 Size_{i,t-1} + \beta_3 Lev_{i,t-1} + \gamma_i + \delta_t + \epsilon_{i,t} \] (29)

where $Iliq_{i,t}$ is Amihud’s measure of illiquidity at quarter $t$ for firm $i$, $Size_{i,t}$ is natural logarithm of market capitalization of the firm, $Lev_{i,t}$ is the leverage of the firm, $\gamma_i$ is firm fixed effect, and $\delta_t$ is time fixed effect. The expected idiosyncratic volatility is the fitted value of the regression.

The results of Panel A are inconsistent with and/or opposite to the results of Table 3 and 4. First, unlike Table 3 and Table 4, we do not observe the established time trend in Model 1. Also, cash flow volatility is important only for $d_1$ in Model 2 and Model 3, while it is important only for $d_{10}$ in previous tables. And the coefficient of Long/Short-Equity is significantly positive for $d_1$ and significantly negative for $d_{10}$, which is opposite to the previous result. Likewise, AUMs excluding Long/Short-Equity has a significant negative sign for $d_1$, while it is generally positive for $d_1$ in previous analysis. Therefore, we conclude that the diverging time trend in the cross-section are not predictable from firm characteristics.

Panel B shows the result of the portfolio sorted by historical volatility. If same stocks have shown extreme realizations relative to the average realization, then those stocks are likely to be in the extreme decile again in the next period. Thus, portfolio sorted by historical volatility would have same trend as we observe in Table 3 and 4. The result reported in Panel B shows that this may be the case. The regression result is generally consistent with those of Table 3 and 4. In Model 1, the decreasing time trend for $d_1$ is observed, as well as the diverging time trend in $d_{10} - d_1$. Long/Short-Equity funds also has same sign as in Table 3. However, the trend for $d_{10}$ is not statistically significant. Also, unlike previous tables, the cash flow volatility is important across all deciles and all specifications. Also, AUMs excluding Long/Short-Equity has significantly positive coefficient for $d_1$ in Model 3. Another noticeable difference from Table 3 is that institutional ownership has strong negative coefficient for $d_1$.

The result in Panel B provide some evidence that it is idiosyncratic volatilities of same stocks that have become more extreme compared to the average. However, in Table 1, we observe that lower deciles other than decile 1 also have negative time trend, while higher deciles other than decile 10 also have positive time trend. Also, in Figure 7, we demonstrate that firms’ affiliation to the extreme deciles changes quickly. Thus, even if a stock in decile 1 (or decile 10) this month is not in the same decile again next month, as long as it is in a relatively low (or high) decile - Figure 7 shows that this is the
case -, we could observe, to the less extent, the established trend in the portfolios sorted by the historical volatilities. In other words, to the extent that volatility is persistent, the trend could be observed even though it is not necessarily same firms.

6. Conclusion

Most studies on idiosyncratic volatility have focused on the time trend of the aggregate idiosyncratic volatility level. Though we also study the time trend of idiosyncratic volatility, our approach has several distinguishing features from previous literature. First, we examine the cross-sectional distribution of idiosyncratic volatilities without being restricted to their cross-sectional mean. Thus, we examine second, third, and fourth moments of the cross-sectional distribution while prior literature has focused only on the first moment. Second, we use Fama-French three factor model to decompose the idiosyncratic components of individual firms’ volatilities instead of the decomposition method of CLMX (2001). To examine the cross-section, we need to estimate idiosyncratic volatilities of individual firm. The decomposition method of CLMX is not applicable and Fama-French factor model is suitable for this purpose. Finally, we develop a statistical measure that evaluate the changes in the shape of the cross-sectional distribution. To investigate the shape of the extreme deciles, we construct the time-series of the share of the extreme deciles in the aggregate idiosyncratic volatility.

Our main results are as follows. First, from our 1963 to 2008 sample, we find 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. Thus, the relative magnitude of high (low) idiosyncratic volatility compared to the mean level have become larger (smaller). The share of top decile of idiosyncratic volatility in the aggregate idiosyncratic volatility has doubled over the sample period, while the share of bottom decile has almost disappeared. This trends are observed regardless industry, liquidity, and size, as well as sign of price change.

Second, in the sample from 1994 to 2008, there is strong evidence that the time trend in the cross-sectional distribution is related to idiosyncratic cash flow volatility, assets under management of hedge funds, and overall institutional ownership. The upward trend in high idiosyncratic volatility is associated with the increase in idiosyncratic cash flow volatility, while the downward trend in low idiosyncratic volatility can be attributed to Long/Short-Equity hedge fund activity. We also find some evidence that Long/Short-Equity funds act as liquidity demanders while non-Long/Short-Equity funds and other institutions act as liquidity providers.
Finally, we verify that it is not same firms that have become more (or less) volatile relative to the average idiosyncratic volatility. Rather the extreme realizations of idiosyncratic volatility to random firms have become larger (or smaller) relative to the average realization. Thus, despite some persistency, firms frequently move their relative position in the cross-sectional distribution of idiosyncratic volatility.
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

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

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

$$\Pi_1 (D_1, p_1, \kappa \theta_t) = \frac{D_1}{p_1} (\kappa \theta_{t+2} + \theta_{t+1} - S - p_1) - \frac{D_1}{p_1} (\kappa \theta_{t+2} + \theta_{t+1} - \kappa \theta_{t+1})$$

$$= D_1 \kappa \theta_{t+1} - S - p_1$$

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

$$\frac{D_1}{p_1} (p_2 + \theta_{t+1} - S - p_1) - \frac{D_1}{p_1} (\kappa \theta_{t+2} + \theta_{t+1} - \kappa \theta_{t+1}) +$$

$$+ \frac{D_2}{p_2} (\theta_{t+2} - \lambda S + \kappa \theta_{t+3} - p_2) - \frac{D_2}{p_2} (\theta_{t+2} + \kappa \theta_{t+3} - \kappa \theta_{t+2})$$

$$= D_1 \frac{p_2 - \kappa \theta_{t+2} + \kappa \theta_{t+1} - S - p_1}{p_1} + D_2 \frac{\kappa \theta_{t+2} - p_2 - S \lambda}{p_2}$$

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

Thus, arbitrageurs solve the problem

$$\max_{D_1, D_2} \left(1 - q \right) \left( D_1 \frac{\kappa \theta_{t+1} - S - p_1}{p_1} \right) + q \left( D_1 \frac{p_2 - \kappa \theta_{t+2} + \kappa \theta_{t+1} - S - p_1}{p_1} + D_2 \frac{\kappa \theta_{t+2} - p_2 - S \lambda}{p_2} \right)$$

s.t.

$$D_1 \leq F_1$$

$$D_2 \leq F_2 (\lambda S) = a D_1 \frac{\kappa \theta_{t+1} - S - p_1}{p_1} + F_1$$

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

$$p_2 = \kappa (\theta_{t+2} - \lambda S) + F_2.$$
Also, from problem (30), there must be a $q^*$ that if $q < q^*$ managers take a maximal position in the first period also. In this case,

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

and

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

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

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

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

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

B. Proof of Proposition 2

Observe that

$$\frac{\partial (\kappa S - F_1)^2}{\partial S} = 2\kappa S > 0.$$ 

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

$$\frac{\partial (\kappa \lambda S)^2}{\partial S} = 2S\kappa^2 \lambda^2 > 0$$

and

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

The third statement is a straightforward consequence of these results.
References


Diamond, Doug and Raghuram Rajan, 2010, Fear of Fire Sales, Illiquidity Seeking, and Credit Freezes, NBER, University of Chicago Booth School.


Table 1
Linear Trend Regression of Idiosyncratic Volatility Deciles

The table reports the results of time series regression of the proportion of each decile of idiosyncratic volatility to the total idiosyncratic volatility on linear time trend. Idiosyncratic volatilities are calculated following Ang, Hodrick, Xing, and Zhang (2006). Specifically, for each month, daily stock returns are regressed on Fama-French three factors. Residuals from the regressions are squared and averaged over the month to get idiosyncratic volatility measure. Then the relative proportion 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 entire stocks in the market. Autocorrelation in the error terms of the regressions are corrected up to six lags using maximum likelihood method. Probabilities of Phillips-Perron unit-root test results are reported in the last two columns.

<table>
<thead>
<tr>
<th>Decile</th>
<th>Intercept Estimate</th>
<th>T-value</th>
<th>Linear Trend Estimate × 10^4</th>
<th>T-value</th>
<th>R^2</th>
<th>Durbin-Watson</th>
<th>Phillips-Perron (Prob: Tau)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0.1323</td>
<td>11.02</td>
<td>-2.1360</td>
<td>-5.67</td>
<td>0.8663</td>
<td>1.9702</td>
<td>0.091</td>
</tr>
<tr>
<td>2</td>
<td>0.1281</td>
<td>14.18</td>
<td>-1.1111</td>
<td>-3.89</td>
<td>0.6498</td>
<td>1.9626</td>
<td>0.173</td>
</tr>
<tr>
<td>3</td>
<td>0.1156</td>
<td>20.17</td>
<td>-0.2986</td>
<td>-1.64</td>
<td>0.3148</td>
<td>1.9984</td>
<td>0.185</td>
</tr>
<tr>
<td>4</td>
<td>0.1125</td>
<td>29.85</td>
<td>-0.0429</td>
<td>-0.36</td>
<td>0.1361</td>
<td>1.9951</td>
<td>0.124</td>
</tr>
<tr>
<td>5</td>
<td>0.1000</td>
<td>30.99</td>
<td>0.2124</td>
<td>2.06</td>
<td>0.1286</td>
<td>1.9954</td>
<td>0.234</td>
</tr>
<tr>
<td>6</td>
<td>0.0912</td>
<td>32.80</td>
<td>0.3036</td>
<td>3.42</td>
<td>0.1675</td>
<td>1.9952</td>
<td>0.184</td>
</tr>
<tr>
<td>7</td>
<td>0.0814</td>
<td>24.55</td>
<td>0.4989</td>
<td>4.71</td>
<td>0.2757</td>
<td>1.9954</td>
<td>0.173</td>
</tr>
<tr>
<td>8</td>
<td>0.0718</td>
<td>13.27</td>
<td>0.6792</td>
<td>3.95</td>
<td>0.4463</td>
<td>2.0121</td>
<td>0.092</td>
</tr>
<tr>
<td>9</td>
<td>0.0688</td>
<td>10.23</td>
<td>0.8736</td>
<td>4.09</td>
<td>0.4575</td>
<td>1.9923</td>
<td>0.058</td>
</tr>
<tr>
<td>10</td>
<td>0.0919</td>
<td>10.19</td>
<td>1.3005</td>
<td>4.52</td>
<td>0.3880</td>
<td>1.9904</td>
<td>0.011</td>
</tr>
<tr>
<td>10-1</td>
<td>-0.0429</td>
<td>-2.80</td>
<td>3.5700</td>
<td>7.35</td>
<td>0.7106</td>
<td>1.9684</td>
<td>0.001</td>
</tr>
</tbody>
</table>
### Table 2
### Linear Trend Regressions in Individual Industries

The table reports the results of time-trend regressions of individual industries. Dependent variables are the share of Decile 1, Decile 10, and Decile 10 minus Decile 1 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 idiosyncratic volatilities of the stocks in the decile to the value weighted sum of entire stocks in the industry, as in equation (7). Industry classification is according to Fama and French (1997). Industries with less than 20 firms a month on average are excluded. Autocorrelation in the error terms of the regressions are corrected up to six lags using maximum likelihood method. The table is sorted by the T-values of the linear trends of Decile 10 minus Decile 1.

<table>
<thead>
<tr>
<th>Industry \ Dependent Variable</th>
<th>d10 - d1</th>
<th>d1</th>
<th>d10</th>
<th>Avg. No of Firms</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. Electronic Equipment</td>
<td>4.4500</td>
<td>9.62</td>
<td>0.3507</td>
<td>-3.6000</td>
</tr>
<tr>
<td>2. Automobiles and Trucks</td>
<td>5.3400</td>
<td>8.95</td>
<td>0.3437</td>
<td>-5.0400</td>
</tr>
<tr>
<td>3. Telecommunications</td>
<td>5.9600</td>
<td>6.96</td>
<td>0.3209</td>
<td>-4.5800</td>
</tr>
<tr>
<td>4. Trading (Finance)</td>
<td>4.5900</td>
<td>5.56</td>
<td>0.4322</td>
<td>-0.9700</td>
</tr>
<tr>
<td>5. Computers</td>
<td>5.2300</td>
<td>4.48</td>
<td>0.3863</td>
<td>-4.3000</td>
</tr>
<tr>
<td>6. Chemicals</td>
<td>1.8100</td>
<td>3.55</td>
<td>0.1246</td>
<td>-1.4900</td>
</tr>
<tr>
<td>7. Shipping Containers</td>
<td>2.2200</td>
<td>2.95</td>
<td>0.1427</td>
<td>-2.2100</td>
</tr>
<tr>
<td>8. Consumer Goods</td>
<td>1.5500</td>
<td>2.88</td>
<td>0.0754</td>
<td>-1.4400</td>
</tr>
<tr>
<td>9. Textiles</td>
<td>1.6200</td>
<td>2.82</td>
<td>0.0904</td>
<td>-0.5700</td>
</tr>
<tr>
<td>10. Insurance</td>
<td>1.8700</td>
<td>2.52</td>
<td>0.1375</td>
<td>-0.0324</td>
</tr>
<tr>
<td>11. Machinery</td>
<td>1.1600</td>
<td>2.27</td>
<td>0.1338</td>
<td>-0.6300</td>
</tr>
<tr>
<td>12. Steel Works, Etc</td>
<td>1.3400</td>
<td>2.11</td>
<td>0.1685</td>
<td>-0.6700</td>
</tr>
<tr>
<td>13. Real Estate</td>
<td>1.6500</td>
<td>2.06</td>
<td>0.1525</td>
<td>-0.0541</td>
</tr>
<tr>
<td>14. Healthcare</td>
<td>1.6300</td>
<td>1.89</td>
<td>0.1164</td>
<td>-0.0293</td>
</tr>
<tr>
<td>15. Nonmetallic Mining</td>
<td>0.7240</td>
<td>1.71</td>
<td>0.0888</td>
<td>-0.9600</td>
</tr>
<tr>
<td>16. Business Supplies</td>
<td>0.7990</td>
<td>1.59</td>
<td>0.0746</td>
<td>0.6640</td>
</tr>
<tr>
<td>17. Transportation</td>
<td>0.5720</td>
<td>1.26</td>
<td>0.0801</td>
<td>0.1780</td>
</tr>
<tr>
<td>18. Banking</td>
<td>0.7770</td>
<td>1.20</td>
<td>0.1912</td>
<td>0.2930</td>
</tr>
<tr>
<td>19. Utilities</td>
<td>1.3300</td>
<td>1.00</td>
<td>0.4167</td>
<td>-0.3100</td>
</tr>
<tr>
<td>20. Measuring and Control Equip</td>
<td>0.7010</td>
<td>1.00</td>
<td>0.0761</td>
<td>0.2710</td>
</tr>
<tr>
<td>21. Recreational Products</td>
<td>0.5560</td>
<td>0.66</td>
<td>0.1325</td>
<td>-1.3800</td>
</tr>
<tr>
<td>22. Entertainment</td>
<td>0.4890</td>
<td>0.53</td>
<td>0.1051</td>
<td>0.7520</td>
</tr>
<tr>
<td>23. Retail</td>
<td>0.3380</td>
<td>0.46</td>
<td>0.2008</td>
<td>-0.2700</td>
</tr>
<tr>
<td>24. Others</td>
<td>0.7950</td>
<td>0.36</td>
<td>0.1627</td>
<td>-1.3300</td>
</tr>
<tr>
<td>25. Apparel</td>
<td>0.1680</td>
<td>0.35</td>
<td>0.0485</td>
<td>-0.3000</td>
</tr>
<tr>
<td>26. Construction</td>
<td>0.0984</td>
<td>0.11</td>
<td>0.1728</td>
<td>0.2640</td>
</tr>
<tr>
<td>27. Electrical Equipment</td>
<td>-0.1400</td>
<td>-0.25</td>
<td>0.0789</td>
<td>0.1880</td>
</tr>
<tr>
<td>28. Personal Services</td>
<td>-0.2700</td>
<td>-0.35</td>
<td>0.0545</td>
<td>-0.1100</td>
</tr>
<tr>
<td>29. Construction Materials</td>
<td>-0.1500</td>
<td>-0.40</td>
<td>0.0366</td>
<td>-0.2200</td>
</tr>
<tr>
<td>30. Priting and Publishing</td>
<td>-0.2700</td>
<td>-0.48</td>
<td>0.0670</td>
<td>0.5240</td>
</tr>
<tr>
<td>31. Restaurants, Hotel, Motel</td>
<td>-0.9500</td>
<td>-1.01</td>
<td>0.2097</td>
<td>0.4320</td>
</tr>
<tr>
<td>32. Rubber and Plastic Products</td>
<td>-1.0500</td>
<td>-1.40</td>
<td>0.0924</td>
<td>0.1030</td>
</tr>
<tr>
<td>33. Wholesales</td>
<td>-0.4900</td>
<td>-1.48</td>
<td>0.0288</td>
<td>0.5100</td>
</tr>
<tr>
<td>34. Petroleum and Natural Gas</td>
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The table reports the results of time-series regression of the shares of idiosyncratic volatility deciles on the linear trend, cash flow volatility, AUM of Long/Short equity hedge funds, and various controls. Cash flow volatilities are calculated following Irvine and Pontiff (2009) with few modifications. Specifically, for each firm in a given quarter, cash flow innovation (dE) is calculated as $dE_{i,t} = \frac{(E_{i,t} - E_{i,t-4})}{B_{i,t-1}}$.

Using the cash flow innovations, we estimate the pooled cross-sectional time-series regression at the industry level: $dE_{i,t} = \alpha + \beta_1 dE_{i,t-1} + \beta_2 dE_{i,t-2} + \beta_3 dE_{i,t-3} + \beta_4 dE_{i,t-4} + \epsilon_i$. The squared difference between the residual of a firm and the average residual in a given quarter is the idiosyncratic cash flow volatility of the firm in the quarter. Then each idiosyncratic cash flow volatility is divided into 10 groups based on the firm's idiosyncratic return volatility. And the shares of deciles are calculated using market value. Long/Short equity AUM is natural logarithm of assets under management of the hedge funds characterized as Long/Short equity style at the end of previous quarter. AUM excluding L/S equity is natural logarithm of assets under management of total hedge funds excluding L/S equity style. 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 total value weighted sum of the leverage of entire stocks in the market. 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 total value weighted sum of Amihud measure of entire stocks in the market. Institutional ownership is the percentage owned by institutions for each decile at the end of previous quarter and are obtained from CDA/Spectrum database. The sample period is from January 1994 to December 2008. T-statistics are reported in brackets.

### Table 3: Time-Series Regression of Extreme Deciles of Idiosyncratic Volatility

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<th>AUM excl L/S Equity</th>
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</table>
The table reports the results of time-series regression of the shares of idiosyncratic volatility deciles within an illiquidity group on the linear trend, the share of cash flow volatility, AUMs of Long/Short equity hedge funds, and various controls. To estimate idiosyncratic volatility, for each quarter stocks are ranked into 5 groups based on the Amihud (2002) measure of illiquidity during previous year. Then within an illiquidity quintile, stocks are ranked into 10 groups based on their idiosyncratic volatility. Finally, within each illiquidity group, the share of each decile in a given quarter is calculated as the ratio of value weighted sum of idiosyncratic volatility of the stocks in the decile to the total value weighted sum of the illiquidity group. Cash flow volatilities are calculated as in Table 3. Then within an illiquidity group, each idiosyncratic cash flow volatility is divided into 10 groups based on the firm's idiosyncratic return volatility. And the shares of deciles within the illiquidity group are calculated using market value. Long/Short equity AUM is natural logarithm of assets under management of the hedge funds characterized as Long/Short equity style at the end of previous quarter. AUM excluding L/S equity is natural logarithm of assets under management of total hedge funds excluding L/S equity style. Leverage of each decile within an illiquidity quintile is calculated as the ratio of value weighted sum of the leverage of the firms in the decile to the total value weighted sum of the leverage of entire stocks in the quintile. Institutional ownership is the percentage owned by institutions for each decile of an illiquidity group at the end of previous quarter and are obtained from CDA/Spectrum database. The sample period is from January 1994 to December 2008. T-statistics are reported in the brackets.

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The table reports the results of time-series regression of the shares of idiosyncratic volatility of decile portfolios sorted by expected idiosyncratic volatility on the linear trend, the share of cash flow volatility, AUMs of hedge funds, and institutional ownership. We use two different proxies for the expected volatility of a firm, the predicted volatility from a panel regression and the historical volatility. Panel A reports the result of the predicted volatility while Panel B shows the result of the historical volatility. The predicted volatility is the fitted value of following panel regression: \[ IV_{i,t} = \alpha + \beta_1 \text{Size}_{i,t-1} + \beta_2 \text{Lev}_{i,t-1} + \gamma_i + \delta_t + \epsilon_{i,t}, \] where \( IV_{i,t} \) is idiosyncratic volatility, \( \text{Size}_{i,t-1} \) is natural logarithm of the market capitalization of previous quarter, \( \text{Lev}_{i,t-1} \) the leverage at the end of the previous quarter, \( \gamma_i \) is the firm fixed effect, and \( \delta_t \) is time fixed effect. The historical volatility in a given year is the average of quarterly realized idiosyncratic volatility during the previous year. To estimate idiosyncratic volatility of decile portfolio, stocks are ranked into 10 groups based on their expected idiosyncratic volatility. Then, the share of each decile portfolio in a given quarter is calculated as the ratio of value weighted sum of idiosyncratic volatility of the stocks in the decile to the total value weighted sum of the liquidity group. Cash flow volatilities are calculated following Irvine and Pontiff (2009) with few modifications as in Table 3. Long/Short Equity AUM is natural logarithm of assets under management of the hedge funds characterized as Long/Short Equity Style at the end of previous quarter. AUM excluding L/S Equity is natural logarithm of assets under management of total hedge funds excluding L/S Equity Style. AUMs are obtained from TASS. Institutional ownership is the percentage owned by institutions for each decile portfolio at the end of previous quarter and are obtained from CDA/Spectrum database. The sample period is from January 1994 to December 2008. T-statistics are reported in the brackets.

### Panel A: Predicted Volatility

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<th>Regression Model</th>
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Table 5: Time Series Regression of Idiosyncratic Volatility of Portfolios sorted by Expected Volatility
Figure 1. **Time trend of the cross-sectional mean of idiosyncratic volatilities.** The figure shows the time-series of cross-sectional mean of annualized monthly idiosyncratic volatilities. The top panel shows the time-series up to December 1997, to compare with the firm volatility in Campbell, Lettau, Malkiel, and Xu (2001). The bottom panel extends the sample period to December 2008. The monthly idiosyncratic volatility is calculated following Ang, Hodrick, Xing, and Zhang (2006). Specifically, for each month and for each stock, daily returns are regressed on Fama-French three factors. Residuals from the regressions are squared and averaged over the month to obtain the idiosyncratic volatility measure. Daily returns of common stocks (share code in 10 and 11) are obtained from CRSP for the shares traded in NYSE, AMEX, and NASDAQ. Stocks with less than $2 at the end of the previous year or less than 100 trading days in the previous year are excluded. The sample period is from July 1963 to December 2008. A 12-month backward moving average is used to get a smoothed time series.
Figure 2. Time trend of the higher cross-sectional moments of idiosyncratic volatilities. The figure shows the time-series of cross-sectional moments of monthly idiosyncratic volatilities. Each panel shows a backward 12-month moving average of variance, skewness, and kurtosis of monthly idiosyncratic volatilities. Market value at the end of previous month is used as a weight for each stock.
Figure 3. Time trend of the share of each decile in the aggregate idiosyncratic volatility. The top panel shows the time-series of the share of each decile of monthly idiosyncratic volatility in the aggregate idiosyncratic volatility of the market. The bottom panel shows the shares of 1st (low volatility) and 10th (high volatility) decile. The share of a decile in the aggregate idiosyncratic volatility is calculated as follows. For each month, daily stock returns are regressed on Fama-French three factors. Residuals from the regressions are squared and averaged over the month to get idiosyncratic volatility measure, following Ang, Hodrick, Xing, and Zhang (2006). Then stocks are ranked into 10 groups based on their idiosyncratic volatility. Finally, the share of each decile in a given month is calculated as the ratio of value weighted sum of idiosyncratic volatility of the stocks in the decile to the total value weighted sum of entire stocks in the market. A 12-month backward moving average is used to get a smoothed time series. In the bottom panel, the value of each decile at the starting point of the time-series is normalized to one for comparison.
Figure 4. Time trend of extreme deciles of idiosyncratic volatility within an illiquidity group. The figure shows the shares of 1st (low volatility) and 10th (high volatility) decile of monthly idiosyncratic volatility within an illiquidity group in the aggregate idiosyncratic volatility of the illiquidity group. Illiquidity Quintile 1 (Quintile 5) is the group of most (least) liquid stocks. The share of a decile in the aggregate idiosyncratic volatility of an illiquidity group is calculated as follows. For each month, stocks are ranked into five groups based on the yearly measure of illiquidity of previous calendar year, following Amihud (2002). Then, in each month, daily stock returns are regressed on Fama-French three factors. Residuals from the regressions are squared and averaged over the month to get idiosyncratic volatility measure, following Ang, Hodrick, Xing, and Zhang (2006). Then for each month and within an illiquidity quintile, stocks are ranked into ten groups based on their idiosyncratic volatilities. Finally, for each illiquidity group, 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 total value weighted sum of the liquidity group. A 12-month backward moving average is used to get a smoothed time-series. The value of each decile at the starting point of the time-series is normalized to one for comparison.
Figure 5. Time trend of extreme deciles of idiosyncratic volatility within a size group. The figure shows the shares of 1st (low volatility) and 10th (high volatility) decile of monthly idiosyncratic volatility within a size group in the aggregate idiosyncratic volatility of the size group. Size Quintile 1 (Quintile 5) is the group of stocks with smallest (largest) market capitalization. The share of a decile in the aggregate idiosyncratic volatility of a size group is calculated as follows. For each month, stocks are ranked into five groups based on the market capitalization at the end of previous month. Then, in each month, daily stock returns are regressed on Fama-French three factors. Residuals from the regressions are squared and averaged over the month to obtain idiosyncratic volatility measure, following Ang, Hodrick, Xing, and Zhang (2006). Then for each month and within a size quintile, stocks are ranked into ten groups based on their idiosyncratic volatilities. Finally, for each size group, 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 total value weighted sum of the size group. A 12-month backward moving average is used to get a smoothed time series. The value of each decile at the starting point of the time-series is normalized to one for comparison.
Figure 6. Time trend of extreme deciles of idiosyncratic volatility within a volatility group. The figure shows the shares of 1st (low volatility) and 10th (high volatility) decile of monthly idiosyncratic volatility within a volatility group in the aggregate idiosyncratic volatility of the volatility group. Volatility Quintile 1 (Quintile 5) is the group of stocks with lowest (highest) total volatility of previous month. The share of a decile in the aggregate idiosyncratic volatility of a volatility group is calculated as follows. For each month, stocks are ranked into five groups based on the standard deviation in the previous month. Then, in each month, daily stock returns are regressed on Fama-French three factors. Residuals from the regressions are squared and averaged over the month to obtain idiosyncratic volatility measure, following Ang, Hodrick, Xing, and Zhang (2006). Then for each month and within a volatility quintile, stocks are ranked into ten groups based on their idiosyncratic volatilities. Finally, for each volatility group, 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 total value weighted sum of the volatility group. A 12-month backward moving average is used to get a smoothed time series. The value of each decile at the starting point of the time-series is normalized to one for comparison.
Figure 7. **Time trend of extreme decile portfolios during event period.** The top panel shows the time trend of the share of decile 1 and decile 10 portfolios in the aggregate idiosyncratic volatility during the event-time period. The bottom panel shows the time trend of average decile of decile 1 and decile 10 portfolios during the event-time period. Decile portfolios are constructed as follows. Stocks are ranked into 10 groups based on their idiosyncratic volatilities at time 0. Each decile portfolio is constructed using the stocks in each idiosyncratic decile group at time 0. The portfolio results are traced for 60 months after formation and 24 months before formation without rebalancing. The share of each decile portfolio in a given month during the event period is calculated as the ratio of value weighted sum of idiosyncratic volatility of the stocks in the portfolio to the total value weighted sum of entire stocks in the market. The average decile of a portfolio in a given month is the average decile of stocks in the portfolio. For the sample period from July 1963 to December 2008, 455 extreme decile portfolios are constructed and the averages time trend of the 455 portfolios is plotted.
Figure 8. Time trend of relative proportion of extreme deciles of sub-samples. The figure shows the share of 1st (low volatility) and 10th (high volatility) Decile of monthly idiosyncratic volatility in the total idiosyncratic volatility of sub-samples. The top panel shows the time series of 1,000 firms that are randomly selected in each month. The bottom panel shows the time series of S&P500 firms. In a given month, each firm has equal chance to be selected in the random sample of 1,000 firms. 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 entire stocks in the sub-sample. A 12-month backward moving average is used to get a smoothed time series. The value of each decile at the starting point of the time-series is normalized to one for comparison.
Figure 9. Time trend of positive and negative idiosyncratic shocks. The top (bottom) panel shows the time-series of monthly positive (negative) idiosyncratic shocks. The monthly idiosyncratic shock is calculated as follows. For each 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 the month to get the positive (negative) idiosyncratic shocks. A 12-month backward moving average is used to get a smoothed time series. The value of each decile at the starting point of the time-series is normalized to one for comparison.
Figure 10. Time trend of idiosyncratic cash flow volatility of idiosyncratic return volatility deciles. The top panel shows the quarterly time-series of the share of idiosyncratic cash flow volatility of 1st (low volatility) and 10th (high volatility) idiosyncratic return volatility decile in the total. The bottom panel shows the time-series of S&P500 firms. Idiosyncratic cash flow volatilities are estimated following Irvine and Pontiff (2009) with few modifications. For each firm in a given quarter, cash flow innovation (dE) is calculated as \( dE_{i,t} = \frac{(E_{i,t} - E_{i,t-4})}{B_{i,t-1}} \). Using the cash flow innovation, we estimate the pooled cross-sectional time-series regression at the industry level: \( dE_{i,t} = \alpha + \beta_1 dE_{i,t-1} + \beta_2 dE_{i,t-2} + \beta_3 dE_{i,t-3} + \beta_4 dE_{i,t-4} + \epsilon_{i,t} \). In a given quarter, the difference of squared residual of a firm from the average squared residual in the quarter is the firm’s idiosyncratic cash flow volatility. Then each idiosyncratic cash flow volatility is divided into ten groups based on the firm's idiosyncratic return volatilities. And the share of a decile in the total is calculated using market value. Quarterly EPS and book value data are obtained from the intersection of Compustat and idiosyncratic return volatility sample of CRSP. The sample period is from January 1972 to December 2008. A 4-quarter backward moving average is used to get a smoothed time series. The value of each decile at the starting point of the time-series is normalized to one for comparison.
Figure 11. Time trend of hedge funds AUM. The figure shows the time-series of the asset under management (AUM) of hedge funds. The top panel shows total hedge funds AUM while the bottom panels shows the AUM of Long/Short-Equity funds. The data are obtained from TASS for the period January 1994 to December 2008.