

Do Hedge Funds Reduce Idiosyncratic Risk?

Internet Appendix

Appendix A: Robustness of the trend

The main text studies the entire cross-section of firms, regardless of industry affiliation and other characteristics. To highlight the robustness of our results we perform the following robustness tests: (a) we check the robustness of the time trends using various decomposition models for idiosyncratic volatility alternative to Equation (1); (b) we test whether the trends exist in various industries and across different firm characteristics; (c) over the sample period, many relatively small firms have been listed. To alleviate concerns that the trends are due to the increasing number of small firms, we control for the number of firms and their size in performing our trend analyses; and (d) we test whether the trends are driven by the either the positive or negative idiosyncratic shocks. All the results support the view that our main findings are not explained by a specific group of firms.

First, to study the sensitivity of the results to different methods of calculation of idiosyncratic volatility, we study whether the main results from Figures 1 and 2 significantly change if we include a momentum factor in Equation (1), or exclude SMB and HML from Equation (1), or apply the Campbell, Lettau, Malkiel, and Xu (2001) method to compute idiosyncratic volatility. Figure A1 plot the cross-sectional skewness and the time trends of extreme deciles that are obtained using these alternative models. The figure clearly shows that the results using these alternative models are qualitatively similar to the results described in Figures 1 and 2.

Second, we examine whether the established time trends remain after controlling for some firm characteristics. We sort stocks into quintiles by a given control variable, and then examine the time trends of d_1 and d_{10} within each quintile. We use illiquidity and size as control variables. We estimate the annual illiquidity of a firm using the Amihud (2002) measure. To form illiquidity quintiles, we sort firms by their illiquidity measured during the prior calendar year. Size is firm's market capitalization at the end of the previous month. We plot the idiosyncratic volatility time trends among the illiquidity and size quintiles in

Figure A2. The trends are apparent in the different illiquidity and size quintiles.

Next, we study the idiosyncratic volatility patterns across different industries. Stocks are classified into 48 industries following Fama and French (1997). We exclude eight industries with less than 20 firms on average during the sample period. We sort firms in each industry into idiosyncratic volatility deciles and run Regression (19) with d_1 , d_{10} , and $d_{10} - d_1$ as the left-hand-side variables. Table A1 reports the regression results. Industries are descendingly ordered in the table according to the t -statistics corresponding to the time-trend coefficients of $d_{10} - d_1$. Overall, 26 industries show a positive coefficient in $d_{10} - d_1$, implying that the diverging time trends in the extreme deciles are prevalent among most industries. There are 14 industries that show a negative (i.e., converging) time trend. Among industries with a positive time trend, 13 industries are statistically significant at the 5% level, while three industries are statistically significant among negative-trend industries. Electronic equipment, Automobiles, Telecommunications, Trading, and Computers are examples of industries that display a particularly strong diverging trend, while Pharmaceutical, Precious metal, and Aircraft show a strong converging trend.

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

face more competition than firms in other industries. Overall, Table 2 shows that the time trends in the cross-sectional distribution of idiosyncratic volatility vary considerably among industries. However, the diverging time trend is observed in the majority of the industries, and the magnitude of the time trend for the industries with a diverging trend is much higher than that of converging-trend industries.

Over the sample period, the number of firms has more than tripled. The sample size at the beginning of 1964 is 1,562, while there are 4,966 firms at the end of 2008. The sample reaches its highest size during the late 1990s, with more than 6,800 firms, but it gradually decreases after the Internet bubble in early 2000s and the financial crisis in 2008. Also, many relatively small firms are listed over the sample period. To evaluate whether these changes in the sample affect our results, we study the trends in idiosyncratic volatility in two subsamples. The first subsample consists of 1,000 firms randomly selected every month during the sample period. This method controls the number of firms in this subsample. The second subsample consists of S&P500—this controls for both the number of firms and their market capitalization. Figure A3 shows that the time trends in idiosyncratic volatility exist in both subsamples. The time trend is even stronger in the subsample of S&P500 firms. Since S&P500 index is typically composed of 500 large firms, the implication is that the time trends in idiosyncratic volatility are not driven by newly listed, smaller firms.

Finally, we study whether the time trends stem from either the positive or negative idiosyncratic shocks. By construction, the daily idiosyncratic shocks during the estimation period sum to zero per firm. If a small number of large negative (positive) shocks are extremely large compared to the average negative (positive) shocks, then the diverging time trend may be mostly due to the diverging trend in the realization of negative (positive) shocks. To investigate this issue, we divide daily idiosyncratic shocks into positive and negative groups. To obtain enough observations of positive or negative shocks for a stock in a given month, we run Regression (1) per firm per year instead of per firm per month.

Then, we average the squared positive and negative shocks separately over each month to obtain the monthly averages of positive and negative idiosyncratic shocks. Figure A4 plots the time trends of the positive and negative shocks of their corresponding top and bottom deciles. The figure confirms that the trends are robust to shocks of both signs. Thus, we conclude that both large positive and large negative shocks have increased over the sample period, while small positive and small negative shocks have decreased over the same period, relative to their respective averages.

Appendix B: Regressions of the volatility of idiosyncratic volatility

In this section, we examine a stock-level measure of volatility-of-volatility to further exclude the alternative “wild stock hypothesis.” The wild stock hypothesis predicts that hedge funds prefer to trade stocks with large fluctuation of period-to-period volatility. Therefore, we regress the measure of volatility of volatility on hedge-funds ownership. According to the wild stock hypothesis, the coefficient on hedge-funds ownership should be positive.

We estimate the future stock-level volatility-of-volatility (at the end of time $t - 1$) as the variance of the percentage change in volatility, that is $(IV_{i,t} - IV_{i,t-1})/IV_{i,t-1}$, calculated over the four-quarter rolling window (the time period t to $t + 3$). Then, we use this measure of volatility-of-volatility as the dependent variable in Equation (12). Table A2 reports the results. The table shows that the coefficient on hedge-fund ownership is mostly negative or insignificant, except for Decile 1 stocks. Therefore, we find no evidence that is consistent with the wild stock hypothesis.

Appendix C: Time-series regressions of illiquidity quintiles

One of our main hypotheses is that the effects of the increasing trading activity of hedge funds are amplified with the illiquidity of the stock. Therefore, we divide the sample into illiquidity quintiles and run the regression (22) within each illiquidity quintile. Table A3 reports the results for Quintile 1 (most liquid stocks) and Quintile 5 (least liquid stocks) for the sample period 1994–2008. Quintiles are formed based on stocks’ illiquidity measured during the previous calendar year. Within each illiquidity quintile, we further form deciles of idiosyncratic volatility and calculate our measure of the relative share of each decile, d_k , in the cross-section of firms that belong to that quintile.

The first model in each panel reports the results of time-trend regressions within illiquidity quintiles. The time trend for d_1 is significantly negative in Quintile 5, with a t -statistic of -8.44, while the trend is not significant for Quintile 1. In contrast, the time trend of d_{10} is significantly positive for both quintiles, with t -statistics of 3.13 and 4.39 for Quintiles 1 and 5, respectively. The second model in each panel reports the results of a regression model that includes idiosyncratic cash-flow volatility and LSE as explanatory variables. The inclusion of these variables eliminates the diverging time trends for both quintiles of illiquidity. The coefficients of cash-flow volatility are not significant except d_1 in Quintile 1. As for the coefficients of LSE , they appear significantly negative for d_1 in both illiquidity quintiles, while for d_{10} the coefficient of LSE is insignificant in Quintile 1 and significantly positive in Quintile 5 (at the 10% level). These results suggest that Long/Short-Equity funds behave as liquidity providers for relative small idiosyncratic shocks regardless of a firm’s liquidity, while they behave as liquidity demanders for illiquid stocks with high-idiosyncratic volatility.

The third model of each panel includes all the control variables except for the TED spread. The results are generally consistent with those of the second model. Nevertheless,

the effect of LSE on d_{10} appears more significant in illiquidity Quintile 5, further emphasizing that Long/Short-Equity funds trading activity both amplifies large shocks and reduces small shocks for less liquid stocks.

Models (4) and (5) in each panel include the TED spread and the interaction term between the TED spread and the AUM of Long/Short-Equity funds in addition to Specification (2) and (3), respectively. Interestingly, comparing Model (7) in Table 8 with Model (4) in Table A3, we observe that our full-sample results are mirrored in the sample of the most liquid stocks. The coefficients of the additional variables are similar to their full-sample equivalents in Model (5) for Quintile 1. This is in contrast to the results for the most illiquid stocks where coefficients change signs compared to their full-sample equivalents. This is consistent with recent works (e.g., Sadka (2010) and Ben-David, Franzoni, and Moussawi (2012)) that show that hedge funds tend to sell out more liquid stocks during liquidity crisis. Thus, the increasing financing costs of short positions affect more the idiosyncratic return shocks of the most liquid stocks.

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

Appendix D: A Model on the limits of arbitrage, capital share of hedge funds, and the cross-section of idiosyncratic volatility

We build a minimalist model of limits to arbitrage and idiosyncratic risk based on Shleifer and Vishny (1997). Consider a market with a large number of assets. In each period, the fundamental value of an asset is a systematic component and a firm-specific component. There are two types of agents participating in the market. While **noise traders**' demand is increasing in the fundamental value and decreasing in the price of the asset, it is also subject to mean reverting, asset-specific sentiment shock. **Managers** of equity funds aim to benefit from the mean reversion of these sentiment shocks by taking a long-short position of some assets with identified sentiment shocks and a well diversified portfolio hedging the systematic exposure of those assets. 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 reduced form constraint is consistent with various proposed mechanisms including capital withdrawals (Shleifer and Vishny (1997)), managers' wealth effects (Xiong (2001)), changing hedging demand (Kondor (2009)), and margin calls (Brunnermeier and Pedersen (2008)). As we show, in equilibrium idiosyncratic return volatility in this market has three components. It depends on (1) the change of the firm-specific part of the fundamental value, (2) the change in noise traders' sentiment, (3) the change in the trading activity of funds. Our main objective is to derive the equilibrium relation between the dynamics of the idiosyncratic return volatility and the capital of managers. In particular, the model illustrates larger amounts of capital under management of funds further increase large idiosyncratic shocks but decrease small idiosyncratic shocks.

We consider a fixed time interval Δt (e.g. a month) and assume that within this interval three phases (e.g. three days) are repeating N times. In particular, we present here the

case of $N = 1$ (i.e. a three-day month), but it will be transparent that our results hold with minimal modification for any N . For simplicity, we suppress the index for the month t , and use only the time index $s = 1, 2, 3$ denoting that the particular random variable is in phase s within the fixed time interval t . Consider a group of managers at the beginning of month t , focusing on a given stock. Suppose they know that the fundamental value of this asset in the next three phases is described by

$$\tilde{\theta}_s = \tilde{X}_s + \tilde{C}_s \quad (1)$$

where \tilde{X}_s is the systematic component and \tilde{C}_s is the idiosyncratic component on the day s . While these managers cannot predict the changes in any of these components over time, they learn that demand of noise traders for the asset in the next period is

$$\frac{\tilde{\theta}_s - \tilde{S}_s}{\tilde{p}_s}, \quad (2)$$

where \tilde{S}_s is the sentiment (i.e., a non-fundamental demand shock) in phase s .¹ In particular, in Phase 1, $\tilde{S}_1 = S > 0$ or $\tilde{S}_1 = -S$ with equal probability. In Phase 2, $\tilde{S}_2 = 0$ or $\tilde{S}_2 = 2\tilde{S}_1$ with probability q and $(1 - q)$, respectively. Thus, the shock either doubles in absolute terms or disappears. In Phase 3, $\tilde{S}_3 = 0$. (We denote a random variable by tilde and its realization by the same character without tilde.) In the description below, we focus on the case when $\tilde{S}_1 = S$, the case when $\tilde{S}_1 = -S$ is symmetric. Let $\Delta C_s \equiv C_{s+1} - C_s$ be the innovation in the firm-specific part of the fundamental value.²

Suppose that the value of the representative manager position in the given asset is D_s .

¹Note that, unlike the components of the fundamental value, noise traders' sentiment is independent of the month t and depends only on the phase (i.e., the day of the month), s .

²Note that each of the variables in the model are stock specific, that is, in principle we should add an i subscript to S, C, θ, p and q . We suppress this extra notation for convenience and reintroduce the stock-specific subscripts only when we define our theoretical measure of idiosyncratic volatility.

Then the market clearing conditions for the given asset in each phase is given by

$$\frac{\tilde{\theta}_s - \tilde{S}_s}{\tilde{p}_s} + \frac{D_s}{\tilde{p}_s} = 1. \quad (3)$$

Additional to the long position D_s in the asset, the manager also holds a short position in a well-diversified portfolio, which exactly offsets the systematic component of returns in the long portfolio. Given that this part implies a relatively small position in a large number of assets, we assume that the short position does not affect the prices of the components of this portfolio. Thus, both the fundamental value and the price of the portfolio giving the short position is

$$\tilde{X}_s \quad (4)$$

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

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

$$F_2(\tilde{S}_2) = \max(0, a\Pi_1(D_1, \tilde{p}_1, \tilde{p}_2) + F_1), \quad (5)$$

where $a\Pi_1(D_1, \tilde{p}_1, \tilde{p}_2)$ is the net profit or loss to the manager by the second phase, given her position D_1 and the prices \tilde{p}_1 and \tilde{p}_2 , and $a \geq 1$ is the parameter from Shleifer-Visnhy (1997) determining the connection between first phase profits and second phase capital.³ We assume that $|S + \Delta C_1| > F_1$, which ensures that managers can only partially absorb the firm-specific shocks in Phase 1.

We are interested in the case when the adverse shock in phase 2 ($S_2 = 2\tilde{S}_0$) is sufficiently

³While Shleifer and Vishny (1997) interpret the parameter a as the strength of the flow-performance relationship, for our purposes the interpretation as a measure of the tightening of capital constraints due to margin calls or internal stop-loss limits is more appropriate.

severe to force managers' to liquidate their position. This is why we consider the extreme case when q and a is sufficiently large.⁴ The parameter restriction q ensures that the worsening of the shock has a sufficiently low chance that managers fully invest in Phase 1. The restriction on a ensures that a worsening shock in Phase 2 fully wipes out the capital of managers taking maximal position in Phase 1. Thus, managers do not hold any assets regardless of the shock in the second phase, because either the trading opportunity disappears or their capital is wiped out. These restrictions also give a natural interpretation to the probability $(1 - q)$. This is the frequency that a representative fund holding asset i experiences a sufficiently large shock which forces this fund to liquidate (part of its) holdings. Thus, $(1 - q)$ is a measure of the vulnerability of this specific group of fund. Clearly, under this interpretation $(1 - q)$ might be time and stock specific.

The following proposition describes the equilibrium in formal terms.

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

1. *In the first phase, managers invest fully, $D_1 = F_1$.*
2. *In the second and third phases, managers liquidate their position and do not hold any assets.*
3. *Prices are given as follows*

$$p_1 = (\theta_1 - S) + F_1 \tag{6}$$

$$p_2 \left(\tilde{S}_2 = 2S \right) = (\theta_2 - 2S) \tag{7}$$

$$p_2 \left(\tilde{S}_2 = 0 \right) = \theta_2 \tag{8}$$

$$p_3 = \theta_3. \tag{9}$$

⁴The analysis of the case when an adverse shock does not result in full liquidation would give similar results. Hence, it is omitted for simplicity.

Before turning to the counterpart of our empirical measure of idiosyncratic volatility, let us spell out the equilibrium distribution of returns and the determinants of the managers' performance in our model. First, observe that the idiosyncratic part of return is given by

$$((p_{s+1} - p_s) - (X_{s+1} - X_s)),$$

the return of the asset minus the return on the systemic component. This return is stochastic.

With the relatively large probability of q , between phases 1 and 2 it is

$$\begin{aligned} (p_2 (\tilde{S}_2 = 0) - p_1) - (X_2 - X_1) &= \tag{10} \\ &= \theta_2 - (\theta_1 - S) - F_1 - (X_2 - X_1) = \\ &= X_2 + C_2 - (X_1 + C_1 - S) - F_1 - (X_2 - X_1) = \\ &= \Delta \tilde{C}_1 + S - F_1. \end{aligned}$$

and between phases 2 and 3 it is

$$\begin{aligned} (p_3 - p_2 (\tilde{S}_2 = 0)) - (X_3 - X_2) &= \tag{11} \\ &= \theta_3 - \theta_2 - (X_2 - X_1) = \\ &= \Delta C_2 \end{aligned}$$

.However, with a small probability of $(1 - q)$ the idiosyncratic component of the return between phases 1 and 2 is

$$\begin{aligned} (p_2 (\tilde{S}_2 = 2S) - p_1) - (X_2 - X_1) &= \tag{12} \\ &= (\theta_2 - 2S) - (\theta_1 - S) - F_1 - (X_2 - X_1) = \\ &= (X_2 + C_2 - 2S) - (X_1 + C_1 - S) - F_1 - (X_2 - X_1) = \\ &= \Delta C_1 - S - F_1. \end{aligned}$$

and between phases 2 and 3 it is

$$\begin{aligned}
\left(p_3 - p_2 \left(\tilde{S}_2 = 2S\right)\right) - (X_3 - X_2) &= \\
&= \theta_3 - (\theta_2 - 2S) - (X_3 - X_2) = \\
&= X_3 + C_3 - (X_2 + C_2 - 2S) - (X_3 - X_2) = \\
&= \Delta C_2 + 2S.
\end{aligned} \tag{13}$$

. Regardless of the shock \tilde{S}_2 , the idiosyncratic component of the return between phases 3 and 1 is

$$(p_1 - p_3) - (X_1 - X_3) = \Delta \tilde{C}_3 - S + F_1. \tag{14}$$

Note that the expressions (10) and (13) are increasing in the sentiment shock S . The reason is that these are the phases when the temporary shock disappears, hence, the price bounces back close to the fundamental value of the asset. The larger the previous shock, the larger the rebound. By similar intuition, expressions (12) and (14) are decreasing in the sentiment shock S , because these are the phases when the temporary shock gets worse.

Turning to the profit of the manager, it is sufficient to focus on the return on the long-short position between phases 2 and 1, because, under our parameter restrictions, this is the only interval when the manager takes a position. That is, expressions (10) and (12) give the returns on each unit of the long-short position of the manager. Clearly, this profit is increasing in the sentiment shock in the high probability state of $\tilde{S}_2 = 0$ and decreasing in the adverse state of $\tilde{S}_2 = 2S$. That is, unless the large, adverse shock happens, managers are profiting from a larger sentiment shock. This is not surprising as their strategy is to speculate on the mean reversion of this shock. Taking the expectations over the shock \tilde{S}_2 , we get that the expected return on every unit of investment is

$$(2q - 1) S,$$

which, under our assumption of large q , is increasing in S . That is, both expected returns between phase 2 and 1 and the expected profit of the manager is increasing in the size of the sentiment shock.

Let us turn to our main object of interest, the analysis of the cross-sectional distribution of idiosyncratic volatility. Consider the expression

$$((p_{s+1} - p_s) - (X_{s+1} - X_s))^2 \quad (15)$$

as the model variant of our measure of a particular daily realization of an idiosyncratic shock. In the empirical part, we construct monthly and quarterly estimates of idiosyncratic volatility by averaging daily realizations over the given interval. Thus, the theoretical counterpart of these estimates should be generated by a series of repetition of the three phases of our model. To simplify the exposition, we present the argument for the case when the month or quarter corresponds exactly to the three phases of our model.⁵ Also, the phases of each stock are independent, so in each month q fraction of the stocks experience the phases corresponding to $S_2 = 0$, while $(1 - q)$ fraction experience $S_2 = 2\tilde{S}_1$. Thus, the observed idiosyncratic shocks of the first group within the month, using expressions (10),(11) and (14), is

$$(S - F_1 + \Delta C_1)^2, (\Delta C_2)^2, (S - F_1 + \Delta C_3)^2$$

regardless whether $\tilde{S}_1 = S$ or $\tilde{S}_1 = -S$. Thus, the monthly estimate of idiosyncratic volatility

⁵Alternatively, to obtain a richer distribution for which deciles are more apparent, we can assume that for a given month in our empirical work the three phases of our model repeat N times. Thus, the distribution of our monthly estimated idiosyncratic volatility will be

$$IV_t = \left(k \frac{2(S-F_1)^2}{N} + (N - k) \frac{(S-F_1)^2 + (S+F_1)^2 + (2S)^2}{3} \quad w.p. \quad \binom{N}{k} q^k (1 - q)^{N-k} \right)$$

for each $k = 0, 1, \dots, N$. Clearly, higher deciles will correspond to lower k , that is, a higher fraction of phases with $S_2 = 2S$. It is easy to see that our proposition would still hold with minimal adjustments.

for this group is

$$IV_{it}(S_2 = 0) = \frac{(S - F_1 + \Delta C_3)^2 + (S - F_1 + \Delta C_1)^2 + (\Delta C_2)^2}{3}.$$

The observed idiosyncratic shocks of the second group ,using expressions (12),(13) and (14), is

$$(S + F_1 + \Delta C_1)^2, (2S + \Delta C_2)^2, (S - F_1 + \Delta C_3)^2$$

giving the monthly estimate of

$$IV_{it}(S_2 = 2\tilde{S}_1) = \frac{(S - F_1 + \Delta C_3)^2 + (S + F_1 + \Delta C_1)^2 + (2S + \Delta C_2)^2}{3}.$$

As $IV_{it}(S_2 = 0) < IV_{it}(S_2 = 2S)$, we can consider the first group of stocks the bottom quantile stocks and the second group of stocks the top quantile stocks. Note that the unconditional idiosyncratic volatility of a given stock i is

$$E(IV_{it}) = (1 - q)IV_{it}(S_2 = 2\tilde{S}_1) + qIV_{it}(S_2 = 0)$$

where $E(\cdot)$ is formed over the states of a given stock i .

Our main hypotheses are a simple consequence of the following Lemma.

Lemma 1. *If $a > a^*$ and $q > q^*$, monthly idiosyncratic volatility is increasing in managers' capital invested in the stock F_1 , in the top quantile and decreasing in the bottom quantile. That is,*

$$\frac{\partial(IV_{it}(S_2 = 0))}{\partial F_1} < 0, \frac{\partial(IV_{it}(S_2 = 2\tilde{S}_1))}{\partial F_1} > 0.$$

Figure 4 illustrates this Lemma. We plot the realized idiosyncratic volatility of a particular stock under different scenarios in each phase u . For simplicity, we assume that the firm-specific component of idiosyncratic risk remains constant, $\Delta C_{t+u} = 0$. When managers

have capital F_1 in Phase 1, the realization follows the dotted line and the dashed line if $S_2 = 0$ and $S_2 = 2\tilde{S}_1$, respectively. It is apparent that the mean of idiosyncratic shocks, i.e., the estimated idiosyncratic volatility is larger when $S_2 = 2S$. Thus, as we pointed out, we think of the group of stocks experiencing the pattern of the dotted line the bottom-quantile, and the group experiencing the pattern of the dashed line the top-quantile stocks. It is apparent that if F_1 is larger, the solid line on Figure 4 is pushed downwards. That is, shocks in the bottom quantile decrease and shocks in the top quantile increase (or do not change). The intuition is that larger capital increases managers' total position against the temporary shock. However, when the underlying shock intensifies, the size of the liquidated positions also increases due to the loss limits. This increases realized return volatility in the top quantile. Note also, that the average idiosyncratic return over the three phases is zero for both groups in our model. This provides a rationale of why we focus on idiosyncratic volatility as opposed to returns.

The following proposition states the model equivalent of our main tested hypotheses.

Corollary 1. *If $a > a^*$ and $q > q^*$, the following statements hold*

1. *Suppose that managers' capital invested in each stock i weakly increases in the aggregate capital of hedge funds, \bar{F}_1 . Then the monthly estimated idiosyncratic volatility in the top (bottom) quantile increases (decreases) in the aggregate capital of hedge funds compared to the cross-sectional mean of idiosyncratic volatility. That is,*

$$\frac{\partial(\bar{E}(IV_{it}(S_2 = 0)) - \bar{E}(E(IV_{it})))}{\partial \bar{F}_1} < 0, \frac{\partial(\bar{E}(IV_{it}(S_2 = 2\tilde{S}_1)) - \bar{E}(E(IV_{it})))}{\partial \bar{F}_1} > 0 \quad (\text{H1})$$

where $\bar{E}(\cdot)$ is the expectation formed over the cross-section of stocks.

2. *The expected month-to-month change in idiosyncratic volatility for a stock moving to the top (bottom) quantile is increasing (decreasing) in first period managers' capital*

invested in the stock F_1 ,

$$\frac{\partial \left(IV_{it} \left(S_2 = 2\tilde{S}_1 \right) - E \left(IV_{it} \right) \right)}{\partial F_1} > 0, \frac{\partial \left(IV_{it} \left(S_2 = 0 \right) - E \left(IV_{it} \right) \right)}{\partial F_1} < 0 \quad (\text{H2})$$

Given that our arguments behind both hypotheses rely on the price effect of funds' trades, if illiquidity is defined by a larger price effect of a dollar trade, then all these effects will be stronger for more illiquid stocks. For brevity, we do not include the formal derivation of this result, but we test for this additional implication in the data.

We also derive the following additional hypotheses.

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

1. *The absolute size of the idiosyncratic return shock increases in each quantile in the innovation of the firm-specific part of the fundamental value. That is,*

$$\frac{\partial IV_{it} \left(S_2 = 0 \right)}{\partial \Delta C_s}, \frac{\partial IV_{it} \left(S_2 = 2\tilde{S}_1 \right)}{\partial \Delta C_s} > 0 \text{ for each } s = 1, 2, 3. \quad (\text{H3})$$

2. *For any $q > q^*$, the average idiosyncratic volatility is increasing in the vulnerability of the group of funds holding the given stock, $(1 - q)$. That is,*

$$\frac{\partial E \left(IV_{it} \right)}{\partial (1 - q)} > 0. \quad (\text{H4})$$

In the main text, we gather supporting evidence for each of our hypotheses. Our main approach is as follows. First, we consider firm-level panel evidence to find support for hypothesis H2. We consider various controls proxying for the fundamental component of idiosyncratic volatility, ΔC_s , in line with hypothesis H3, and we also show that our effects are stronger for less liquid stocks. We augment this approach with a natural experiment related to the Lehman bankruptcy which creates exogenous variation across the vulnerability

of funds to directly test hypothesis H4. Finally, we consider aggregate time-series evidence to find support for hypothesis H1.

Appendix E: Proofs of Proposition 1 and Lemma 1

It is easy to see that in Phase 3 managers will not hold any position, so the price of the asset is given by

$$\theta_3 = p_3.$$

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

$$\theta_2,$$

and

$$\begin{aligned}\Pi_1(D_1, p_1, \theta_1) &= \frac{D_1}{p_1}(\theta_2 + \theta_1 - S - p_1) - \frac{D_1}{p_1}\theta_2 \\ &= D_1 \frac{\theta_1 - S - p_1}{p_1},\end{aligned}$$

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

$$\begin{aligned}\frac{D_1}{p_1}(p_2 + \theta_1 - S - p_1) - \frac{D_1}{p_1}(\theta_2) + \\ + \frac{D_2}{p_2}(\theta_2 - 2S + \theta_3 - p_2) - \frac{D_2}{p_2}(\theta_2 + \theta_3 - \theta_2) \\ = D_1 \frac{p_2 - \theta_2 + \theta_1 - S - p_1}{p_1} + D_2 \frac{\theta_2 - p_2 - S}{p_2},\end{aligned}$$

where $p_2 = \tilde{p}_2(2S)$. Thus, arbitrageurs solve the problem

$$\begin{aligned} \max_{D_1, D_2} q & \left(D_1 \frac{\theta_1 - S - p_1}{p_1} \right) + (1 - q) \left(D_1 \frac{p_2 - \theta_2 + \theta_{t+1} - S - p_1}{p_1} + D_2 \frac{\theta_2 - p_2 - S}{p_2} \right) \quad (16) \\ \text{s.t. } D_1 & \leq F_1 \\ D_2 & \leq F_2(2S) = aD_1 \frac{\theta_1 - S - p_1}{p_1} + F_1 \end{aligned}$$

We solve for the equilibrium backwards. It is easy to see that if $\tilde{S}_2 = 2S$, managers take a maximal position which implies

$$p_2 = (\theta_2 - 2S) + F_2.$$

Also, from problem (16), there must be a q^* that if $q > q^*$ managers take a maximal position in the first period as well. In this case,

$$(\theta_1 - S) + F_1 = p_1,$$

and

$$F_2(2\tilde{S}_1) = \max(0, a\Pi_1(D_1, \tilde{p}_1, \tilde{p}_2) + F_1) = \max(0, F_1 \left(1 - a \frac{F_1}{\theta_1 - S + F_1} \right)).$$

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

$$F_2(2\tilde{S}_1) = 0.$$

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

phase. Thus,

$$p_2 = \theta_2 - 2S.$$

This concludes the proof of Proposition 1.

Lemma 1 and Conjectures 1 and 2 are simple consequences of the formulas derived in the main-text.

Table A1: Time-Trend Regressions of the Extreme Deciles in Individual Industries

The table reports the results of time-series regressions of the shares of the extreme deciles in the aggregate idiosyncratic volatility of an individual industry on a time trend. Dependent variables are the share of Decile 1, Decile 10, and Decile 10 minus Decile 1 of the idiosyncratic volatility in each industry. The share of each decile of an industry in a given month is calculated as the ratio of the value-weighted sum of the idiosyncratic volatility of the stocks in the decile to the value-weighted sum of the idiosyncratic volatility of stocks in the entire cross-section of the industry. Industry classification is according to Fama and French (1997). Industries with less than 20 firms per month on average are excluded. Autocorrelations 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 time trend of Decile 10 minus Decile 1. Daily returns of common stocks (share code in 10 and 11) are obtained from CRSP for the shares traded in NYSE, AMEX, and Nasdaq for the period 1963-2008. Stocks with less than \$2 at the end of the previous year or less than 100 trading days during the previous year are excluded.

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

Table A2: Panel Regressions of the Volatility of Idiosyncratic Volatility

The table reports the results of regressions of the volatility of the volatility on various explanatory variables. The dependent variable is the log of the volatility of idiosyncratic volatility. The volatility of idiosyncratic volatility at quarter t is measured as the variance of the percentage changes in volatility, that is $(IV_{i,t} - IV_{i,t-1})/IV_{i,t-1}$, calculated over the four-quarter rolling window from t to $t+3$. The independent variables are $\Delta CF_{i,t}$, the changes in the log of idiosyncratic cash-flow volatility, $HF_{i,t-1}$, the level of hedge-fund ownership at the end of quarter $t-1$, $IO_{i,t-1}$, the non-hedge-fund institutional ownership at the end of quarter $t-1$, $ILLIQ_{i,t-1}$, the Amihud (2002) illiquidity in quarter $t-1$, firm leverage in quarter $t-1$, and size at the end of $t-1$. Idiosyncratic cash-flow volatility is estimated following Irvine and Pontiff (2010). Hedge-fund ownership is the percentage holdings of institutions which are identified as hedge funds from a list of hedge fund names obtained from Lipper/TASS. Institutional holding data based on 13F filings are available through the CDA/Spectrum database of Thompson Financials. Size is the log of market capitalization. Standard errors are clustered within each firm, and the time (quarter) fixed effect is included for each regression. The t-statistics are reported in square brackets. The sample period is 1994–2008.

| Subsample | Entire Sample | | Decile 1 | | Decile 10 | | Middle Deciles | |
|----------------|---------------|----------|----------|---------|-----------|---------|----------------|----------|
| Variable\Model | (1) | (2) | (1) | (2) | (1) | (2) | (1) | (2) |
| Intercept | 0.96 | 2.12 | 1.10 | 4.46 | 1.34 | 0.40 | 0.86 | 1.94 |
| | [35.95] | [41.40] | [7.21] | [17.14] | [14.24] | [2.01] | [31.37] | [36.63] |
| ΔCF | 0.01 | 0.01 | 0.00 | 0.00 | 0.01 | 0.01 | 0.01 | 0.01 |
| | [10.31] | [10.13] | [0.29] | [0.07] | [2.43] | [2.29] | [8.92] | [8.88] |
| HF | 0.00 | -0.16 | 1.22 | 0.75 | -0.03 | -0.13 | -0.01 | -0.15 |
| | [0.06] | [-2.28] | [4.09] | [2.66] | [-0.11] | [-0.58] | [-0.14] | [-2.20] |
| IO | -0.58 | -0.11 | -1.00 | -0.14 | 0.57 | 0.37 | -0.51 | -0.10 |
| | [-16.37] | [-2.93] | [-7.36] | [-1.10] | [4.45] | [2.73] | [-14.65] | [-2.61] |
| LEV | | 0.20 | | 0.21 | | 0.56 | | 0.19 |
| | | [7.87] | | [1.87] | | [7.79] | | [7.79] |
| ILLIQ | | -0.02 | | 0.20 | | -0.01 | | -0.02 |
| | | [-3.89] | | [7.15] | | [-0.75] | | [-3.22] |
| Size | | -0.14 | | 0.03 | | 0.05 | | -0.12 |
| | | [-16.44] | | [0.69] | | [1.86] | | [-14.74] |
| Adj. R^2 | 0.083 | 0.097 | 0.134 | 0.193 | 0.101 | 0.108 | 0.083 | 0.095 |

The table presents the results of time-series regression of subsamples that are formed based on stocks' illiquidity quintiles. In each illiquidity-quintile subsample, the shares of the extreme deciles of the idiosyncratic volatility in the aggregate idiosyncratic volatility are regressed on a time trend, cash-flow volatility, the AUMs of Long/Short-Equity hedge funds, and various controls, including firm leverage, illiquidity, the AUM of non-Long/Short-Equity hedge funds, the institutional ownership, the TED Spread, and the interaction between the AUM of Long/Short-equity hedge funds and the TED spread. Each illiquidity-quintile subsample is constructed based on the Amihud (2002) measure of illiquidity estimated during previous calendar year. Then within an illiquidity-quintile subsample, stocks are divided into deciles based on their idiosyncratic volatility. Finally, the shares of the extremes decile of the idiosyncratic volatility in a given quarter are calculated as the ratio of value-weighted sum of the idiosyncratic volatility of the stocks in the decile to the value-weighted sum of stocks in the entire cross-section of the illiquidity-quintile subsample. Other variables are defined within each subsample in the same manner as in Table 8. The *t*-statistics are Newey-West adjusted using 4 lags and are reported in square brackets. The sample period is 1994–2008.

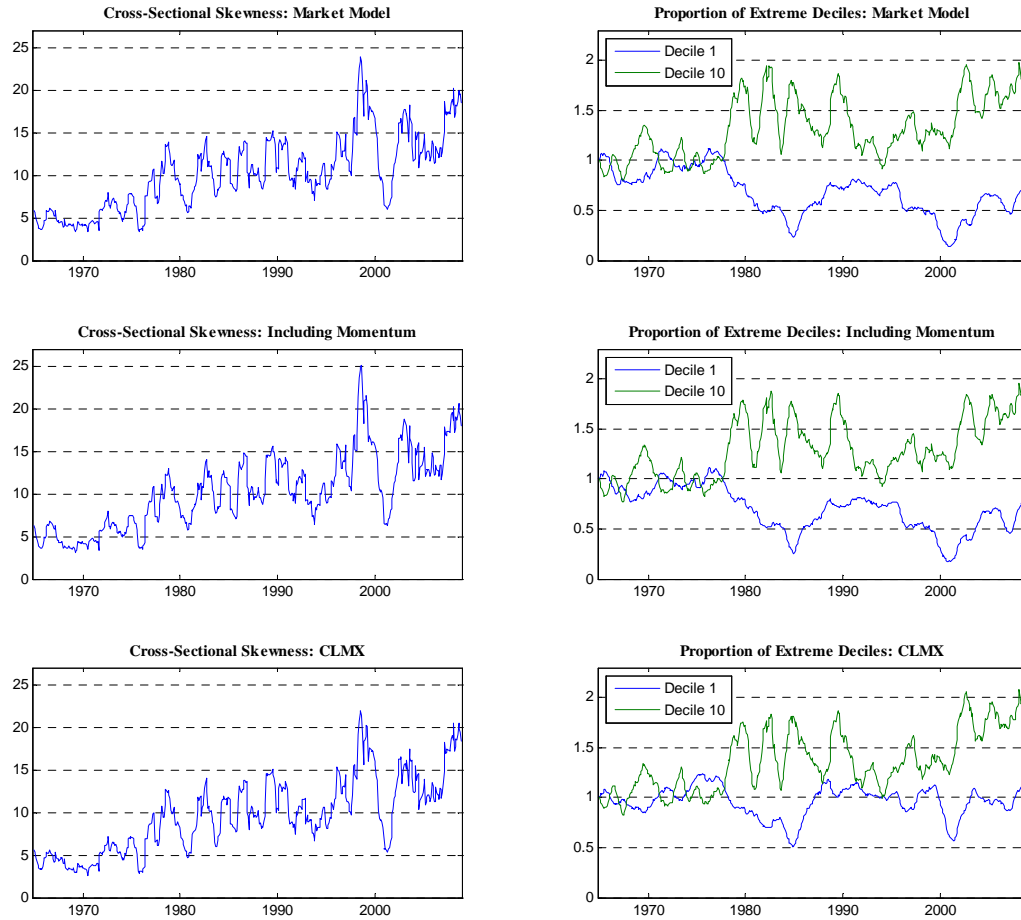


Figure A1. Time trends of idiosyncratic volatility using alternative models. The first column plots the time series of 12-month backward moving average of the cross-sectional skewness of monthly idiosyncratic volatility estimated from alternative models for decomposition. The second column shows the time series of the share of the 1st and the 10th deciles of the idiosyncratic volatility in the aggregate idiosyncratic volatility (Equation (7)). The first row uses the market model to decompose the idiosyncratic volatility. The second row uses a four-factor model that includes the momentum factor, in addition to Fama-French three factors. The last row uses the method of Campbell, Lettau, Malkiel, and Xu (2001). The sample period is 1963–2008.

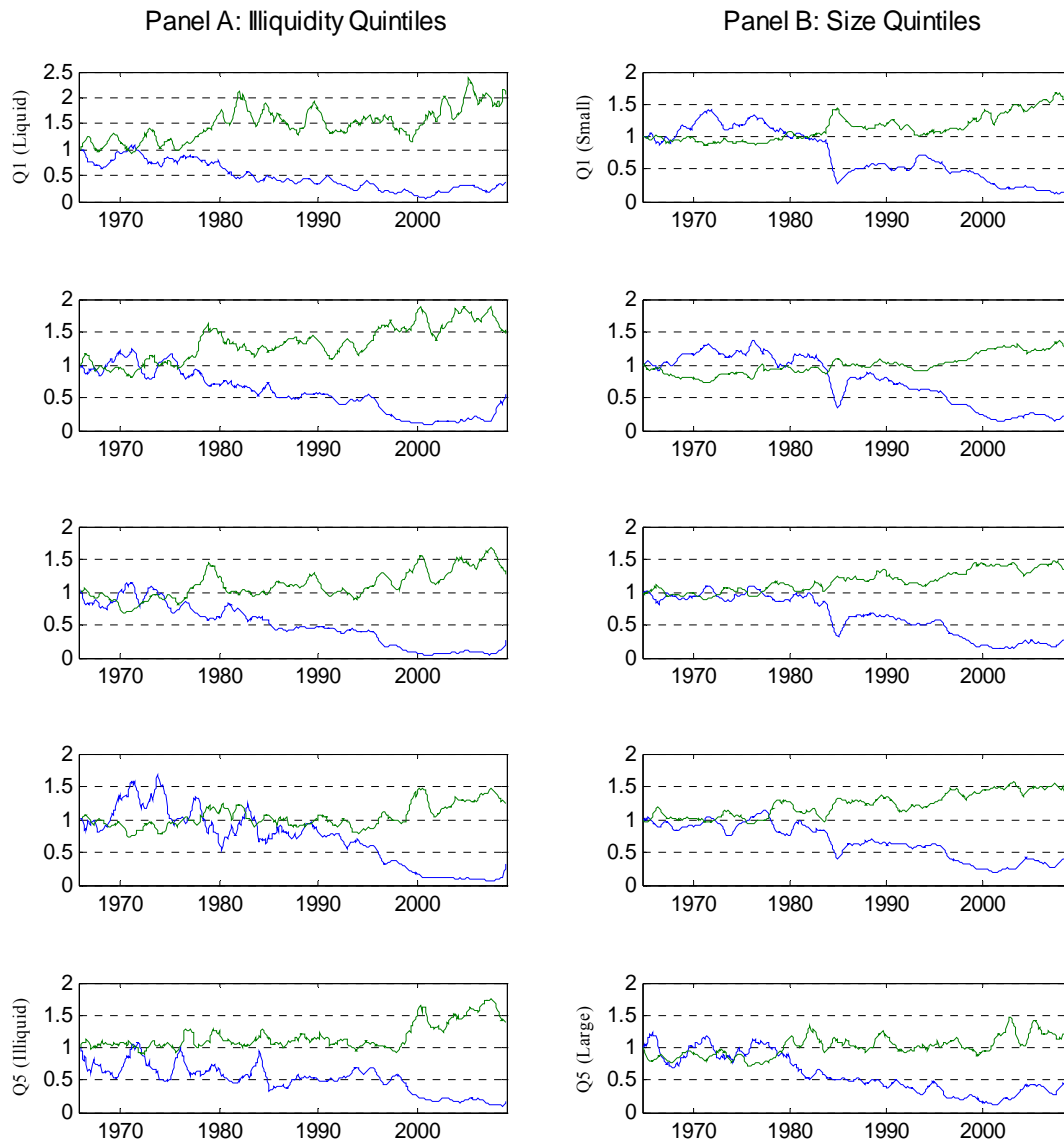


Figure A2. Time trends of the extreme deciles of the idiosyncratic volatility in illiquidity and size quintiles. The figure plots the shares of the 1st and the 10th deciles of the idiosyncratic volatility in illiquidity and size quintiles. A 12-month backward moving average is used and each time series is normalized through dividing by its beginning-of-the-sample value. The first row shows illiquidity and size Quintile 1 and the last row shows illiquidity and size Quintile 5. Illiquidity Quintile 1 (Quintile 5) is the group of the most (least) liquid stocks and size Quintile 1 (Quintile 5) is the group of stocks with the smallest (largest) market capitalization. Illiquidity quintiles are based on the yearly Amihud (2002) measure of illiquidity during the previous calendar year and size quintiles are constructed using the market capitalization of the previous month. Within a quintile, stocks are divided into deciles based on their idiosyncratic volatility. Then, the shares of the extreme deciles of the idiosyncratic volatility in a given month are computed as the ratio of value-weighted sum of the idiosyncratic volatility of the stocks in the decile to the value-weighted sum of stocks in the entire cross-section of the quintile. Daily returns of common stocks (share code in 10 and 11) are obtained from CRSP for the shares traded in NYSE, AMEX, and Nasdaq for the period 1963–2008. Stocks with less than \$2 at the end of the previous year or less than 100 trading days during the previous year are excluded.

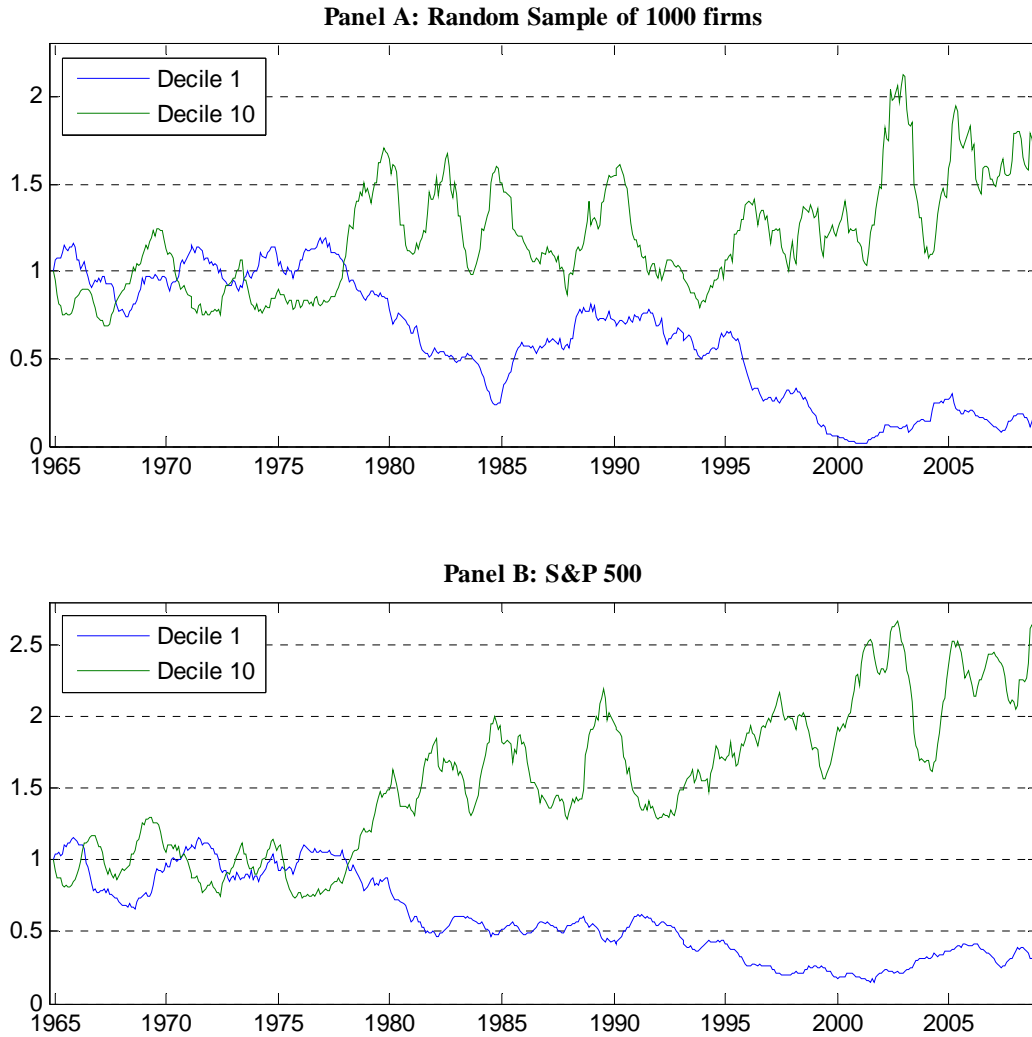


Figure A3. Time trends of the extreme deciles of idiosyncratic volatility in a sample of randomly selected firms and the S&P 500 index. Panel A plots the time trends of the shares of the 1st and the 10th deciles of the idiosyncratic volatility in the aggregate idiosyncratic volatility of the sample that consists of 1,000 firms randomly selected every month. Panel B plots the time trends in the sample that consists of firms in S&P 500 index. A 12-month backward moving average is used and each time series is normalized through dividing by its beginning-of-the-sample value. For each stock-month, daily returns are regressed on Fama-French three factors. Residuals from the regressions are squared and averaged over the month to obtain idiosyncratic volatility, following Ang, Hodrick, Xing, and Zhang (2006). The share of each decile in a given month is calculated as the ratio of the value-weighted sum of idiosyncratic volatility of the stocks in the decile to the value-weighted sum of stocks in the entire cross-section of the samples. The sample period is 1963–2008.

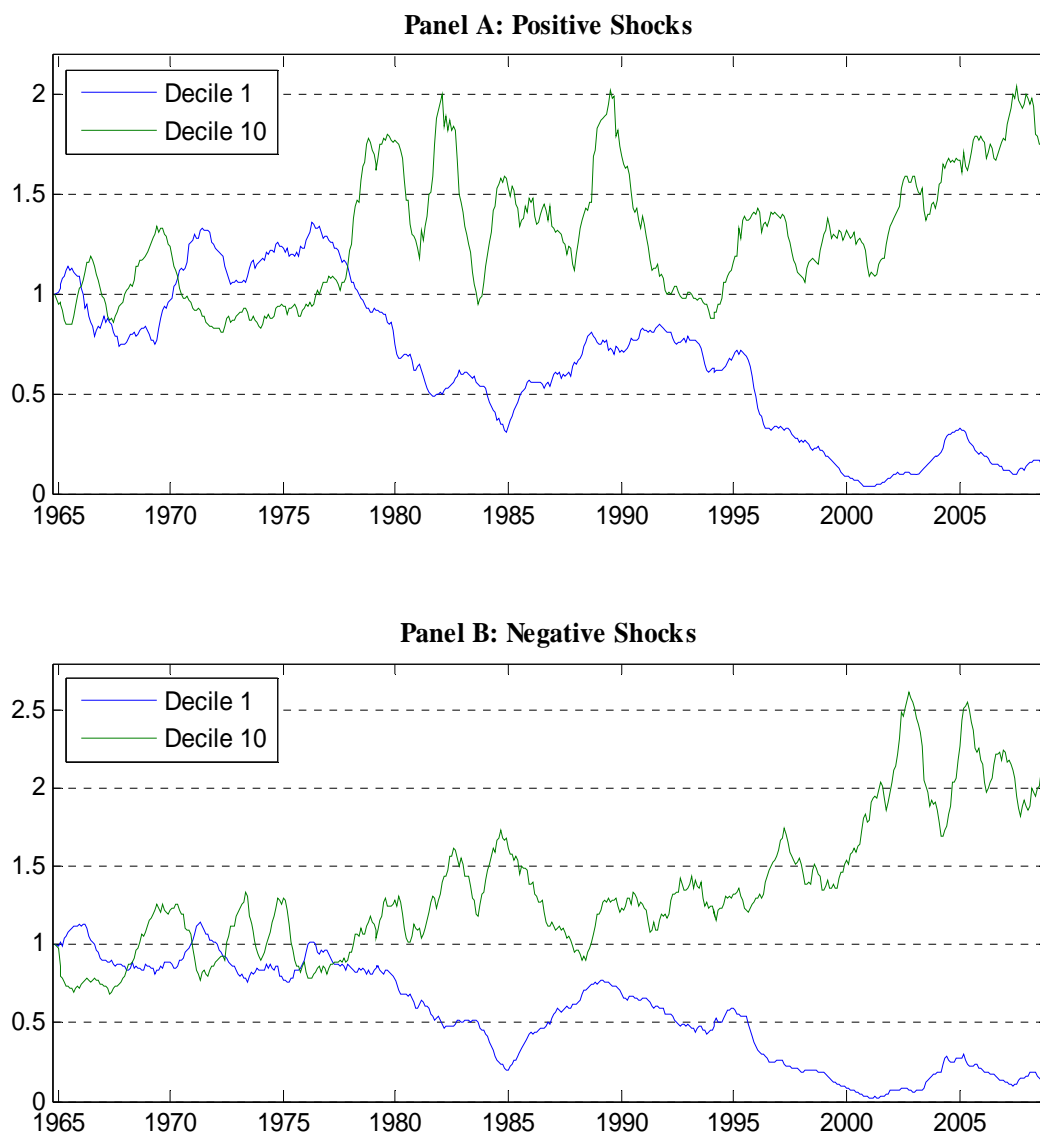


Figure A4. Time trends of the extreme deciles of positive and negative idiosyncratic shocks. The top (bottom) panel plots the time-series of the shares of the extreme deciles of positive (negative) idiosyncratic shocks in the aggregate positive (negative) shocks. A 12-month backward moving average is used and each time series is normalized through dividing by its beginning-of-the-sample value. For each stock-year, daily returns are regressed on the Fama-French three factors. Residuals from the regressions are divided into positive and negative groups. Within each group, residuals are squared and averaged over a month to estimate the positive (negative) idiosyncratic shocks for the month. Daily returns of common stocks (share code in 10 and 11) are obtained from CRSP for the shares traded in NYSE, AMEX, and Nasdaq for the period 1963–2008. Stocks with less than \$2 at the end of the previous year or less than 100 trading days during the previous year are excluded.

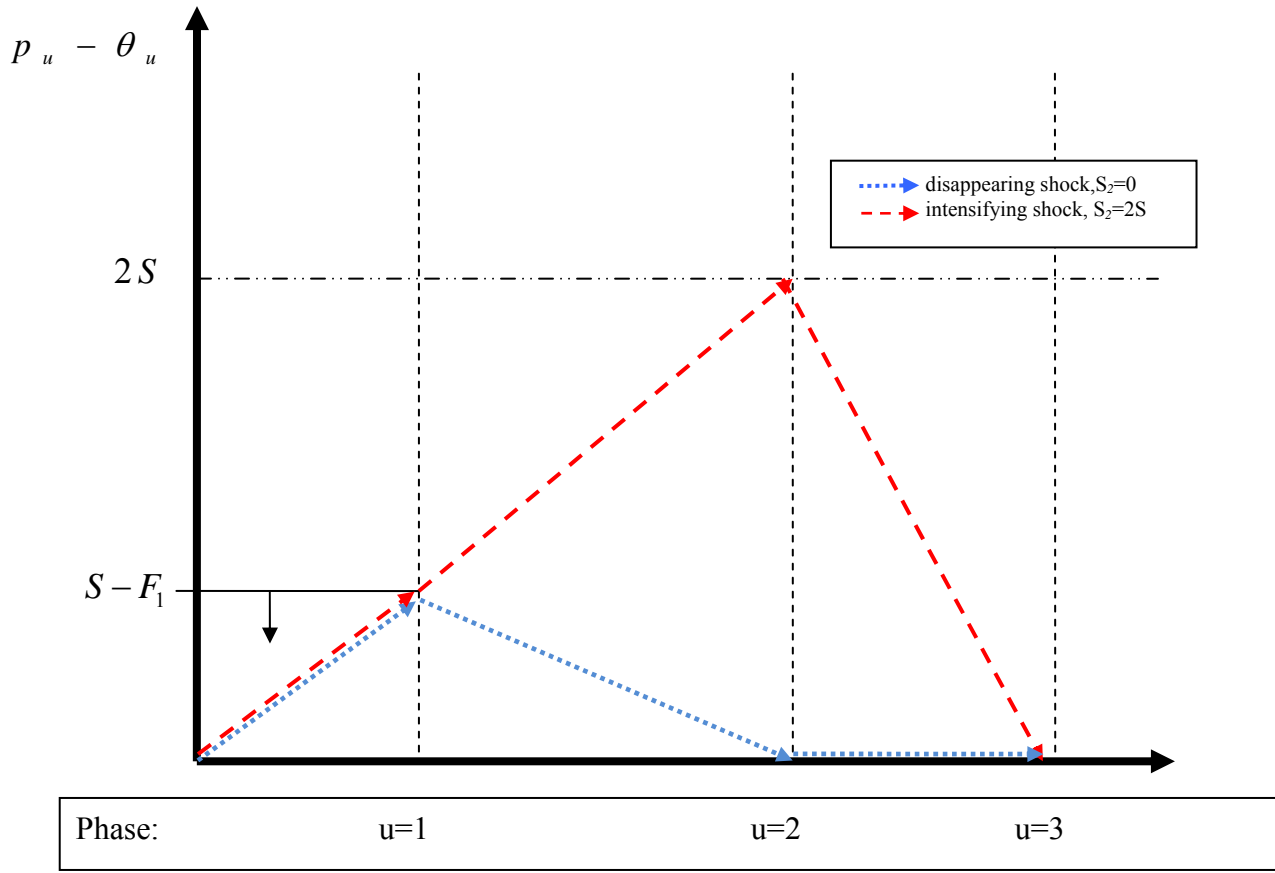


Figure A5. Dynamics of the idiosyncratic risk. The figure illustrates the evolution of idiosyncratic shock of a stock under various scenarios. F_1 is the initial capital of hedge-fund manager, and S is the cash-flow shock to the stock in Phase one. In Phase two, the shock either intensifies to $2S$ or disappears. Dotted arrows and dashed arrows represent the dynamics of idiosyncratic shock when the shock disappears by Phase two and when it intensifies, respectively. As initial capital, F_1 , increases, $S - F_1$ (the solid line) moves down decreasing bottom-quintile idiosyncratic return shocks and increasing top-quintile idiosyncratic return shocks.