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T. Bali • F. Weigert

centre for financial Research
cologne

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Turan G. Bali and Florian Weigert*

ABSTRACT

While it is established that idiosyncratic volatility has a negative impact on the cross-section of future stock returns, the relationship between idiosyncratic volatility and future hedge fund returns is largely unexplored. We document that hedge funds with high idiosyncratic volatility outperform and this pattern is explained by the positive return effect of idiosyncratic volatility in their equity portfolio holdings. Hedge funds select stocks wisely by picking high-volatility stocks when they are undervalued and shying away from high-volatility stocks when they are overvalued or display lottery-like payoffs. They also trade derivatives in a way to profit from the positive volatility effect.

Keywords: Hedge Funds, Idiosyncratic Volatility Puzzle, Equity Portfolio Holdings, Derivatives, Managerial Incentives, Investment Performance.

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* Turan G. Bali is Robert Parker Chair Profesor of Finance at Georgetown University, McDonough School of Business, 37th and O Streets, NW, Washington, DC 20057, USA. Email: turan.bali@georgetown.edu. Tel: +1-202-687-5388. Florian Weigert is Full Professor of Financial Risk Management at the University of Neuchâtel, Institute of Financial Analysis, Rue A.-L. Breguet 2, 2000 Neuchâtel, Switzerland. Email: florian.weigert@unine.ch. Tel: +41-32-718-1331. We thank Vikas Agarwal, George Aragon, Alexander Hillert, Alexander Kempf, Alexandra Niessen-Ruenzi, Stefan Ruenzi, Olaf Stotz, Günter Strobl, Melvyn Teo, Grigory Vilkov, Robert Whitelaw and seminar participants at the CFR Asset Management Colloquium 2019, Frankfurt School of Finance & Management, University of Cologne, University of Frankfurt, and University of Mannheim for their valuable comments. The research project was financially supported by grant IZSEZ0_189982 of the Swiss National Fund (SNF).

1. Introduction

Hedge funds have become one of the main players in the financial industry with more than three trillion assets under management as of the second quarter of 2020 (according to BarclayHedge). They are known to pursue flexible investment strategies involving leverage, derivative usage and short-selling, making it difficult for researchers to understand the common drivers of their return-generating process. Although various promising attempts have been proposed in the literature to identify the main risk factors and determinants of hedge funds' return series (starting with Fung and Hsieh (1997, 2001)), it is still a challenging task to adequately predict future hedge fund performance.[1] As a consequence, recent research has started to investigate to which degree an individual fund deviates from common risk factors (Titman and Tiu, 2011), competitors in the same strategy segment (Sun, Wang, and Zheng, 2012), and its disclosed long equity portfolio holdings (Agarwal, Ruenzi, and Weigert, 2020) with the common result that deviating funds tend to outperform.

Motivated by these empirical findings, this paper proposes a new determinant for the cross-section of average hedge fund returns: a fund's idiosyncratic volatility (*Fund Idio Vola)*. This measure is computed as the standard deviation of fund-specific returns (i.e., residual risk) to a nine-factor model (Fung and Hsieh, 2004, seven-factor model augmented by the Fama and French, 1993, HML book-to-market and the Carhart, 1997, UMD momentum factors) and captures the idiosyncratic component of a fund's return distribution not explained by common hedge fund risk factors.[2] Hence, funds with high *Fund Idio Vola* tend to deviate substantially from common factor models and show strongly idiosyncratic (fund-specific) patterns in their investment strategies. In this paper, we document that funds with high *Fund Idio Vola* outperform funds with low *Fund Idio Vola* and show that this is largely explained by the *positive* return effect of idiosyncratic volatility in the funds' disclosed equity portfolio holdings.

[1] A partial list of articles that study hedge fund risk factors include Agarwal and Naik (2004) for non-linear risk exposure, Aragon (2007), Sadka (2010), and Teo (2011) for liquidity risk, Agarwal, Arisoy, and Naik (2017) for volatility risk, Bali, Brown, and Caglayan (2011, 2012) for default and systematic risk, Buraschi, Kosowski, and Trojani (2014) for correlation risk, Bali, Brown, and Caglayan (2014) for macroeconomic risk, and Agarwal, Ruenzi, and Weigert (2017) for tail risk. Several papers also study fund characteristics that affect performance such as Agarwal, Daniel, and Naik (2009) and Lim, Sensoy, and Weisbach (2016) for incentives based on managers' contracts, Fung, Hsieh, Naik, and Ramadorai (20008) and Joenväärä, Kosowski, and Tolonen (2019) for fund size, Ramadorai (2013) for capacity constraints, Aggarwal and Jorion (2010) and Papageorgiou, Parwada, and Tan (2014) for manager experience, Li, Zhang, and Zhao (2011) for manager education, Teo (2009) for a fund's geographical location, and Patton, Ramadorai, and Streatfield (2015) for the reliability of voluntary return disclosure.

[2] We show in Section 4.3 that our results are robust when we compute *Fund Idio Vola* using other factor models of hedge funds.

In our empirical analysis we compute *Fund Idio Vola* based on a rolling estimation window of 36 months for 8,931 equity-oriented hedge funds in the Union Hedge Fund Database (which consists of four merged major databases; Eureka, Hedge Fund Research (HFR), Morningstar, and Lipper TASS) for the period from January 1997 to December 2017.[3] We find that average *Fund Idio Vola* is 2.72% across all funds and months in the sample with a median of 2.15% and a standard deviation of 1.97%. Among the different strategies, *Fund Idio Vola* is relatively low for Equity Market Neutral (1.87%) and Event Driven (1.97%), while it is relatively high for Emerging Markets (3.74%), Equity Long Only (3.09%), and Equity Long-Short (2.74%) funds. Moreover, we observe that *Fund Idio Vola* is a persistent attribute of a fund: Results from a 36-month-ahead transition matrix analysis indicate that funds sorted into the quintile portfolio with the highest (lowest) *Fund Idio Vola* in month t–36 remain in this top (bottom) quintile portfolio in month t with a likelihood of 67% (64%).

We show that *Fund Idio Vola* has significant predictive power for the cross-section of future hedge fund returns using univariate portfolio sorts. The return spread between the quintile portfolios of funds with the highest *Fund Idio Vola* and the lowest *Fund Idio Vola* amounts to 0.60% per month and is statistically significant at the 1% level with a Newey-West (1987) t-statistic of 2.72. When controlling for the widely used risk factors of the Fung and Hsieh (2004) nine-factor model, the risk-adjusted return spread only slightly reduces to 0.43% per month and remains statistically significant at the 5% level. This economically large premium remains strong when we apply other factor models for the risk adjustment.

The positive pricing effect of a fund's idiosyncratic volatility is confirmed in a multivariate framework. Results from Fama and MacBeth (1973) regressions of future fund returns and Fung and Hsieh (2004) nine-factor alphas in month $t+1$ on a fund's idiosyncratic volatility and additional fund characteristics in month t (such as a fund's monthly return, size, age, delta of the incentive fee contract, management and incentive fees, minimum investment amount, lockup and restriction period, and indicator variables that equal one if the fund is an offshore fund, employs leverage, has a high water mark and a hurdle rate, respectively, and zero otherwise) indicate that *Fund Idio Vola* is a positive determinant of future fund returns. Depending on the specification, it has a coefficient estimate between 0.078 and 0.104 and is statistically significant at the 5% level with a Newey-West t-statistic between 2.11 and 2.66.

[3] We could in principle extend our analysis to non-equity hedge funds, too. However, we retrict ourselves to equity-related funds to link a fund's idiosyncratic volatility to idiosyncratic volatility induced from its long equity portfolio positions in Section 5.

Our results from multivariate regressions and bivariate portfolios (double-sorts) also reveal that the impact of *Fund Idio Vola* is different from the impact of other activeness measures, such as the Titman and Tiu (2011)'s R2 measure (average correlation of –0.16 to *Fund Idio Vola*) and the Sun, Wang, and Zheng (2012)'s strategy distinctiveness index (SDI, avg. correlation of 0.08 to *Fund Idio Vola*). To determine the economic significance of the pricing effect, we consult both the results of multivariate regressions and the portfolio level analysis. The spread in average *Fund Idio Vola* between quintile 5 (high *Fund Idio Vola*) and quintile 1 (low *Fund Idio Vola*) is approximately 5.06% = (5.95% – 0.89%); multiplying this spread by the coefficient estimates between 0.078 and 0.104 in the multivariate regressions yields an estimated monthly premium between 39 and 53 basis points which translates into an annualized premium between 4.72% and 6.31%.

Which fund characteristics are associated with *Fund Idio Vola*? We observe several relationships that are consistent with the prior literature on activeness being a proxy for fund manager skill. High idiosyncratic volatility funds tend to be small which makes them more nimble and lets them face less capacity constraints compared to large funds (Aggarwal and Jorion, 2010). *Fund Idio Vola* is also significantly associated with a fund manager's incentive structure (proxied by the management fee, incentive fee, delta, and the hurdle rate; see Agarwal, Daniel, and Naik, 2009), discretion (proxied by the lock-up period of a fund), and fund distinctiveness (proxied by the R2 measure of Titman and Tiu (2011) and the SDI measure of Sun, Wang, and Zheng (2012)).

After examining different fund characteristics, we take a closer look at actual equity portfolio data of hedge funds and investigate whether idiosyncratic volatility of stocks is transmitted into idiosyncratic volatility of hedge funds. For this purpose, we merge the reported fund data from the Union Hedge Fund Database with the reported 13F long equity portfolio holdings of hedge fund firms. Our results indicate a strongly positive relationship between a fund firm's idiosyncratic volatility, *Fund Firm Idio Vola* (computed as the standard deviation of fund firm-specific returns to the Fung and Hsieh (2004) nine-factor model), and a fund firm's idiosyncratic volatility derived from its imputed long equity portfolio return, *Equity Idio Vola*. In a multivariate regression of *Fund Firm Idio Vola* on *Equity Idio Vola*, when controlling for other portfolio characteristics, the coefficient estimate on *Equity Idio Vola* is 0.345 and statistically significant at the 1% level with a *t*-statistic of 7.69. A standard deviation increase of *Equity Idio Vola* is associated with an increase of *Fund Firm Idio Vola* by 0.52 (i.e., an 0.4

standard deviation increase of *Fund Firm Idio Vola*). Hence, a substantial part of *Fund Firm Idio Vola* can be traced back to idiosyncratic volatility of a fund firm's disclosed long equity portfolio holdings.[4]

Based on this result, we aim to reconcile the *positive* effect of idiosyncratic volatility on future hedge fund returns with the seemingly contradicting pattern of a *negative* effect of idiosyncratic volatility on the cross-section of future stock returns, i.e., the so-called *idiosyncratic volatility puzzle* (e.g., Ang, Hodrick, Xing, and Zhang, 2006). We document that the link between idiosyncratic volatility and future returns strongly differs for stocks with high versus low hedge fund ownership. While the relationship between idiosyncratic volatility and future returns is significantly negative for stocks with low hedge fund ownership (spread of –1.55% per month with a *t*-statistic of –4.52), it is significantly positive for stocks with high hedge fund ownership (spread of 0.85% per month with a *t*-statistic of 3.06).

How can we rationalize these empirical findings? We show that hedge funds' stock picks are wise in the sense that their investments in high volatility stocks are not exposed to low future returns. Hedge funds, first, shy away from the subset of stocks with the unconditionally highest idiosyncratic volatility in the cross-section (which are the stocks that subsequently earn the lowest returns, see Ang, Hodrick, Xing, and Zhang, 2006). Second, hedge funds avoid investing in high idiosyncratic volatility stocks with strong lottery characteristics (approximated by a stock's past maximum daily return, *MAX*). Indeed, Bali, Cakici, and Whitelaw (2011) show that when controlling for a stock's *MAX*, the idiosyncratic volatility – future return relationship becomes positive. Third, hedge funds do not invest in high volatility stocks that are overvalued. Stambaugh, Yu, and Yuan (2015) find that the link between idiosyncratic volatility and future returns depends on the degree of mispricing of individual stocks to 11 stock market anomalies. Hence, by investing in high idiosyncratic volatility stocks in a prudent way, hedge funds profit from a *positive* idiosyncratic volatility – future return relationship at the individual stock level.

Finally, we show that hedge fund firms' investments into high idiosyncratic volatility are not limited to individual stocks, but they also actively seek exposure using derivative securities. To investigate this pattern, we merge our sample with fund firm's long positions in call and put options retrieved from the SEC's EDGAR (Electronic Data Gathering, Analysis,

[4] We confirm this result on a sample of 19 hedge fund firms that provide detailed portfolio transaction data for long and short positions to the Abel Noser Database. Hence, we are confident that neglecting idiosyncratic volatility from short positions in our main sample does not affect the positive relationship between *Fund Firm Idio Vola* and *Equity Idio Vola*.

and Retrieval) database. Consistent with their displayed behavior in picking stocks, hedge fund firms select derivative positions wisely in such a way that they shy away from call options on stocks with the unconditionally highest idiosyncratic volatility in the cross-section, stocks with strong lottery payoffs, and overvalued stocks. Instead, hedge fund ownership of call options is high for idiosyncratic volatility stocks that are undervalued. This prudent way of investing is not restricted to call options; we also observe that hedge fund firms buy put options written on high idiosyncratic volatility stocks that are overvalued and exhibit strong lottery-like payoffs.

This paper is structured as follows. Section 2 provides a brief literature review. Section 3 describes the data used in our empirical analysis. Section 4 introduces the idiosyncratic volatility measure and analyzes its relationship with future hedge fund performance and fund characteristics. Section 5 investigates the relationship between a hedge fund firm's idiosyncratic volatility based on reported returns and idiosyncratic volatility derived from actual equity portfolio positions. Section 6 disentangles the impact of idiosyncratic volatility on future returns for stocks with high and low hedge fund ownership. Section 7 examines the relationship between stocks' idiosyncratic volatility and hedge fund firms' investment behavior using derivative positions. Section 8 concludes the paper.

2. Literature Review

This paper makes several contributions to the literature. First, we add on identifying a relevant determinant of the cross-section of future hedge fund returns. Agarwal, Daniel, and Naik (2009) and Lim, Sensoy, and Weisbach (2016) show that incentives based on the managers' contracts matter for average hedge fund returns. Aragon (2007) finds that more illiquid funds earn higher future returns, while Joenväärä, Kosowski, and Tolonen (2019) document that larger funds tend to underperform. Aggarwal and Jorion (2010), Papageorgiou, Parwada, and Tan (2014), and Li, Zhang, and Zhao (2011) find that manager experience and education affect future returns. Teo (2009) shows that proximity to investments of hedge funds influences their future performance. In terms of hedge funds' risk characteristics, Bali, Gokcan, and Liang (2007) show that surviving funds with high Value-at-Risk outperform those with low Value-at-Risk and Agarwal, Ruenzi, Weigert (2017) find that a fund's tail risk predicts future returns. We contribute to this strand of literature by documenting that a fund's idiosyncratic volatility is a positive predictor for the cross-section of future hedge fund returns.

Second, we contribute by investigating the impact of hedge funds' trading channels on their risk and return characteristics using actual portfolio holdings. Agarwal, Ruenzi, and Weigert (2017) examine the relationship between a fund firm's return-based tail risk and the tail risk of the individual long equity positions of the funds that belong to the respective firm. Agarwal, Ruenzi, and Weigert (2020) compute a hedge fund firm's unobserved performance in computing the risk-adjusted return difference between a fund firm's reported return and the hypothetical portfolio return derived from its disclosed long equity holdings. In this paper, we show that a fund firm's idiosyncratic volatility is directly affected by the idiosyncratic volatility of actual equity portfolio holdings. Moreover, we document that fund firms actively seek exposure to idiosyncratic volatility of individual equities using call and put options.

Third, we extend the literature on the idiosyncratic volatility puzzle in the cross-section of individual stocks. The literature on this asset pricing anomaly starts with Ang, Hodrick, Xing, and Zhang (2006) who document that stocks with high idiosyncratic volatility deliver low future returns. Consequently, many papers have been written to explain the puzzle: Among others, potential explanations have been proposed based on liquidity (Bali and Cakici, 2008), expected idiosyncratic skewness (Boyer, Mitton, and Vorkink, 2010), lottery demand (Bali, Cakici, and Whitelaw, 2011), one-month return reversal (Fu, 2009), average variance beta (Chen and Petkova, 2012), and retail trading proportion (Han and Kumar, 2013).[5] Hou and Loh (2016) evaluate a large number of explanations for the idiosyncratic volatility puzzle and conclude that these account for 29% to 54% of the puzzle in individual stocks and 78% to 84% of the puzzle in idiosyncratic volatility-sorted portfolios. We contribute by documenting that the idiosyncratic volatility puzzle reverses for stocks with high hedge fund ownership since hedge funds pick stocks in a prudent manner.

3. Data

The data are obtained from a wide variety of sources. First, we use data from the *Union Hedge Fund Database*, which stores self-reported monthly returns and time series of assets under management values of hedge funds together with a comprehensive snapshot of different

[5] In addition, there are studies showing that the idiosyncratic volatility puzzle only holds (or is more pronounced) for a certain group of stocks, such as stocks with prices of at least five dollars (George and Hwang, 2011), stocks with low analyst coverage (Ang, Hodrick, Xing, and Zhang, 2009), and low credit ratings (Avramov, Chordia, Jostova, and Philipov, 2013). Bali and Cakici (2008) show that the magnitude and statistical significance of the idiosyncratic volatility effect for stocks strongly depends on the data frequency used to estimate idiosyncratic volatility and the weighting scheme applied in asset pricing tests. In particular, the idiosyncratic volatility effect is more pronounced in value-weighted portfolio sorts than in equal-weighted portfolio sorts.

fund characteristics. Second, we employ data from 13F equity portfolio disclosures from Thomson Reuters (formerly known as the CDA/Spectrum database). We complement the equity portfolio data by corresponding stock price and accounting information from CRSP Stocks and Compustat. Third, we also employ the Securities and Exchange Commission's (SEC's) EDGAR (Electronic Data Gathering, Analyis, and Retrival) database. It consists of extracted 13F filings data of a fund firm's long positions in call and put options. Finally, we retrieve data from Abel Noser, a proprietary broker that tracks actual trading transactions of institutional investors.

The Union Hedge Fund Database is constructed by merging four different major commercial databases; Eureka, Hedge Fund Research (HFR), Morningstar, and Lipper TASS. The merge of the different databases is important since 71% of the funds only report to one database (e.g., Lipper TASS has only 19% unique funds). We display the overlap between the four databases in Figure A.1 of the Appendix. The Union Hedge Fund Database includes data for a total of 39,938 funds from 1994 to 2017.

For our sample selection we apply multiple standard filters. To mitigate survivorship bias, we start our sample period in 1994, the year in which commercial hedge fund databases started to track defunct hedge funds. Furthermore, we require a fund to have at least 36 monthly return observations. We filter out all funds that are denominated in a currency other than US dollars and eliminate the first 12 months of a fund's return series to avoid the backfill bias. Since our analysis is to some extent related to the equity market (i.e., we relate idiosyncratic volatility of hedge funds to idiosyncratic volatility of stocks in Sections 5 and 6), we only include funds with an equity-oriented focus. We follow Agarwal and Naik (2004) and Agarwal, Ruenzi, and Weigert (2017) and classify funds with an investment strategy of 'Emerging Markets', 'Event Driven', 'Equity Long-Short', 'Equity Long Only', or 'Equity Market Neutral' as equity-oriented. Finally, our main variable of interest, *Fund Idio Vola* (see Section 4.1), is estimated based on a rolling window of 36 monthly return observations which uses the first three years of our sample. This filtering process leaves us with a final sample of 8,931 equity-oriented hedge funds for the period from January 1997 to December 2017. We report the summary statistics of funds' excess returns (i.e., returns in excess of the risk-free rate) and fund characteristics in Panel A of Table 1.

Summary statistics are calculated over all funds and months in our sample period and show that the average (median) excess return amounts to 0.59% (0.51%) per month. All fund characteristics are defined in Panel A of Table A.1 in the Appendix. More detailed descriptions of the 13F Thomson Reuters Ownership, the SEC EDGAR, and Abel Noser database are provided in Sections 5 and 7.

4. Idiosyncratic Volatility and Hedge Fund Returns

4.1. Defining Idiosyncratic Volatility

In this section, we define our main measure for the empirical analysis, a hedge fund's idiosyncratic volatility (*Fund Idio Vola)*, and investigate some of its properties. To compute this measure, we first regress the excess return of hedge fund *i* in month *t* on the risk factors of the Fung and Hsieh (2004) seven-factor model which is augmented by an equity book-to-market and a momentum factor using a rolling estimation window of 36 months:

$$r_{i,t} = \alpha_{i,t} + \beta_{1,i,t} S\&P_t + \beta_{2,i,t} SCMLC_t + \beta_{3,i,t} BD10RET + \beta_{4,i,t} BAAMTSY_t + \beta_{5,i,t} PTFSBD_t$$
$$+\beta_{6,i,t} PTFSFX_t + \beta_{7,i,t} PTFSCOM_t + \beta_{8,i,t} HML_t + \beta_{9,i,t} UMD_t + \varepsilon_{i,t}, \quad (1)$$

where $r_{i,t}$ denotes fund i's excess return in month *t*, $S\&P_t$, $SCMLC_t$, $BD10RET_t$, $BAAMTSY_t$, $PTFSBD_t$, $PTFSFX_t$, and $PTFSCOM_t$ denote the risk factors of the Fung and Hsieh (2004) seven-factor model, HML_t denotes the Fama and French (1993) book-to-market factor and UMD_t denotes the Carhart (1997) momentum factor. In the rest of the paper, we will refer to this model as the Fung and Hsieh nine-factor model. All risk factors are defined in Panel B of Table A.1 in the Appendix. Then, we compute fund *i*'s idiosyncratic volatility (*Fund Idio Vola*) in month *t* as the standard deviation of the 36 monthly residuals of the regression in eq. (1):

$$\text{Fund Idio Vola}_{i,t} = STDEV(\varepsilon_{i,t}). \quad (2)$$

Following this definition, *Fund Idio Vola* captures the idiosyncratic component of a fund's return distribution which is not explained by the risk factors of the Fung and Hsieh (2004) nine-factor model. Hence, hedge funds with high *Fund Idio Vola* conduct investment strategies that are not easily replicated by common asset pricing factors and show a fund-specific investment strategy.

We report summary statistics of *Fund Idio Vola* in Panel B of Table 1. Average *Fund Idio Vola* is 2.72% across all funds and months in the sample with a median of 2.15% and a standard deviation of 1.97%. Among the different strategies, *Fund Idio Vola* has the lowest values for Equity Market Neutral (1.87%) and Event Driven (1.97%), while it is highest for

Emerging Markets (3.74%), Equity Long Only (3.09%), and Equity Long-Short (2.74%) hedge funds. Correlations between *Fund Idio Vola* and contemporaneous returns and fund characteristics are reported in Panel C of Table 1. Our results indicate that *Fund Idio Vola* is positively correlated with a fund's management fee, a fund's offshore location, the delta of the fund manager's contract, and a fund return. It is negatively related to a fund's size, minimum investment, and age. Being a measure that describes a form of fund distinctiveness, we also observe correlations with Titman and Tiu (2011)'s R2 of –0.16 and Sun, Wang, and Zheng (2012)'s SDI of 0.08. All variables included in the correlation table are defined in Panel A of Table A.1 in the Appendix. We will discuss the relationships between *Fund Idio Vola* and fund characteristics more thorougly in a multivariate context in Section 4.4.

If idiosyncratic volatility is a characterizing attribute of a fund's investment strategy, it should show significant cross-sectional perseverance over time. Hence, we now turn to investigate the persistence of *Fund Idio Vola* at the individual fund level. Table 2 reports the results of a *Fund Idio Vola* transition matrix (à la, Bali, Cakici, and Whitelaw, 2011), i.e., the relative frequency by which a fund is sorted into *Fund Idio Vola* quintile portfolio i in month t given that it was in *Fund Idio Vola* quintile portfolio j in month t–36 during our sample period from January 1997 to December 2017.

If there were no persistence in *Fund Idio Vola*, all frequencies would be 20% because high (low) *Fund Idio Vola* in month t–36 should have no predictive ability about high (low) *Fund Idio Vola* in month t.[6] Instead we find evidence of substantial persistence in *Fund Idio Vola*: Funds which are sorted into portfolio 5 (1) in month t–36 show up again in portfolio 5 (1) with a likelihood of 67% (64%). As an additional test for long-term persistence of a fund's idiosyncratic volatility, we analyze the equal-weighted average *Fund Idio Vola* of funds over time. In a first step, funds are sorted into quintiles based on their *Fund Idio Vola* in month t. Then, the evolution of equal-weighted average of *Fund Idio Vola* of these portfolios are examined over the following $4 \times 36 = 144$ months. Figure 1 displays the results.

We observe that funds in quintile portfolio 5 (i.e., funds with high *Fund Idio Vola*) consistently show higher *Fund Idio Vola* in the following months than funds in quintile portfolio 1 (i.e., fund firms with low *Fund Idio Vola*). Hence, our results indicate that *Fund Idio Vola* is

[6] Since *Fund Idio Vola* is estimated using monthly returns over the past 36 months, we investigate the 36-month-ahead cross-sectional persistence of idiosyncratic volatility of hedge funds to avoid the issue of monthly overlapping observations that would induce artificial persistence.

indeed a long-term persistent attribute of hedge funds which is likely to have a significant impact on fund performance. We will investigate this hypothesis in the following section.

4.2. Idiosyncratic Volatility and Hedge Fund Performance

To assess the predictive power of differences in a fund's idiosyncratic volatility on the cross-section of future hedge fund returns, we first consider univariate portfolio sorts. For each month t from January 1997 to December 2017, we form quintile portfolios by sorting hedge funds based on their *Fund Idio Vola*, where quintile 1 contains funds with the lowest fund-specific idiosyncratic volatility and quintile 5 contains funds with the highest fund-specific idiosyncratic volatility. Panel A of Table 3 shows the average *Fund Idio Vola*, the next month average return in month t+1, and the Fung and Hsieh (2004) nine-factor alpha for each quintile. The last row in Panel A of Table 3 displays the average return and 9-factor alpha differences between quintiles 5 and 1 along with the Newey-West t-statistics in parentheses.

Moving from quintile 1 to quintile 5, we observe that average raw returns on the *Fund Idio Vola* portfolios increase monotonically from 0.29% to 0.89% per month. This indicates a monthly average raw return difference of 0.60% between quintiles 5 and 1 with a t-statistic of 2.72, showing that this positive return difference is economically and statistically significant at the 1% level. Hence, hedge funds in the highest *Fund Idio Vola* quintile generate about 7.20% higher annual returns compared to funds in the lowest *Fund Idio Vola* quintile. We also find that the nine-factor alpha difference between quintiles 5 and 1 is 0.43% with a t-statistic of 2.07, indicating that after controlling for the Fung and Hsieh (2004) model, the risk-adjusted return spread between high idiosyncratic volatility and low idiosyncratic volatility funds remains positive and significant.

Is the significant return difference due to outperformance by the high *Fund Idio Vola* funds, or underperformance by the low high *Fund Idio Vola* funds, or both? To answer this question, we compare the economic and statistical significance of the average returns and nine-factor alphas of quintile 1 vs. quintile 5. Panel A of Table 3 shows that the average return and the nine-factor alpha of quintile 1 are 0.29% and 0.18% per month with t-statistics of 1.13 and 1.23, respectively, indicating that the average raw and risk-adjusted returns of the low *Fund Idio Vola* funds are economically and statistically insignificant. On the other hand, the average return and the nine-factor alpha of quintile 5 are 0.89% and 0.61% per month with t-statistics of 4.76 and 2.84, respectively, implying economically large and statistically significant positive raw and risk-adjusted returns for the high *Fund Idio Vola* funds. These results provide evidence that the positive and significant return spread is due to outperformance by the high idiosyncratic volatility funds.

Can the return spread due to *Fund Idio Vola* be explained by other asset pricing models? To answer this question, we regress the 5 minus 1 *Fund Idio Vola* return spread on different risk factors and report the results in Panel B of Table 3. Our results reveal that the respective spread is positive and statistically significant when controlling for extended versions of the Fung and Hsieh (2004) model including the Fama and French (2015) profitability and investment factors, the Fung and Hsieh (2001) emerging markets equity factor, the Baker and Wurgler (2006) sentiment factor, the Pástor and Stambaugh (2003) traded liquidity factor, the Frazzini and Pedersen (2014) betting-against-beta factor, the Bali, Brown, and Caglayan (2014) macroeconomic uncertainty factor, the Buraschi, Kosowski, and Trojani (2014) correlation risk factor, the Gao, Gao, and Song (2018) RIX factor, and the Agarwal and Naik (2004) out-of-the money call and put option factors. All risk factors included in the time-series regressions are defined in Panel B of Table A.1 in the Appendix. Panel B of Table 3 shows that these additional asset pricing factors are not able to explain the positive relation between *Fund Idio Vola* and future returns of hedge funds.

In addition to univariate portfolio sorts, we run Fama and MacBeth (1973) regressions of future fund returns and alphas in month t+1 on fund idiosyncratic volatility and additional fund characteristics in month t:

$$r_{i,t+1} = \alpha + \beta_1 FIV_{i,t} + \beta_2 X_{i,t} + \varepsilon_{i,t+1}, \tag{3}$$

where $r_{i,t+1}$ denotes fund i's excess return (or alpha) in month $t+1$, $FIV_{i,t}$ denotes *Fund Idio Vola* of fund i in month t, and $X_{i,t}$ is a vector of fund characteristics, which includes a fund's monthly return, size, age, the delta of the fund manager's contract incentive, the management and incentive fees, minimum investment amount, the length of a fund's lockup and restriction period, indicator variables that equal one if the fund is an offshore fund, employs leverage, has a high water mark, has a hurdle rate, and zero otherwise, as well as a fund's R2 and SDI. All variables included in the regression analysis are defined in Panel A of Table A.1 in the Appendix. To adjust standard errors for potential serial correlation in monthly slope coefficients, we use the Newey and West (1987) adjustment with 36 lags.[7] Panel C of Table 3 presents the results.

In regression (1), we include *Fund Idio Vola* as the only explanatory variable. It has a coefficient estimate of 0.099 and is statistically significant at the 5% level with a *t*-statistic of 2.11. In regressions (2) and (3), we include the additional fund characteristics in our model. We confirm several results of the literature: a fund's past one-month return (Getmansky, Lo, and Makarov, 2004), constituents of the incentive fee contract (Agarwal, Daniel, and Naik, 2009), and fund illiquidity (Aragon, 2007) are positively related to future fund performance, while size (Agarwal, Daniel, and Naik, 2003, and Joenväärä, Kosowski, and Tolonen, 2019) has a negative impact. We also verify the results of Titman and Tiu (2011) and Sun, Wang, and Zheng (2012) of a negative (positive) impact of R2 (SDI) on future hedge fund performance. More importantly in our context, the results indicate that the inclusion of fund characteristics does not affect the positive and statistically significant return impact of *Fund Idio Vola*.

In regression (4), we repeat model set up (3) but use Fung and Hsieh (2004) nine-factor alphas instead of fund raw returns as the independent variable. We compute a fund's individual Fung and Hsieh (2004) nine-factor alpha at month $t+1$ as the difference between a fund's monthly return at month $t+1$ and the expected return at month $t+1$. The expected return at month $t+1$ is based on the sensitivites of a fund's return to the Fung and Hsieh (2004) risk factors estimated over the time period from month t–36 to t. Our results indicate that the impact of *Fund Idio Vola* on future alphas is only slightly reduced (in comparison to using returns as the dependent variable) and remains economically and statistically significant at the 5% level.

We compare the economic significance of the cross-sectional relation between *Fund Idio Vola* funds and future returns from fund-level Fama-MacBeth regressions and portfolio-level analysis. According to our portfolio sorts the spread in average *Fund Idio Vola* between quintiles 5 and 1 is 5.06% = (5.95% – 0.89%). Multiplying this spread by the average slope coefficients in the regressions between 0.078 and 0.104 in Panel A of Table 3 yields estimated

[7] Following Newey and West (1994), earlier studies set the number of lags to $4(T/100)^{\gamma}$, where T is the number of periods in the time-series, $\gamma = 2/9$ when using the Bartlett kernel, and $\gamma = 4/25$ when using the quadratic spectral kernel to calculate the autocorrelation and heteroscedasticity-adjusted standard errors of Newey and West (1987). Plugging in the value $T = 252$ for our sample period, January 1997 – December 2017, and taking γ to be either 2/9 or 4/25 results in a value close to five, whereas we use 36 lags to account for the number of overlapping monthly observations in the estimation of idiosyncratic volatility. The Newey-West *t*-statistics calculated with five lags turn out to be somewhat higher than those computed with 36 lags so that we report conservative results in the paper.

monthly premia ranging from 39 to 53 basis points. This translates into a range of annualized fund-specific volatility premia between 4.72% and 6.31%.

Although the multivariate regression results in models (3) and (4) of Panel C depict a significant impact, the return effect of *Fund Idio Vola* could be similar to that of other fund distinctiveness measures. To examine these patterns in a detailed way, we conduct dependent bivariate portfolio sorts based on R2 and *Fund Idio Vola* as well as SDI and *Fund Idio Vola*. First, we form quintile portfolios based on R2 (SDI). Then, within each R2 (SDI) quintile, we sort funds into five portfolios based on *Fund Idio Vola*. We report the equal-weighted average return and Fung and Hsieh (2004) nine-factor alphas at month $t+1$ of the 25 *Fund Idio Vola* × *R2* (*Fund Idio Vola* × *SDI*) in Panel D of Table 3. Our results reveal that funds with high *Fund Idio Vola* have higher returns and alphas than funds with low *Fund Idio Vola* in all R2 (SDI) quintiles. The average spread in return (alphas) between funds with high *Fund Idio Vola* and funds with low *Fund Idio Vola* controlling for R2 is 0.52% (0.41%) per month and statistically significant at the 5% level; the return (alpha) spread between funds with high *Fund Idio Vola* and funds with low *Fund Idio Vola* controlling for SDI is 0.50% (0.42%) per month and statistically significant at the 5% level.

In summary, we find that *Fund Idio Vola* has strong predictive power to forecast the cross-sectional variation in future hedge fund returns. It is a statistically and economically significant determinant even when we control for a large number of fund characteristics and the standard set of hedge fund risk factors.

4.3. Idiosyncratic Volatility and Hedge Fund Returns: Robustness Checks

To confirm the results concerning a fund's idiosyncratic volatility and future fund returns, a battery of stability checks are conducted. We investigate the robustness of our results by (i) estimating *Fund Idio Vola* using a rolling estimation window of 24 months instead of 36 months, (ii) estimating *Fund Idio Vola* using the Fama-French-Carhart four-factor model, the Fung and Hsieh (2004) seven-factor model, and the Fung and Hsieh (2004) model augmented with the Agarwal and Naik (2004) OTM call and put option factors, (iii) applying the Goetzmann, Ingersoll, Spiegel, and Welch (2007) manipulation-proof performance measure with a risk aversion parameter of two as the dependent variable, (iv) restricting our sample to hedge funds with an equity long-short strategy and to hedge funds that use /do not use leverage in their investment strategies, (v) assigning a delisting return of −1.61% as in Hodder, Jackwerth, and Kolokolova (2014) to those hedge funds that leave the database, (vi) applying the correction method of Getmansky, Lo, and Makarov (2004) to unsmooth hedge fund returns, (vii) controlling for backfill bias as in Jorion and Schwarz (2019), and (viii) using two-month- and three-month-ahead returns as the dependent variable.

Table 4 reports the results from Fama and MacBeth (1973) regressions (as in model (4) of Panel C in Table 3) of future Fung and Hsieh (2004) nine-factor alphas on *Fund Idio Vola* and the large number of fund characteristics measured in month *t*.

We only report the average slope coefficient estimates for *Fund Idio Vola*. The large set of control variables is included in the regressions, but we suppress them in the table. For ease of comparison, we report in the first column of Table 4 the baseline results from model (4) of Panel C in Table 3. Across all robustness checks, we continue to find a positive and statistically significant effect of *Fund Idio Vola* on future fund alphas.

4.4. Idiosyncratic Volatility and Fund Characteristics

Sections 4.2 and 4.3 document that *Fund Idio Vola* is a robust variable that predicts the cross-sectional dispersion in future hedge fund returns. We now examine which fund characteristics are associated with *Fund Idio Vola*. To do so, we estimate regressions of *Fund Idio Vola* of hedge fund *i* in month t+1 on fund characteristics measured in month *t* using the Fama and MacBeth (1973) methodology:

$$FIV_{i,t+1} = \alpha + \beta X_{i,t} + \varepsilon_{i,t+1}, \tag{4}$$

where $FIV_{i,t+1}$ denotes a fund's idiosyncratic volatility in month t+1, and $X_{i,t}$ is a vector of fund characteristics that are described in Panel A of Table A.1 in the Appendix. Table 5 reports the results.

In model (1), we include time-varying fund characteristics, such as a fund's monthly return, size, age, and manager's delta as the independent variables. We find a significantly positive link between *Fund Idio Vola* and fund returns, whereas a negative relation between *Fund Idio Vola* and size is observed. The latter relationship indicates that smaller funds engage in more idiosyncratic investment strategies and is consistent with Aggarwal and Jorion (2010) who find that these funds are more nimble and less affected by capacity constraints. *Fund Idio Vola* is also positively related to delta (Agarwal, Daniel, and Naik, 2009) which suggests that better incentivized managers tend to employ more distinctive trading strategies.

Model (2) includes time-invariant fund characteristics such as a fund's management and incentive fees, minimum investment, lockup and restriction periods, as well as indicator variables for a fund's offshore domicile, leverage, high watermark, and hurdle rate. In line with the idea that managers of funds with a longer lockup period have greater discretion in managing their portfolios, we find a positive relation between *Fund Idio Vola* and a fund's lockup period. Consistent with our results in model (1) we again reveal that better incentivized managers (approximated by higher management fees and the existence of a hurdle rate) show higher *Fund Idio Vola*. In model (3), we include the time-varying and time-invariant fund characteristics together. We continue to observe that *Fund Idio Vola* exhibits a significant positive assocation with a fund's monthly return, delta, management fee, lockup period, offshore domicile, and hurdle rate, as well as negative relationships with fund size and minimum investment. Finally, model (4) is augmented by a fund's R2 and SDI: As expected, we find that funds with low R2 (high SDI) also display high *Fund Idio Vola*.

To summarize, we provide evidence that a fund's idiosyncratic volatility is significantly related to certain fund characteristics. Most prominently, we find that smaller funds, funds with higher discretion, funds with higher incentive structures, and funds with higher distinction in their trading strategies show higher *Fund Idio Vola*.

5. Determinants of Idiosyncratic Volatility: Evidence from Actual Portfolio Holdings

The previous section examined which fund characteristics are associated with a fund's idiosyncratic volatility. We now delve into *actual trading channels* of hedge funds that transmit idiosyncratic volatility in reported returns. Specifically, we examine whether we can find direct evidence of the sources of *Fund Idio Vola* using their disclosed 13F portfolio holdings consisting of long positions in equities.

To establish a direct link between idiosyncratic volatility of reported fund returns and idiosyncratic volatility induced from equity holdings, we use institutional investor data from the Thomson Reuters 13F database. The 13F Thomson Reuters Ownership database consists of quarterly equity holdings of 8,705 institutional investors during the period from 1980 (when Thomson Reuters data start) to 2017. Unfortunately, hedge fund firms are not separately identified in the database. Hence, we follow Agarwal, Fos, and Jiang (2013) and Agarwal, Ruenzi, and Weigert (2017) and classify hedge fund firms among the 13F filing institution manually.[8] We end up with a sample of 2,512 unique hedge fund firms among the 13F filing institutions holding a total value of \$3.25 trillion of long equity positions in 2017. This amount is almost equivalent to the size of the hedge fund industry in the year 2017 (which is, according to HFR, estimated to be \$3.21 trillion).

Next, we merge the hedge fund firms in the 13F Thomson Reuters Ownership database with the hedge fund firms listed in the Union Hedge Fund Database. We match institutions by name allowing for minor variations. In addition, we compute the correlation between returns imputed from the 13F quarterly holdings and returns reported in the Union Database and eliminate all pairs in which the correlation is neither negative nor defined due to lack of overlapping periods of data from both data sources. We also eliminate all pairs in which there are fewer than 36 overlapping periods of data from both data sources. We end up with 679 hedge fund firms managing 2,628 distinct funds during the period from 1997 to 2017.

Since 13F portfolio holdings are reported only at the firm level, our investigation shifts to the hedge fund firm level and we need to compute a fund firm's idiosyncratic volatility. For this purpose, we first compute a fund firm's return as the value-weighted average of its individual fund returns. Second, in the same way as for individual hedge funds, we regress the return of hedge fund firm *i* in month *t* on the risk factors of the Fung and Hsieh (2004) nine-factor model using a rolling estimation window of 36 months. Finally, we compute fund firm *i*'s idiosyncratic volatility (*Fund Firm Idio Vola*) in month *t* as the standard deviation of the 36 monthly residuals originated from the rolling estimation.

To detect direct evidence of a relationship between *Fund Firm Idio Vola* and fund firms' actual trading channels, we use portfolio information of their long 13F equity holdings to compute a fund firm's equity portfolio volatility, *Equity Idio Vola*. We proceed as follows: Our premise is that a fund firm retains the portfolio positions over the months t+1 to t+3 which are disclosed at the end of month *t*.[9] For each fund firm *i* in month *t*, we then compute a monthly hypothetical portfolio return as the value-weighted average of its individual long equity returns. Afterwards, we compute *Equity Idio Vola* as the idiosyncratic volatility based on a regression

[8] A 13F filing institution is classified as a hedge fund firm if it satisfies at least one of the following criteria: (i) it matches the name of one or multiple funds from the Union Hedge Fund Database, (ii) it is listed by industry publications (e.g., Hedge Fund Group, Barron's, Alpha Magazine) as one of the top hedge funds, (iii) on the firm's website, hedge fund management is identified as a major line of business, (iv) Factiva lists the firm as a hedge fund firm, and (v) if the 13F filer name is one of an individual, we classify this case as a hedge fund firm if the person is the founder, partner, chairman, or other leading personnel of a hedge fund firm.
[9] As an example, we use the disclosed portfolio positions of firm *i* at the end of December 2011 to obtain monthly return series for the months from January 2012 to March 2012.

of the hypothetical portfolio return on the risk factors of the Fung and Hsieh (2004) nine-factor model using a rolling estimation window of 36 months.

To examine the relation between the two measures, we regress *Fund Firm Idio Vola* of hedge fund firm *i* in month t+1 on its *Equity Idio Vola* in month *t* controlling for different equity portfolio risk characteristics:

$$FFIV_{i,t+1} = \alpha + \beta_1 EIV_{i,t} + \beta_2 Y_{i,t} + \varepsilon_{i,t+1}, \tag{5}$$

where $FFIV_{i,t+1}$ denotes a fund firm's idiosyncratic volatility in month t+1, $EIV_{i,t}$ denotes equity portfolio idiosyncratic volatility in month *t*, and $Y_{i,t}$ is a vector of equity portfolio characteristics. As equity portfolio characteristics, we include the number of assets in the portfolio, the Herfindahl index based on different portfolio positions, the Herfindahl index based on different industries in a portfolio, portfolio turnover, portfolio beta, the one-month portfolio return, the twelve-month portfolio return, portfolio skewness, portfolio kurtosis, average portfolio stock size, average portfolio book-to-market value, average portfolio illiquidity, average portfolio investment, average portfolio profitability, and average portfolio leverage. All variables are defined in Panel C of Table A.1 in the Appendix. Table 6 presents the results.

In model (1), we use *Equity Idio Vola* as the only explanatory variable. It shows a positive impact (coefficient of 0.262) and is statistically significant at the 1% level with a Newey-West *t*-statistic of 14.49. This result provides direct evidence of a strong positive relationship between a fund firm's idiosyncratic volatility and its equity portfolio idiosyncratic volatility.

Model (2) expands our specification by controlling for the equity portfolio characteristics mentioned above. As expected, we find that *Fund Firm Idio Vola* is positively related to the Herfindahl index of the equity portfolio (i.e., the more concentrated a fund's equity positions, the higher a fund's idiosyncratic volatility), as well as negatively related to the number of assets and portfolio size. We also find significant associations between *Fund Firm Idio Vola* and portfolio beta, average portfolio book-to-market value, and average portfolio illiquidity. Importantly, our results indicate that the inclusion of the control variables does not affect the significant assocation between *Fund Firm Idio Vola* and *Equity Idio Vola*. In contrast, we find that the coefficient estimate increases to 0.345 and remains statistically significant at the 1% level. To assess the economic significance, we calculate a positive one standard deviation change in *Equity Idio Vola* that leads to a rise in *Fund Firm Idio Vola* of 0.345 × 1.51 = 0.520.

This is almost 40% of the standard deviation of *Fund Firm Idio Vola* in the merged sample. Hence, a fund firm's idiosyncratic volatility is strongly positively related to its equity portfolio idiosyncratic volatility.

A potential concern is that our examination of hedge fund firms' equity is restricted to 13F long positions that are quarterly disclosed to the SEC. Consequently, we cannot account for portfolio changes that take place on a more frequent basis (than quarterly) and are not aware of the fund firms' short positions. To mitigate this concern, we repeat our analysis for hedge fund firms in our sample that provide transaction data of all trades to the brokerage firm Abel Noser in the time period from January 1999 to September 2011.[10] As in Jame (2018), we manually merge this data with the Union Hedge Fund Database and Thomson 13F based on fund firm names: Successful merges on 19 fund firms are obtained through this process.

We follow the procedure of Choi, Park, Pearson, and Sandy (2020) to compute short sales of fund firms and construct a monthly value-weighted hypothetical portfolio return for each fund firm which accounts for daily transactions and short positions. As above, *Equity Idio Vola* is then computed as the idiosyncratic volatility based on a regression of this hypothetical portfolio return on the risk factors of the Fung and Hsieh (2004) nine-factor model using a rolling estimation window of 36 months.

In model (3) of Table 6, we regress *Fund Firm Idio Vola* on *Equity Idio Vola* for fund firms in the Abel Noser subsample. Although the sample size is considerably reduced, we still find a positive relationship which is statistically significant at the 1% level. This positive and statistically significant result also remains robust when controlling for additional equity portfolio characteristics in model (4).

To summarize, this section provides direct evidence of a strong positive relationship between idiosyncratic volatility of a hedge fund firm's reported returns and idiosyncratic volatility of its long equity holdings. This is surprising in the sense that (as reported in Section 4) idiosyncratic volatility of hedge funds *positively* predicts future hedge fund returns, while there is a well-established literature (starting with Ang, Hodrick, Xing, and Zhang, 2006) which documents that idiosyncratic volatility *negatively* predicts future stock returns (also termed as the *idiosyncratic volatility puzzle*).

[10] The analysis is restricted to the time period from January 1999 to September 2011 due to the unavailability of identifying information of institutional investors provided by Abel Noser before 1999 and after September 2011.

6. Idiosyncratic Volatility: Impact on Hedge Fund vs. Stock Returns

In this section we reconcile the finding that idiosyncratic volatility positively predicts future hedge fund returns with the established empirical pattern that idiosyncratic volatility negatively predicts future returns in the cross-section of individual stocks. Section 6.1 investigates the cross-section of future returns for stocks with high versus low hedge fund ownership. In Section 6.2, we focus on the magnitude of idiosyncratic volatility of individual stocks in volatility-sorted portfolios with high and low hedge fund ownership. In Section 6.3, we examine the relationship between hedge fund ownership, idiosyncratic volatility, and future returns when we condition on the lotteriness of a stock (proxied by its maximum daily return in a month, MAX, as in Bali, Cakici, and Whitelaw, 2011). Finally, Section 6.4 analyzes the association between hedge fund ownership, idiosyncratic volatility, and future returns conditional on the degree of a stock's mispricing (as in Stambaugh, Yu, and Yuan, 2015).

6.1. Idiosyncratic Volatility and the Cross-Section of Future Stock Returns

The literature on the idiosyncratic volatility puzzle is extensive and begins with Ang, Hodrick, Xing, and Zhang (2006) that identify a negative link between a stock's idiosyncratic volatility and its future return. Different explanations for this surprising finding are provided by a stock's liquidity (Bali and Cakici, 2008), expected idiosyncratic skewness (Boyer, Mitton, and Vorkink, 2010), maximum daily return (Bali, Cakici, and Whitelaw, 2011), one-month return reversal (Fu, 2009), average variance beta (Chen and Petkova, 2012), and retail trading proportion (Han and Kumar, 2013). Other papers contribute by documenting that the idiosyncratic volatility puzzle is more pronounced for stocks with prices of at least five dollars (George and Hwang, 2011), stocks with low analyst coverage and low credit ratings (Avramov, Chordia, Jostova, and Philipov, 2013). Moreover, Stambaugh, Yu, and Yuan (2015) show that the negative relationship between idiosyncratic volatility and future returns is only visible for stocks that are overvalued according to 11 different equity market anomalies. In this section, we contribute to the existing literature that the relationship between idiosyncratic volatility and future stock returns is negative (positive) for stocks with low (high) hedge fund coverage.

We start our analysis by examining the impact of idiosyncratic volatility on the cross-section of future stock returns using univariate portfolio sorts. Our stock sample is obtained from CRSP and covers all U.S. common stocks traded on the NYSE/AMEX/NASDAQ in our main sample period from January 1997 to December 2017. So that our results are not driven by very small stocks, we exclude return data from firms that are in the bottom 1% of market capitalization of all stocks in the previous year. Furthermore, we require at least 100 valid daily return observations per stock and year. We merge our sample with Compustat, which is used to obtain accounting-related measures (such as book-to-market, investment, profitability, and leverage) for each stock. For each month *t*, we sort all stocks into quintile portfolios based on their idiosyncratic volatility, *Idio Vola,* again computed using the factors of the Fung and Hsieh (2004) nine-factor model with a rolling horizon of 36 months, in increasing order. We then compute the value-weighted monthly returns and Fung and Hsieh (2004) nine-factor alphas of these portfolios in month *t*+1. Panel A of Table 7 reports the results.

Specification (1) confirms the results of Ang, Hodrick, Xing, and Zhang (2006) that stocks with high idiosyncratic volatility significantly underperform stocks with low idiosyncratic volatility. The average return (alpha) difference amounts to –0.92% (–0.78%) per month and is statistically different from zero at the 10% (5%) significance level with a *t*-statistic of –1.92 (–2.01). Specifications (2) and (3) investigate the effect of idiosyncratic volatility for stocks with high and low hedge fund ownership, respectively. To define the degree of hedge fund ownership for an individual stock, we first compute the number of appearances of the stocks in all fund firm portfolios and months. We classify hedge fund ownership of a stock *j* in month *t* as high, when hedge fund ownership of the stock is in the top half (in terms of the number of hedge fund firms holding the stock in their long equity portfolio), conditional that there is at least one hedge fund firm holding the stock. We classify hedge fund ownership of a stock *j* in month *t* as low, when hedge fund ownership is in the bottom half (in terms of the number of hedge funds holding the stock in their long equity portfolio), conditional that there is at least one hedge fund firm holding the stock. We also classify hedge fund ownership of a stock *j* in month *t* as low if no hedge fund firm is holding the stock at all.[11] The results are remarkable: While we continue to find a (more pronounced) significantly negative relationship between *Idio Vola* and future returns (alphas) with low hedge fund ownership, the relationship reverses for stocks with high hedge fund ownership. Specifically, the monthly average return (alpha) spread is –1.53% (–1.10%) per month for stocks with low hedge fund ownership,

[11] Since there are stocks that are not held by any hedge fund firm in each month, the number of low hedge fund ownership stocks exceeds the number of high hedge fund ownership stocks. Our results are robust to other definitions of hedge fund ownership. We obtain similar results when we classifiy hedge fund ownership of a stock *j* in month *t* as high (low), when hedge fund ownership of the stock is in the top (bottom) tercile or quartile. Empirical results of this alternative sample split are available upon request.

whereas it is +0.70% (+0.68%) per month for stocks with high hedge fund ownership. Hence, the difference in the idiosyncratic volatility return (alpha) spread between stocks with high and low hedge fund ownership amounts to 2.23% (1.78%) per month and highly statistically significant.

Panel B of Table 7 repeats the portfolio sorts for a longer sample period from January 1980 to December 2017.[12] We find similar results as in Panel A, but the magnitudes of the return (alpha) spreads for stocks with high and low hedge fund ownership widen. We document a monthly average return (alpha) spread of –1.81% (–1.55%) with a *t*-statistic of –5.49 (–4.52) for stocks with low hedge fund ownership, whereas the monthly average return (alpha) spread amounts to 0.99% (0.85%) with a *t*-statistic of 3.34 (3.06) for stocks with high hedge fund ownership. Hence, differences in the relationship between idiosyncratic volatility and future returns become even larger when extending the sample period to January 1980.

Panel C of Table 7 reports the results in a multivariate context using Fama and MacBeth (1973) regressions controlling for a number of stock characteristics. We regress a stock's return in month t+1 on *Idio Vola* controlling for the stock-level characteristics and risk measures, including the market beta, the one-month stock return, the twelve-month stock return, skewness, kurtosis, size, book-to-market ratio, illiquidity, investment, profitability, and leverage, all measured in month *t*. All variables are defined in Panel D of Table A.1 in the Appendix. We obtain similar results as in the case of the univariate portfolio sorts: The impact of *Idio Vola* on future returns is significantly negative for stocks with low hedge fund coverage (coefficient estimate of –0.0320 with a *t*-statistic of –3.01), while it is significantly positive for stocks with high hedge fund coverage (coefficient estimate of 0.0408 with a *t*-statistic of 4.44).

It is important to note that, among institutional investors, the relationship between idiosyncratic volatility and future returns is significantly positive only among stocks with high *hedge fund* ownership. We do not find a significantly positive relationship among stocks with high *bank* ownership (Thomson Reuters Type Code 1), high *insurance company* ownership (Thomson Reuters Type Code 2), high *investment company* ownership (Thomson Reuters Type Code 3), and high *independent investment advisor* ownership (Thomson Reuters Type Code 4). Hence, we believe that hedge funds are able to pick stocks wisely in the sense that their

[12] We are able to expand the sample period since Thomson Reuters 13F equity portfolio holdings data go back to 1980 and we do not require variables from the Union Hedge Fund Database in this analysis. When computing the portfolio alphas, we do not account for the Fung and Hsieh (2004) trend-following factors as they are not available in the period from January 1980 to December 1993.

investments in high volatility stocks are not affected by low future returns. In the following sections, we show that hedge funds do not invest in stocks with the unconditionally highest idiosyncratic volatility in the cross-section (Section 6.2), do not invest in high volatility stocks with strong lottery payoffs (Section 6.3), and do not invest in high volatility stocks that are overvalued (Section 6.4).

6.2. Rationalizing the Positive Idiosyncratic Volatility Effect for Stocks with High Hedge Fund Ownership: Level of Idiosyncratic Volatility

Specification (1) in Panel B of Table 7 documents that stocks' future returns and alphas monotonically decrease in the level of idiosyncratic volatility, i.e., stocks in the highest idiosyncratic volatility quintile underperform the most with an average return (alpha) of –0.17% (–0.52%). Hence, a part of the explanation of the positive (negative) relation between idiosyncratic volatility and future returns for stocks with high (low) hedge fund ownership could be determined by the behavior of hedge funds to shy away from stocks with the highest *Idio Vola* in the cross-section. We investigate this hypothesis in Table 8.

Panel A of Table 8 reports the frequencies of stocks that are classified as stocks with high and low hedge fund ownership in portfolio sorts based on idiosyncratic volatility. Due to our definition of hedge fund ownership (see Section 6.1), the unconditional frequency of stocks with high (low) hedge fund ownership in the sample is 36.83% (63.17%). When examining each of the five idiosyncratic volatility sorted portfolios individually in columns (1) and (2), we observe that this frequency is not stable: While the frequency of stocks with high (low) hedge fund ownership in *Idio Vola* portfolio 1 (Q1) is 47.71% (52.29%), it is only 15.41% (84.59%) in the portfolio with the highest *Idio Vola* (Q5). Column (3) reports the difference in frequencies between stocks with high and low hedge fund ownership for each *Idio Vola* portfolio. Finally, in column (4), we also account for the difference in unconditional hedge fund ownership, i.e., we add 63.17% – 36.83% = 26.34% to the value of column (3). We refer to this value as the *adjusted frequency difference of hedge fund ownership*. We observe that the adjusted frequency difference of hedge fund ownership is monotonically declining from idiosyncratic volatility portfolio 1 (+21.77%) to idiosyncratic volatility portfolio 5 (–43.83%). Hence, Panel A of Table 8 provides the first evidence that hedge funds shy away from very high idiosyncratic volatility stocks.

Institutional investors are shown to prefer certain stock characteristics for their investment strategies (see, e.g., Gompers and Metrick (2001) for a stock's size and Edelen, Ince, and Kadlec (2006) for a stock's book-to-market value). Hence, it is likely that hedge funds are also inclined to invest in certain stock characteristics that are, at the same time, correlated with idiosyncratic volatility. To control for these effects, we run multivariate Fama and MacBeth regressions of stock *j*'s hedge fund ownership on *Idio Vola* and other stock characteristics in month *t*. Results are displayed in Panel B. We use the identical stock characteristics as control variables used in Panel C of Table 7.

Specification (1) implements a stock's idiosyncratic volatility as a linear and quadratic regressor. Consistent with our idea that hedge funds like to invest in idiosyncratic volatility driven strategies, but shy away from the highest *Idio Vola* stocks in the cross-section, we find that the coefficient estimate of linear (quadratic) idiosyncratic volatility is significantly positive (negative). To examine this non-linear interaction between hedge fund ownership and idiosyncratic volatility in a more detailed way, in specification (2), we construct a series of dummy variables that take the value of one if a certain stock is included in *Idio Vola* portfolio k ($k=2,3,4,5$) and zero otherwise. Our results reveal that the relationship between *Idio Vola* and hedge fund ownership is positive for the *Idio Vola* portfolio dummies 2, 3, and 4. However, the coefficient estimate for the impact of *Idio Vola* portfolio dummy 5 is significantly negative, suggesting that the non-linear effect is due to the stocks with the highest idiosyncratic volatility.

To summarize, Section 6.2 provides empirical evidence that hedge funds like to invest in portfolios with varying degrees of idiosyncratic volatility of individual stocks. However, this relationship is not linear; hedge funds shy away from the quintile of stocks with the highest *Idio Vola* which are subsequently displaying the strongest future return discount.

6.3. Rationalizing the Positive Idiosyncratic Volatility Effect for Stocks with High Hedge Fund Ownership: Idiosyncratic Volatility vs. MAX

Bali, Cakici, and Whitelaw (2011) find that stocks with lottery-like payoffs, proxied by their maximum daily return in a month (*MAX*), earn low returns in the future. Interestingly, they also show that including *MAX* in a multivariate regression of future returns on stock characteristics reverses the puzzling negative relationship between idiosyncratic volatility and future returns and hence solves the idiosyncratic volatility puzzle. We investigate how *MAX* is related to the relationship between idiosyncratic volatility and future returns for stocks with high and low hedge fund coverage in Table 9. In line with Bali, Cakici, and Whitelaw (2011), we define *MAX* as the stock's maximum daily return over the past one month.

Panel A of Table 9 reports the average *MAX* values for the idiosyncratic volatility sorted portfolios of stocks with high and low hedge fund coverage. As in the case for idiosyncratic volatility, we find that the average *MAX* is positively increasing in the portfolios and is higher for stocks with low hedge fund ownership.[13] More importantly, we find that the average spread in *MAX* between stocks with high and low hedge fund ownership becomes disproportionately larger in the portfolios' level of idiosyncratic volatility. While the difference in idiosyncratic volatility between stocks with high and low hedge fund ownership has increased by 10.9 ($=\frac{7.14\%-0.60\%}{0.60\%}$), the corresponding relative change in *MAX* is much larger at 71.6 ($=\frac{10.89\%-0.15\%}{0.15\%}$). Hence, when hedge funds invest in high idiosyncratic volatility stocks, these stocks are likely to be ranked into low *MAX* domains.

We support this empirical finding in Panel B of Table 9, where we report the adjusted frequency differences of hedge fund ownership (see Section 6.2) for portfolios dependently double-sorted by a stock's *Idio Vola* and *MAX*. Our results reveal that, given a stock is characterized as a high *Idio Vola and* high *MAX* stock (i.e., it is sorted into idiosyncratic volatility portfolio 5 and *MAX* portfolio 5), the adjusted frequency difference of hedge fund ownership is –41.68%. This number implies that hedge fund ownership is significantly reduced by 41.68% for stocks in the high *Idio Vola* and high *MAX* portfolio compared to the unconditional frequency of hedge fund ownership in the cross-section of stock returns. To the contrary, given a stock is characterized as a high *Idio Vola* and low *MAX* stock (i.e., it is sorted into idiosyncratic volatility portfolio 5 and *MAX* portfolio 1), the adjusted frequency difference of hedge fund ownership is +9.57%, implying that hedge fund ownership for these stocks is significantly higher compared to the unconditional frequency.

Finally, we investigate these patterns in a multivariate setting and regress stock *j*'s hedge fund ownership on *Idio Vola*, *MAX*, and other stock characteristics in month *t*. We implement the Fama and MacBeth (1973) methodology and display the results in Panel C of Table 9.

In specification (1), we incorporate *MAX* and the interaction term between *Idio Vola* and *MAX* into the setup of model (1) in Panel C of Table 8. In addition to the finding that (linear) *MAX* is a negative regressor, our results reveal that an increase in *Idio Vola* × *MAX* significantly decreases a stock's hedge fund ownership at the 1% significance level. To investigate the drivers of the interaction term's impact, a series of dummy variables is constructed that take the

[13] The strong link between idiosyncratic volatility and *MAX* is not surprising since both measures are significantly positively related with a correlation of 0.69 at the individual stock level in our sample.

value of *MAX* if a certain stock is included in *Idio Vola* portfolio k ($k=1,2,3,4,5$) and zero otherwise. Our results show that high values of *MAX* lead to lower hedge fund ownership in all idiosyncratic volatility portfolios with the highest impact displayed in *Idio Vola* portfolio 5 (coefficient estimate of –0.0529 with a *t*-statistic of –4.37).

In summary, our findings in Section 6.3 document that hedge funds do not invest in high *MAX* stocks, in particular, when these stocks are characterized as high *Idio Vola*. Consequently, hedge funds do not suffer from the abnormal low future returns for this subset of stocks.

6.4. Rationalizing the Positive Idiosyncratic Volatility Effect for Stocks with High Hedge Fund Ownership: Idiosyncratic Volatility vs. Mispricing

Stambaugh, Yu, and Yuan (2015) show that the relationship between a stock's idiosyncratic volatility and future returns depends on the degree of mispricing: The idiosyncratic volatility – return relation is negative among overpriced stocks, but positive among underpriced stocks. We conjecture that mispricing is also an important factor when analyzing the idiosyncratic volatility – return relationship for stocks with high and low hedge fund coverage. As in Stambaugh, Yu, and Yuan (2015), we characterize a stock's mispricing (*MP*) according to 11 different equity market anomalies.[14] The lower (higher) values of MP indicate a higher degree of underpricing (overpricing) of individual stocks. The results from investigating the interaction between idiosyncratic volatility and *MP* are reported in Table 10.

Panel A presents the average *MP* values for the idiosyncratic volatility sorted portfolios of stocks with high and low hedge fund coverage. In line with our findings for a stock's *MAX*, we document that the average *MP* is increasing in the idiosyncratic volatility portfolios and is higher for stocks with low hedge fund ownership, i.e., hedge funds on average hold more undervalued stocks. Moreover, we also show that the average spread in *MP* between stocks with high and low hedge fund ownership becomes larger when idiosyncratic volatility in the underlying stocks is rising. Hence, when hedge funds invest in high volatility stocks, these stocks are likely to be ranked into low *MP* domains, i.e., undervalued stocks.

[14] These 11 anomalies include financial distress (Campbell, Hilsher, and Szilagyi, 2008), the O-score bankruptcy probability (Ohlson, 1980), net stock issues (Ritter, 1991, Loughran and Ritter, 1995, and Fama and French, 2008), composite equity issues (Daniel and Titman, 2006), total accruals (Sloan, 1996), net operating assets (Hirshleifer, Hou, Teoh, and Zhang, 2004), momentum (Jegadeesh and Titman, 1993), gross profitability (Novy-Marx, 2013), asset growth (Cooper, Gulen, and Schill, 2008), return on assets (Fama and French, 2006), and investments-to-assets (Titman, Wei, and Xie, 2004, and Xing, 2008).

We further investigate this empirical pattern in Panel B, where we report the adjusted frequency differences of hedge fund ownership (see Section 6.2) for portfolios that are dependently double-sorted by a stock's *Idio Vola* and *MP*. We find that, given a stock is characterized as a high *Idio Vola and* high *MP* stock (i.e., it is sorted into idiosyncratic volatility portfolio 5 and *MP* portfolio 5), the adjusted frequency difference of hedge fund ownership is –35.95%, i.e., it is significantly reduced by 35.95% compared to the unconditional frequency of hedge fund ownership in the cross-section of individual stocks. In comparison, a stock that is characterized as a high *Idio Vola* and low *MP* stock (i.e., it is sorted into idiosyncratic volatility portfolio 5 and *MP* portfolio 1) is overweighted by hedge funds.

We confirm these results also in a multivariate setting. For this purpose, we regress hedge fund ownership of stock *j* on *Idio Vola*, *MP*, and other stock characteristics in month *t* using the Fama and MacBeth methodology, and we display the results in Panel C of Table 10.

In specification (1), we incorporate *MP* and the interaction term between *Idio Vola* and *MP* into the setup of model (1) in Panel C of Table 8. Our results indicate that (i) hedge fund ownership significantly decreases with *MP* (i.e., hedge funds are shying away from overvalued stocks) and (ii) hedge fund ownership significantly decreases with *Idio Vola* × *MP* (i.e., hedge funds particularly do not invest in overvalued stocks when they are characterized by high idiosyncratic volatility). We also examine the detailed drivers of the interaction term's impact and construct a series of dummy variables that take the value of *MP* if a certain stock is included in *Idio Vola* portfolio *k* (*k=1,2,3,4,5*) and zero otherwise. Our results indicate that all interaction terms carry significantly negative coefficient estimates with the highest influence displayed in *Idio Vola* portfolio 5 (coefficient estimate of –0.814 with a *t*-statistic of –6.37).

To summarize, Section 6.4 provides compelling evidence that hedge funds shy away from overvalued equities. This is particularly true for stocks in the high idiosyncratic volatility domain: hedge funds do not invest in stocks with high idiosyncratic volatility and high *MP*, so that they are not affected by the abnormal low future returns for this subset of stocks.

7. Idiosyncratic Volatility and Individual Derivative Positions

The previous section documents that hedge funds earn high future returns by picking idiosyncratic volatility stocks wisely. A closely related question is whether hedge funds use derivative securities in a similar manner to profit from this documented positive idiosyncratic volatility effect.

For this purpose, we use long call and put option holdings data from 13F filings in the SEC EDGAR database for the sample period from April 1999 to December 2017. The 13F filing institutions need to report holdings of long option positions on individual 13F securities and provide information on whether these options are calls or puts. We merge the hedge fund firms in the SEC EDGAR database manually by name with reported fund firm data in the Union Hedge Fund database. Out of the 679 hedge fund firms in our sample, 338 fund firms (i.e., 49.8% of our sample firms) file at least one long option positions.

To match fund firms that disclose their derivative positions quarterly with monthly *Fund Firm Idio Vola* estimates, we again apply the convention that dislosed positions in month t are carried forward for the subsequent months $t+1$ to $t+3$. Then, for each stock j in month t, we compute a stock's *call option hedge fund ownership* as the number of appearances of call options on this stock over all fund firm portfolios. In the same way, for each stock j in month t, we compute a stock's *put option hedge fund ownership* as the number of appearances of put options on this stock over all fund firm portfolios.[15]

To examine the relationship between option ownership of hedge funds and a stock's *Idio Vola*, we rely on a multivariate regression framework using the Fama and MacBeth (1973) methodology. More specifically, we regress call option and put option hedge fund ownership of stock j on *Idio Vola*, *MAX*, *MP*, different interactions, as well as other stock characteristics in month t. The results are presented in Panel A of Table 11.

In specification (1), we regress a stock's *call option hedge fund ownership* on linear and quadratic *Idio Vola*. As in the case for equity, we find that the coefficient estimate for linear (quadratic) idiosyncratic volatility is significantly positive (negative). This finding is consistent with the idea that hedge funds buy call options to invest in stocks with moderate level of idiosyncratic volatility, but shy away from the highest *Idio Vola* stocks in the cross-section. Specification (2) documents a reversed pattern for the impact of idiosyncratic volatility on *put option hedge fund ownership*. This relationship is consistent with the notion that hedge funds buy put options on stocks with the highest *Idio Vola* stocks in the cross-section to profit from low future returns for this subset of stocks.

In specifications (3) and (4), we extend our regression setup by incorporating *MAX* and the interaction term between *Idio Vola* and *MAX*. We observe that *MAX* is a negative (positive)

[15] Our results are robust to other definitions of call and put option ownership of hedge funds. As an example, we obtain similar results when we compute call (put) option hedge fund ownership as the value of equity positions underlying the call (put) positions on this stock over all fund firm portfolios. Results are available upon request.

regressor for call option (put option) hedge fund ownership, while the interaction term is a negative (positive) predictor. These results show that hedge funds trade derivative securities in a consistent way to earn money from falling stock prices of high *MAX* stocks that are at the same time characterized as high *Idio Vola* stocks.

Finally, specifications (5) and (6) investigate the relationship between derivative ownership of hedge funds and *Idio Vola*, and the level of under- and over-valuation of a stock. To do so, we incorporate *MP* and the interaction term between *Idio Vola* and *MP* into the setup of model (1) in Panel C of Table 8. Again, we obtain empirical results that are consistent with hedge funds' trading behavior in equities: Call (put) option hedge fund ownership is falling (rising) in a stock's *MP*. Moreover, this effect is particularly pronounced if under- and over-valuation of a stock is interacted with the degree of idiosyncratic volatility.

A potential bias of this analysis is that there are no options written on small stocks which are consequently classified as stocks with no *call option hedge fund ownership* and no *put option hedge fund ownership*. To mitigate this concern, we run regressions (1) – (6) of Panel A of Table 11 for a reduced sample where we exclude the smallest 30% of stocks in the cross-section in each month. We report the corresponding results in Panel B of Table 11; we find that all results are qualitatively stable and become even stronger in magnitude for some specifications (e.g., in regressions 1 and 2).

In summary, we find that hedge fund firms' investments into high idiosyncratic volatility are not limited to individual stocks, but they also actively seek exposure using derivative securities. Hedge funds prefer to invest in call options on stocks with moderate level of idiosyncratic volatility, which at the same time do not display lottery characteristics and are undervalued. Consistent with this investment behavior, hedge funds also buy put options on stocks with very high level of idiosyncratic volatility, which at the same time display lottery-like features and are overvalued.

8. Conclusion

This paper investigates hedge funds' idiosyncratic volatility and relates it to future fund performance. We empirically show that funds with high idiosyncratic volatility outperform funds with low idiosyncratic volatility by a statistically and economically significant margin of up to 7.20% per annum. This premium remains significant after controlling for standard hedge fund risk factors and a large set of fund characteristics. Hence, idiosyncratic volatility is an important determinant of the cross-sectional dispersion in hedge fund returns.

We then delve deeper and examine which fund characteristics and trading channels are associated with a fund's idiosyncratic volatility. Our results indicate that proxies for managerial incentives, discretion, and distinctiveness are positively associated with a fund's idiosyncratic volatility. Moreover, we find that a substantial part of a fund’s idiosyncratic volatility can be traced back to idiosyncratic volatility of a fund’s disclosed long equity portfolio holdings.

Finally, we contribute to the well-documented idiosyncratic volatility puzzle in the cross-section of individual stocks, i.e., the negative relationship between a stock's idiosyncratic volatility and its future return. We show that equity positions of hedge funds are not affected by this association. To the contrary, the cross-sectional relation between idiosyncratic volatility and future returns for stocks with high hedge fund coverage is positive and highly significant. This positive link is due to prudent stock picks by hedge funds with ability to shy away from investing in stocks with (i) the highest idiosyncratic volatility, (ii) high volatility stocks with strong lottery characteristics, and (iii) high volatility stocks that are overvalued. This prudent way of investing into idiosyncratic volatility is not restricted to trading equities, but hedge funds also actively seek exposure using call and put options.

Appendix

Figure A.1: Venn Diagram of the Union Hedge Fund Database

The Union Hedge Fund Database contains a sample of 39,938 hedge funds created by merging four commercial databases in the time period from 1994 to 2017: Eureka, HFR, Morningstar, and Lipper TASS. This figure shows the percentage of funds covered by each database individually and by all possible combinations of multiple databases.

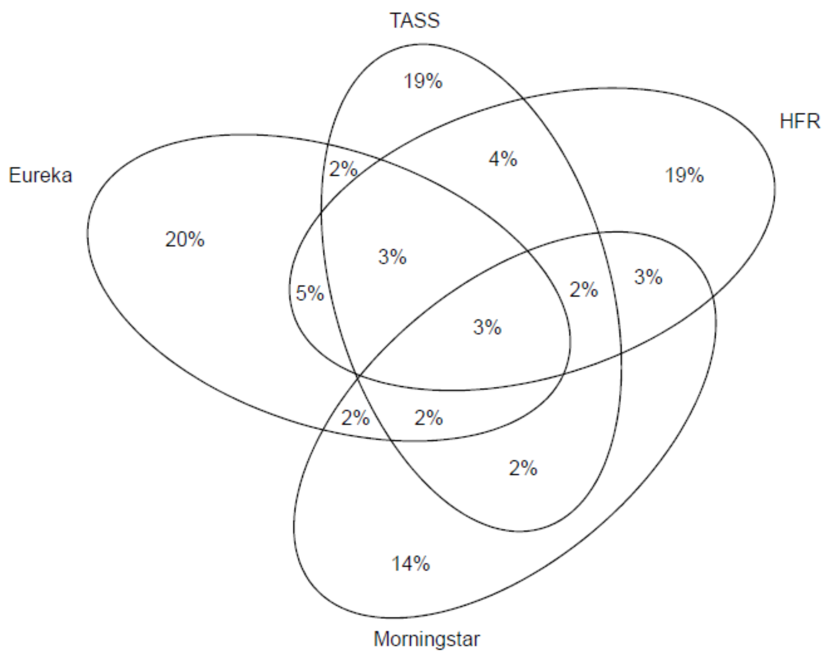

Table A.1. Definitions and Data Sources of Main Variables

This table briefly defines the main variables used in the empirical analysis. The data sources are; (i) UNION: Union Hedge Fund Database constructed from combining the Eureka, HFR, Morningstar, and Lipper TASS databases, (ii) 13F: Thomson Reuter's 13F institutional portfolio holdings, (iii) KF: Kenneth French Data Library, (iv) DH: David A. Hsieh's webpage, (v) FRS: Data library of the Federal Reserve System, (vi) CRSP: CRSP Stocks Database, and (vii) Compustat: Compustat Database. EST indicates that the variable is estimated or computed based on original variables from the respective data sources.

Panel A: Fund Returns, Fund Idiosyncratic Volatility, and Fund Characteristics

Variable Name	Description	Source
Fund Return	Monthly raw excess return of a hedge fund over the risk-free rate. As risk-free rate, the one-month T-Bill rate is used.	UNION, KF, EST
Fund Vola	Standard Deviation of a hedge fund's reported returns over the past 36 months.	UNION, EST
Fund Idio Vola	Idiosyncratic component of a hedge fund's volatility. Computed as the standard deviation of a fund's residual return to the extended Fung and Hsieh (2004) nine-factor model as detailed in Section 3.1.	UNION, KF, DH, EST
Size	Natural logarithm of the hedge fund's asset under management (in million USD).	UNION
Age	The age of a hedge fund since its inception (in months).	UNION
Delta	Hedge fund manager's delta computed as the expected dollar change in the manager's compensation for a 1% change in the fund's net asset value (in $100 thousands) as in Agarwal, Daniel, and Naik (2009).	Author Homepage
Management Fee	The annual hedge fund management fee (in percentage).	UNION
Incentive Fee	The annual hedge fund incentive fee (in percentage).	UNION
Min Investment	Hedge fund's minimum investment amount (in $100 thousands).	UNION
Lockup Period	The lockup period of a hedge fund, defined as the minimum amount of time that an investor is required to keep his money invested in the fund (in years).	UNION
Restriction Period	The restriction period of a hedge fund. Computed as the sum of its notice period and redemption period (in years).	UNION, EST
Offshore	Indicator variable that takes the value of one if the hedge fund is located outside of the USA and zero otherwise.	UNION
Leverage	Indicator variable that takes the value of one if the hedge fund uses leverage and zero otherwise.	UNION
HWM	Indicator variable that takes the value of one if the hedge fund uses a high-watermark and zero otherwise.	UNION
Hurdle Rate	Indicator variable that takes the value of one if the hedge fund uses a hurdle rate and zero otherwise.	UNION
R^2	Titman and Tiu (2011)'s R2 measure of a fund to the extended Fung and Hiseh (2004) nine-factor model. Estimated based on the past 36 months.	UNION, EST
SDI	Sun, Wang, and Zheng (2012)'s strategy distinctiveness index, Computed as one minus the correlation between a fund firm's return and the average return of the style group estimated based on the past 36 months.	UNION, EST

Panel B: Hedge Fund Risk Factors

Variable Name	Description	Source
S&P	The S&P 500 index monthly total return.	DH
SCMLC	The size spread factor, computed as the difference between the Russell 2000 index monthly return and the S&P 500 monthly return.	DH
BD10RET	The bond market factor, computed as the monthly change in the 10-year treasury maturity yield.	FRS
BAAMTSY	The credit spread factor, computed as the monthly change in the Moody's Baa yield less 10-year treasury constant maturity yield.	FRS
PTFSBD	Monthly return on trend-following risk factor in bonds.	DH
PTFSFX	Monthly return on trend-following risk factor in currencies.	DH
PTFSCOM	Monthly return on trend-following risk factor in commodities.	DH
HML	Monthly return on Fama and French (1993)'s high-minus-low value factor.	KF
UMD	Monthly return on Carhart (1997)'s momentum factor.	KF
RMW	Monthly return on Fama and French (2015)'s robust-minus-weak profitability factor.	KF
CMA	Monthly return on Fama and French (2015)'s conservative-minus-aggressive investment factor.	KF
EM	The MSCI Emerging Market index monthly total return.	DH
SENTI	The Baker and Wurgler (2006) sentiment factor.	Author Homepage
PS Liqui	The Pástor and Stambaugh (2003) traded liquidity factor.	Author Homepage
BAB	The Frazzini and Pedersen (2014) betting-against-beta factor.	Author Homepage
MACRO	The Bali, Brown, and Caglayan (2014) macroeconomic uncertainty factor.	Author Homepage
CORR	The Buraschi, Kosowski, and Trojani (2014) correlation risk factor.	Author Homepage
RIX	The Gao, Gao, and Song (2018) RIX factor.	Author Homepage
OTM Call	The Agarwal and Naik (2004) out-of-the-money call option factor.	Author Homepage
OTM Put	The Agarwal and Naik (2004) out-of-the-money put option factor.	Author Homepage

Panel C: Equity Portfolio Characteristics

Variable Name	Description	Source
Equity Portfolio Return	Monthly raw excess return of a hedge fund firm. Computed as value-weighted average return of the fund firm's equity portfolio positions as detailed in Section 4.1. As risk-free rate, the 1-month T-Bill rate is used.	13F, CRSP, KF, EST
Fund Firm Idio Vola	Idiosyncratic component of a hedge fund firm's volatility over the past 36 months. Computed as the standard deviation of a fund firm's residual return to the extended Fung and Hsieh (2004) nine-factor model as detailed in Section 4.1.	UNION, KF, DH, EST
Equity Idio Vola	Idiosyncratic component of a hedge fund firm's equity portfolio volatility over the past 36 months. Computed as the standard deviation of a fund firm's residual equity portfolio return to the extended Fung and Hsieh (2004) nine-factor model as detailed in Section 4.1.	13F, CRSP, KF, DH, EST
Number of Assets	The number of different stocks in a hedge fund firm's portfolio.	13F, EST
Herfindahl Index	The herfindahl index computed based on assets under management of different portfolio positions in a hedge fund firm's portfolio.	13F, EST
Industry Herfindahl Index	The herfindahl index computed based on assets under management of different industry positions in a hedge fund firm's portfolio.	13F, CRSP, EST
Portfolio Turnover	Turnover of a hedge fund firm's portfolio. Computed as the total of its stock purchases and sales in quarter *t* divided by its total equity portfolio market capitalization in quarter *t*-1.	13F, EST
Portfolio Beta	A hedge fund firm's portfolio market beta. Computed based on the fund firm's monthly equity portfolio return series and the S&P 500 market over the past 36 months.	13F, CRSP, EST
Equity 1m Portfolio Return	Monthly equity portfolio return of a hedge fund firm.	13F, CRSP, EST
Equity 12m Portfolio Return	Annual equity portfolio return of a hedge fund firm. Estimated over the past 12 months	13F, CRSP, EST
Portfolio Skewness	A hedge fund firm's portfolio skewness. Computed as the skewness of a fund firm's monthly equity portfolio return series over the past 36 months.	13F, CRSP, EST
Portfolio Kurtosis	A hedge fund firm's portfolio kurtosis. Computed as the kurtosis of a fund firm's monthly equity portfolio return series over the past 36 months.	13F, CRSP, EST
Portfolio Stock Size	Value-weighted average of stocks' size, computed as the natural logarithm of the stocks' market capitalization	13F, CRSP, EST
Portfolio Book-to-Market	Value-weighted average of stocks' book-to-market ratios in a hedge fund firm's portfolio.	13F, CRSP, Compustat, EST
Portfolio Illiquidity	Value-weighted average of stocks' illiquidity in a hedge fund firm's portfolio measured by the Amihud (2002) illiquidity ratio.	13F, CRSP, EST
Portfolio Investment	Value-weighted average of stocks' investment (relative growth of total assets from year *t-1* to year *t*) in a hedge fund firm's portfolio.	13F, CRSP, Compustat, EST
Portfolio Profitability	Value-weighted average of stocks' operating profitability in a hedge fund firm's portfolio.	13F, CRSP, Compustat, EST
Portfolio Leverage	The value-weighted average of stocks' leverage in a hedge fund firm's portfolio.	13F, CRSP, Compustat, EST

Panel D: Stock Characteristics

Variable Name	Description	Source
Stock Return	Monthly raw excess return of a stock including re-investment of dividends. As risk-free rate, the 1-month T-Bill rate is used.	CRSP, KF
Idio Vola	Idiosyncratic component of a hedge fund firm's volatility over the past 36 months. Computed as the standard deviation of a fund firm's residual return to the extended Fung and Hsieh (2004) nine-factor model as detailed in Section 5.1.	CRSP, KF, DH, EST
Beta	A stock's portfolio market beta. Computed based on the stock's monthly excess return series and the S&P 500 excess market over the past 36 months.	CRSP, EST
1m Stock Return	Monthly raw excess return of a stock. As risk-free rate, the 1-month T-Bill rate is used.	CRSP, KF
12m Stock Return	Annual raw excess return of a stock (estimated over the past 12 months). As risk-free rate, the 1-month T-Bill rate is used.	CRSP, KF, EST
Skewness	A stock's skewness. Computed based on the stock's monthly excess return series over the past 36 months.	CRSP, EST
Kurtosis	A stock's kurtosis. Computed based on the stock's monthly excess return series over the past 36 months.	CRSP, EST
Size	Natural logarithm of the stock's market capitalization	CRSP, EST
Book-to-Market	A stock's book-to-market ratio. Computed as the ratio of CS book value of equity per share.	CRSP, Compustat, EST
Illiquidity	A stock's illiquidity measured by the Amihud (2002) illiquidity ratio based on a stock's daily absolute returns and daily trading volume in a month.	CRSP, EST
Investment	A stock's investment computed as the relative growth of total assets from year *t*-1 to year *t*.	CRSP, Compustat, EST
Profitability	A stock's operating profitability. Computed as annual revenues minus cost of goods sold, interest expense, and selling, general, and administrative expense divided by the sum of of book equity and minority interest for the last fiscal year.	CRSP, Compustat, EST
Leverage	A stock's leverage ratio. Computed as the ratio of debt in current liabilities to common/ordinary total equity.	CRSP, Compustat, EST

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Figure 1. Persistence of a Fund's Idiosyncratic Volatility

This figure displays the evolution of average equal-weighted *Fund Idio Vola* of tercile portfolios. Firms are sorted into terciles based on their *Fund Idio Vola* in month *t*. Then, the equal-weighted average of *Fund Idio Vola* of these portfolios is computed in month *t*+36, *t*+72, *t*+108, and *t*+144. Our sample covers equity-oriented hedge funds from the Union Hedge Fund Database constructed from combining the Eureka, HFR, Morningstar, and Lipper TASS databases. The sample period is from January 1997 to December 2017. All variables are defined in the Appendix.

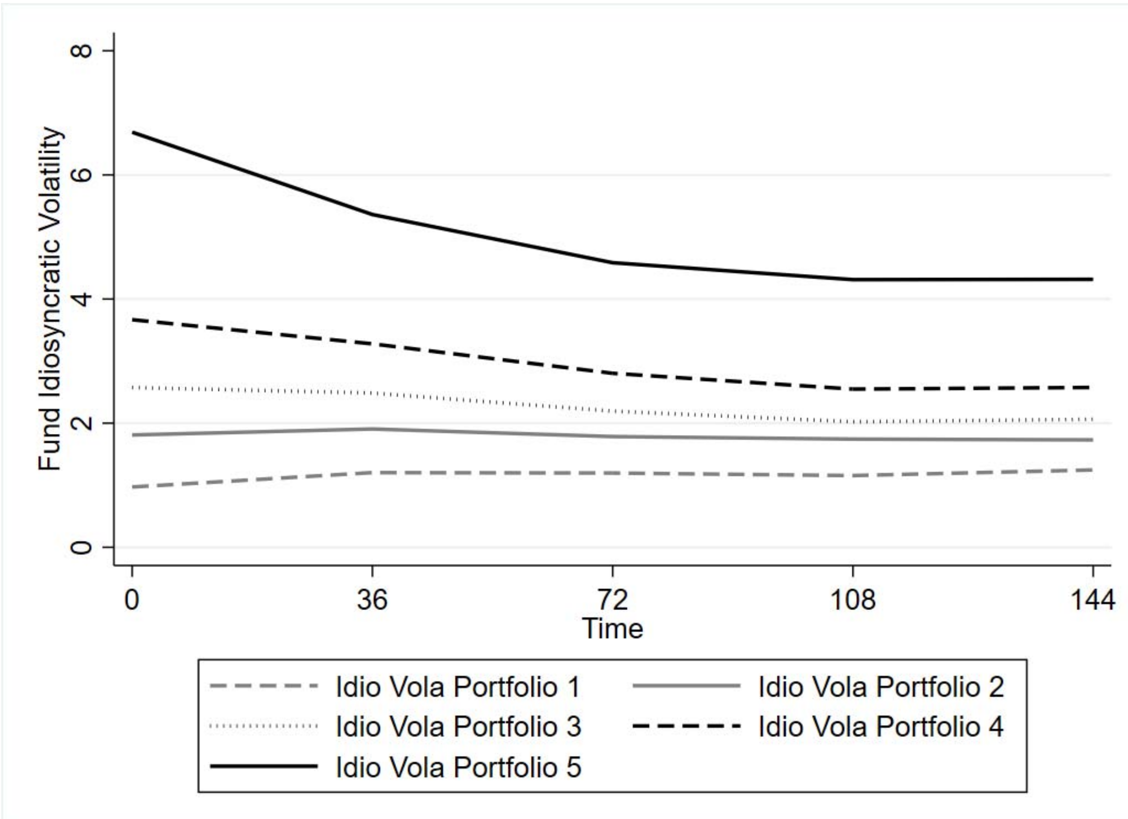

Table 1. Summary Statistics and Correlations

This table provides summary statistics for the main variables in our empirical study. Panel A displays summary statistics for the monthly excess returns (over the risk-free rate) of hedge funds and fund characteristics. Panel B displays summary statistics for a fund's idiosyncratic volatility. Summary statistics are calculated over all hedge funds and months in our sample period. We also display correlations between a fund's idiosyncratic volatility, returns and different fund characteristics in Panel C. Our sample covers equity-oriented hedge funds from the Union Hedge Fund Database constructed from combining the Eureka, HFR, Morningstar, and Lipper TASS databases. The sample period is from January 1997 to December 2017. All variables are defined in Table A.1.

Panel A: Returns and Fund Characteristics

Variable	Mean	25%	Median	75%	StdDev
Fund Return	0.59%	-1.33%	0.51%	2.52%	5.73
Fund Idio Vola	2.72%	1.36%	2.15%	3.45%	1.97%
Size	3.41	2.29	3.46	4.60	1.76
Age (in months)	68.32	23.00	51.00	154.00	64.43
Delta (in $100 thousands)	1.98	0.07	0.37	1.48	5.14
Management Fee (in %)	1.42	1.00	1.50	2.00	0.48
Incentive Fee (in %)	17.64	20.00	20.00	20.00	5.94
Min Investment (in $100 thousands)	8.74	1.00	5.00	10.00	18.98
Lockup Period (in years)	0.36	0.00	1.00	1.00	0.59
Restriction Period (in years)	0.32	0.16	0.25	0.37	0.30
Offshore	0.54	0.00	1.00	1.00	0.50
Leverage	0.54	0.00	1.00	1.00	0.49
HWM	0.82	1.00	1.00	1.00	0.38
Hurdle Rate	0.19	0.00	0.00	0.00	0.39
R2	0.56	0.26	0.56	0.72	0.20
SDI	0.49	0.26	0.41	0.65	0.31

Panel B: *Fund Idio Vola*

Strategy	Number of Fund Firms	Mean	25%	Median	75%	StdDev
Emerging Markets	662	3.74%	1.96%	3.23%	4.97%	2.32%
Event Driven	1,164	1.97%	0.87%	1.42%	2.33%	1.81%
Equity Long-Short	6,119	2.74%	1.46%	2.20%	3.42%	1.89%
Equity Long Only	718	3.09%	1.63%	2.69%	4.03%	2.04%
Equity Market Neutral	268	1.87%	1.02%	1.58%	2.31%	1.36%
All	8,931	2.72%	1.36%	2.15%	3.45%	1.97%

Panel C: Correlations between Returns, *Fund Idio Vola,* and Fund Characteristics

	Fund Return	Fund Idio Vola	Size	Age	Delta	Management Fee	Incentive Fee	Min Investment	Lockup Period	Restriction Period	Offshore	Leverage	HWM	Hurdle Rate	R2	SDI
Fund Return	+1.00															
Fund Idio Vola	+0.04	+1.00														
Size	-0.00	-0.22	+1.00													
Age	-0.02	-0.05	+0.25	+1.00												
Delta	+0.03	+0.08	+0.53	+0.25	+1.00											
Mgmt. Fee	+0.00	+0.11	+0.02	-0.13	+0.03	+1.00										
Inc. Fee	+0.00	+0.02	-0.02	-0.03	+0.11	+0.10	+1.00									
Min Inv	+0.00	-0.09	+0.21	+0.02	+0.22	-0.05	+0.00	+1.00								
Lockup	+0.01	+0.03	-0.00	+0.02	+0.01	-0.03	+0.16	+0.09	+1.00							
Restriction	+0.02	-0.04	+0.06	+0.08	+0.08	-0.08	+0.19	+0.09	+0.33	+1.00						
Offshore	-0.01	+0.09	+0.14	-0.11	+0.07	+0.21	-0.07	-0.08	-0.27	-0.29	+1.00					
Leverage	+0.00	+0.02	-0.01	-0.01	+0.05	+0.04	+0.20	+0.01	+0.04	+0.05	-0.03	+1.00				
HWM	+0.01	-0.01	+0.01	-0.03	+0.07	+0.09	+0.47	+0.01	+0.16	+0.13	-0.06	+0.13	+1.00			
Hurdle Rate	+0.00	+0.01	-0.06	+0.02	-0.04	-0.10	+0.04	-0.02	+0.03	-0.01	-0.13	-0.05	-0.02	+1.00		
R2	+0.00	-0.16	+0.00	+0.09	+0.01	-0.14	-0.13	+0.00	+0.04	+0.03	-0.15	-0.07	-0.07	+0.03	+1.00	
SDI	-0.00	+0.08	-0.10	-0.13	-0.09	+0.02	+0.11	+0.04	-0.02	-0.02	-0.02	+0.08	+0.05	-0.00	-0.56	+1.00

Table 2. Transition Matrix

This table presents the 36-month-ahead transition matrix based on a fund's idiosyncratic volatility. It shows the relative frequency that a stock is sorted into *Fund Idio Vola* quintile portfolio *i* in month *t* given that it was in *Fund Idio Vola* quintile portfolio *j* in month *t-36*. Our sample covers equity-oriented hedge funds from the Union Hedge Fund Database constructed from combining the Eureka, HFR, Morningstar, and Lipper TASS databases. The sample period is from January 1997 to December 2017.

Portfolios	1 (month *t*)	2 (month *t*)	3 (month *t*)	4 (month *t*)	5 (month *t*)
1 (month *t-36*)	0.64	0.23	0.08	0.03	0.02
2 (month *t-36*)	0.24	0.38	0.25	0.10	0.03
3 (month *t-36*)	0.08	0.27	0.35	0.23	0.07
4 (month *t-36*)	0.03	0.10	0.25	0.41	0.21
5 (month *t-36*)	0.01	0.02	0.07	0.23	0.67

Table 3. *Fund Idio Vola* and Future Returns

Panel A of this table reports the results from equal-weighted univariate portfolio sorts based on *Fund Idio Vola* in month *t* and risk-adjusted returns in month *t*+1. In each month *t*, we sort all hedge funds into quintile portfolios based on their *Fund Idio Vola* estimate in increasing order. We then compute equal-weighted monthly average excess returns of these portfolios in month *t*+1. The column "Return" reports the average portfolio return in excess of the one-month T-bill rate in the following month. The column labeled "FH-9-Factor" report the monthly alpha using the Fung and Hsieh (2004) seven-factor model extended by the HML and UMD factor. In Panel B, we regress the return of a portfolio consisting of funds in portfolio 1 with the lowest *Fund Idio Vola* subtracted from the returns of the funds in portfolio 5 with the highest *Fund Idio Vola*, on different risk factors. As risk factors, we use in addition to the factors of the Fung and Hsieh (2004) nine-factor model presented in the first column, the profitability *(CMA)* and investment *(RMW)* factors of Fama and French (2015), the MSCI emerging market index *(EM)*, the Baker and Wurgler (2006) sentiment factor *(Senti)*, the Pástor and Stambaugh (2003) traded liquidity factor (*PS Liqui*), the Frazzini and Pedersen (2014) betting-against-beta factor *(BAB)*, the Bali, Brown, and Caglayan (2014) macroeconomic uncertainty factor (*Return Macro*), the Buraschi, Kosowski, and Trojani (2014) correlation risk factor (*Return CORR*), the Gao, Gao, and Song (2018) RIX factor (*Return RIX*), and the Agarwal and Naik (2004) out-of-the-money call and put option factors (*OTM Call* and *OTM Put*). Panel C of this table reports the results of Fama and MacBeth (1973) regressions of excess returns and Fund and Hsieh (2004) nine-factor alphas in month *t*+1 on a fund's idiosyncratic volatility and different fund characteristics in month *t*. For fund characteristics, we include a fund's monthy return, size, age, delta of the fund manager's contract, management and incentive fee (in %), minimum investment amount (in 100 thousands), the length of a fund's lockup and restriction period (in months), indicator variables that equal one if the fund is an offshore fund, employs leverage, has a high water mark, and has a hurdle rate, and are otherwise zero, as well as a fund's R2 and SDI. All control variables are defined in Panel B of Table A.1. Panel D reports the results of dependent bivariate portfolio sorts based on R2 and *Fund Idio Vola* as well as SDI and *Fund Idio Vola*. First, we form quintile portfolios based on R2 (SDI) in month *t*. Then, we sort hedge funds into quintile portfolios based on *Fund Idio Vola* in month *t*. We then compute equally weighted monthly average excess returns of these portfolios in month *t*+1. The column "5-1" reports the difference in monthly average excess returns with corresponding statistical significance. Our sample covers equity-oriented hedge funds from the Union Hedge Fund Database constructed from combining the Eureka, HFR, Morningstar, and Lipper TASS databases. The sample period is from January 1997 to December 2017. We use the Newey-West (1987) adjustment with 36 lags to adjust the standard errors for serial correlation. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

Panel A: Univariate Portfolio Sorts

Quintiles	Average *Fund Idio Vola*	Return	FH-9-Factor
Q1	0.89%	0.29%	0.18%
		(1.13)	(1.23)
Q2	1.61%	0.42%**	0.26%
		(2.08)	(1.58)
Q3	2.29%	0.48%***	0.29%**
		(2.77)	(2.13)
Q4	3.27%	0.56%***	0.32%**
		(3.39)	(2.41)
Q5	5.95%	0.89%***	0.61%***
		(4.76)	(2.84)
Q5 - Q1	5.06%	0.60%***	0.43%**
t-statistic		(2.72)	(2.07)

Panel B: Additional Risk Factors

	(1) Q5 - Q1	(2) Q5 - Q1	(3) Q5 - Q1	(4) Q5 - Q1	(5) Q5 - Q1	(6) Q5 - Q1	(7) Q5 - Q1	(8) Q5 - Q1	(9) Q5 - Q1	(10) Q5 - Q1
S&P	0.172***	0.108***	-0.0546	0.198***	0.166***	0.164***	0.177***	0.197***	0.194***	0.131*
	(3.52)	(3.20)	(-1.28)	(3.76)	(3.37)	(3.59)	(3.66)	(4.20)	(3.54)	(1.68)
SCMLC	0.193***	0.0923	0.119**	0.230***	0.191***	0.187***	0.191***	0.212***	0.219***	0.190***
	(3.73)	(1.45)	(2.59)	(3.75)	(3.72)	(3.44)	(3.62)	(3.52)	(3.77)	(3.55)
BD10RET	-0.187*	-0.152*	-0.216**	-0.213*	-0.163*	-0.186**	-0.193**	-0.221*	-0.208*	-0.188**
	(-1.95)	(-1.76)	(-2.59)	(-1.83)	(-1.68)	(-1.98)	(-1.99)	(-1.89)	(-1.75)	(-1.99)
BAAMTSY	0.355***	0.373***	0.204***	0.354***	0.334***	0.370***	0.343***	0.353***	0.331***	0.348***
	(3.64)	(4.50)	(3.72)	(3.22)	(3.83)	(3.78)	(3.28)	(3.30)	(2.84)	(3.88)
PTFSBD	-0.0156	-0.0177	-0.00519	-0.00202	-0.0164	-0.0163	-0.0153	-0.00722	-0.00105	-0.0145
	(-1.15)	(-1.37)	(-0.39)	(-0.13)	(-1.24)	(-1.37)	(-1.12)	(-0.50)	(-0.08)	(-1.14)
PTFSFX	0.0167**	0.0193***	0.0135*	0.0177***	0.0167**	0.0170**	0.0164**	0.0236***	0.0206***	0.0172**
	(2.31)	(2.71)	(1.90)	(2.77)	(2.30)	(2.43)	(2.25)	(3.89)	(3.81)	(2.13)
PTFSCOM	-0.0122	-0.0150*	-0.00980	-0.0123	-0.0121	-0.0129	-0.0116	-0.0136	-0.0127	-0.0124
	(-1.43)	(-1.77)	(-1.21)	(-1.01)	(-1.48)	(-1.32)	(-1.38)	(-1.23)	(-1.19)	(-1.48)
HML	-0.0924**	0.0678	-0.0314	-0.0480	-0.0890*	-0.0761	-0.0906**	-0.0801*	-0.0943**	-0.0905**
	(-2.13)	(1.05)	(-1.06)	(-1.24)	(-1.94)	(-1.38)	(-2.05)	(-1.94)	(-2.46)	(-2.06)
UMD	-0.0120	0.00690	0.0101	0.0115	-0.0195	-0.00409	-0.00731	0.000920	-0.00948	-0.0130
	(-0.30)	(0.16)	(0.23)	(0.29)	(-0.46)	(-0.06)	(-0.20)	(0.02)	(-0.18)	(-0.30)
RMW		-0.252***								
		(-3.88)								
CMA		-0.129**								
		(-2.33)								
EM			0.240***							
			(9.41)							
Senti				-0.006***						
				(-4.97)						
PS Liqui					0.0612**					
					(2.36)					
BAB						-0.0266				
						(-0.28)				
Return Macro							0.0498			
							(0.82)			
Return CORR								-0.0002		
								(-0.01)		
Return RIX									-0.148	
									(-1.36)	
OTM Call										0.0009
										(0.01)
OTM Put										-0.0026
										(-0.99)
Constant	0.431**	0.538**	0.478***	0.830***	0.399**	0.443**	0.425**	0.590**	0.592***	0.384**
	(2.07)	(2.46)	(3.08)	(3.82)	(2.00)	(2.00)	(1.99)	(2.18)	(2.69)	(2.04)
Observations	252	252	252	168	252	252	252	192	180	250
Adjusted R^2	0.350	0.352	0.455	0.398	0.355	0.351	0.351	0.376	0.380	0.381

Panel C: Fama-MacBeth (1973) Regressions

	(1) Future Fund Return	(2) Future Fund Return	(3) Future Fund Return	(4) Fung and Hsieh Alpha
Fund Idio Vola	0.0990**	0.101**	0.104**	0.0777**
	(2.11)	(2.58)	(2.57)	(2.66)
Fund Return		0.0926***	0.0868***	0.0694***
		(7.29)	(7.12)	(5.05)
Size		-0.0307*	-0.0282*	-0.0218*
		(-1.67)	(-1.68)	(-1.95)
Age		-0.000779***	-0.000906***	-0.00228***
		(-3.52)	(-4.80)	(-5.55)
Delta		0.0151**	0.0173***	0.0100***
		(2.41)	(2.60)	(4.66)
Management Fee		-0.0203	-0.0121	-0.0174
		(-0.25)	(-0.15)	(-0.32)
Incentive Fee		-0.00304	-0.000787	0.0116***
		(-1.04)	(-0.26)	(2.63)
Minimum Investment		0.00158**	0.00149***	0.000777
		(2.20)	(3.39)	(1.45)
Lockup Period		0.0690**	0.0530*	0.0733***
		(2.07)	(1.73)	(2.80)
Restriction Period		0.00825	-0.0199	0.0316
		(0.25)	(-0.66)	(1.38)
Offshore		-0.0946	-0.105	-0.164
		(-1.34)	(-1.60)	(-1.26)
Leverage		0.00528	0.00780	0.00322
		(0.11)	(0.17)	(0.06)
High Watermark		0.0569*	0.0676**	0.0355*
		(1.91)	(2.44)	(1.91)
Hurdle Rate		-0.0833	-0.0915	-0.114
		(-1.01)	(-1.19)	(-1.56)
R2			-0.247*	-0.387**
			(1.92)	(-2.47)
SDI			0.127*	0.289***
			(1.86)	(3.19)
Constant	0.252**	0.388*	0.365**	0.138
	(2.50)	(1.86)	(1.99)	(1.38)
Observations	610,341	316,091	316,091	312,050
Adjusted R^2	0.055	0.143	0.189	0.112

Panel D: Bivariate Portfolio Sorts

R2 and *Fund Idio Vola*

	R2 Q1	R2 Q2	R2 Q3	R2 Q4	R2 Q5	Average
Q1	0.27%	0.28%	0.35%*	0.32%	0.40%*	0.33%
	(1.24)	(1.61)	(2.03)	(1.65)	(1.95)	(1.70)
Q2	0.33%*	0.38%*	0.41%**	0.44%**	0.47%**	0.41%**
	(1.84)	(1.83)	(2.13)	(2.43)	(2.44)	(2.13)
Q3	0.43%**	0.45%**	0.48%***	0.51%***	0.51%***	0.48%***
	(2.54)	(2.61)	(2.91)	(3.04)	(2.88)	(2.80)
Q4	0.54%***	0.66%***	0.58%***	0.58%***	0.55%***	0.58%***
	(3.02)	(4.03)	(3.56)	(4.14)	(3.97)	(3.74)
Q5	0.81%***	0.86%***	0.91%***	0.83%***	0.84%***	0.85%***
	(4.26)	(5.61)	(5.68)	(4.92)	(5.42)	(5.18)
Q5 - Q1	0.54%**	0.58%**	0.56%**	0.51%**	0.43%**	0.52%**
t-statistic	(2.19)	(2.19)	(2.34)	(2.00)	(2.21)	(2.21)
FH-9-Factor	0.38%*	0.51%**	0.46%**	0.34%	0.36%**	0.41%**
t-statistic	(1.92)	(2.43)	(2.32)	(1.45)	(2.04)	(2.03)

SDI and *Fund Idio Vola*

	SDI Q1	SDI Q2	SDI Q3	SDI Q4	SDI Q5	Average
Q1	0.38%*	0.33%*	0.30%	0.26%	0.30%	0.31%*
	(2.15)	(2.19)	(1.49)	(1.51)	(1.59)	(1.79)
Q2	0.41%**	0.47%**	0.45%**	0.38%*	0.35%	0.41%**
	(2.19)	(2.43)	(2.38)	(1.82)	(1.57)	(2.08)
Q3	0.49%**	0.51%**	0.50%***	0.44%**	0.49%**	0.49%**
	(2.61)	(2.45)	(3.02)	(2.31)	(2.29)	(2.54)
Q4	0.53%***	0.56%***	0.66%***	0.72%***	0.54%**	0.60%***
	(3.01)	(3.41)	(3.78)	(4.03)	(4.32)	(3.71)
Q5	0.59%***	0.84%***	0.93%***	0.84%***	0.85%***	0.83%***
	(3.75)	(4.99)	(6.02)	(5.46)	(5.08)	(5.06)
Q5 - Q1	0.21%	0.51%*	0.63%**	0.59%**	0.55%***	0.50%**
t-statistic	(1.10)	(1.87)	(2.16)	(2.40)	(3.11)	(2.13)
FH-9-Factor	0.11%	0.42%**	0.56%**	0.47%**	0.53%***	0.42%**
t-statistic	(0.45)	(2.44)	(2.29)	(2.33)	(3.02)	(2.11)

Table 4. *Fund Idio Vola* and Future Returns: Robustness

This table reports the results from robustness checks of the relation between a fund's idiosyncratic volatility in month t and their monthly Fung and Hsieh (2004) nine-factor alphas in month t+1. We investigate the robustness when we estimate a fund's idiosyncratic volatility using a rolling estimation horizon of 24 months instead of 36 months, estimate a fund's idiosyncratic volatility using the four-factor model of Fama-French-Carhart, the Fung and Hsieh (2004) seven-factor model, and the Fung and Hsieh (2004) seven-factor model extended with the OTM call and put option factors of Agarwal and Naik (2004), apply the Goetzmann, Ingersoll, Spiegel, and Welch (2007) manipulation-proof performance measure (MPPM) with a risk aversion parameter of two as the dependent variable, restrict our sample to hedge funds with an equity long-short strategy, restrict our sample to hedge funds which use (do not use) leverage, assign a delisting return of −1.61% as in Hodder, Jackwerth, and Kolokolova (2014) to those hedge funds that leave the database, apply the correction method of Getmansky, Lo, and Makarov (2004) to unsmooth hedge fund returns, account for another computation of the backfill bias as illustrated in Jorion and Schwarz (2019), and use future two-month ahead and three-month ahead returns as the dependent variable. We report the results of Fama and MacBeth (1973) regressions as in specification (4) of Panel C in Table 3 of future nine-factor alphas on *Fund Idio Vola* and different fund characteristics measured in month t. We only display the results of the relation between *Fund Idio Vola* and future alphas (control variables are included, but suppressed in the table). Our sample covers equity-oriented hedge funds from the Union Hedge Fund Database constructed from combining the Eureka, HFR, Morningstar, and Lipper TASS databases. The sample period is from January 1997 to December 2017. We use the Newey-West (1987) adjustment with 36 lags to adjust the standard errors for serial correlation. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

	(1) Baseline	(2) 24 months	(3) Carhart 4-Factor Model	(4) Fung and Hsieh 7-Factor Model	(5) 7-Factor Model Extended by Option Factors	(6) MPPM	(7) Equity Long-Short Funds
Fund Idio Vola	0.0777**	0.0782***	0.0889***	0.0792**	0.0756**	0.0623**	0.0756**
	(2.66)	(2.89)	(3.26)	(2.56)	(2.42)	(2.29)	(2.63)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.112	0.112	0.113	0.111	0.112	0.103	0.115

	(8) Using Leverage	(9) Not using Leverage	(10) Delisting Return	(11) Return Smoothing	(12) Backfill Bias	(13) 2 months ahead	(14) 3 months ahead
Fund Idio Vola	0.0734**	0.0798**	0.0754**	0.0657**	0.0823***	0.134**	0.§87**
	(2.34)	(2.04)	(2.61)	(2.15)	(2.99)	(2.54)	(2.14)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.107	0.119	0.112	0.106	0.116	0.134	0.148

Table 5. Determinants of *Fund Idio Vola*

This table reports the results of Fama and MacBeth (1973) regressions of a fund's idiosyncratic volatility in month *t*+1 on fund characteristics in month *t*. For fund characteristics, we include a fund's monthy return, size, age, delta of the fund manager's contract, management and incentive fee (in %), minimum investment amount (in 100 thousands), the length of a fund's lockup and restriction period (in months), indicator variables that equal one if the fund is an offshore fund, employs leverage, has a high water mark, and has a hurdle rate, and are otherwise zero, as well as a fund's R2 and SDI. Our sample covers equity-oriented hedge funds from the Union Hedge Fund Database constructed from combining the Eureka, HFR, Morningstar, and Lipper TASS databases. The sample period is from January 1997 to December 2017. We use the Newey-West (1987) adjustment with 36 lags to adjust the standard errors for serial correlation. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

	(1) Fund Idio Vola	(2) Fund Idio Vola	(3) Fund Idio Vola	(4) Fund Idio Vola
Fund Return	0.0208**		0.0202**	0.0201**
	(2.32)		(2.49)	(2.41)
Size	-0.286***		-0.290***	-0.296***
	(-6.70)		(-7.42)	(-7.61)
Age	-0.000396		0.000304	0.000306
	(-0.51)		(0.44)	(0.46)
Delta	0.0238***		0.0258***	0.0313***
	(4.20)		(3.21)	(3.39)
Management Fee		0.472***	0.508***	0.416***
		(12.70)	(12.30)	(7.31)
Incentive Fee		0.00504	0.00715	0.0133**
		(0.62)	(1.27)	(2.06)
Minimum		-0.00958***	-0.00262***	-0.00274***
Investment		(-4.81)	(-4.13)	(-3.66)
Lockup Period		0.320***	0.282***	0.278***
		(7.56)	(9.46)	(8.59)
Restriction Period		0.271	0.222	0.257
		(0.77)	(0.71)	(1.21)
Offshore		0.292***	0.406***	0.232***
		(4.74)	(8.46)	(5.47)
Leverage		-0.000174	-0.000538	-0.000468
		(-1.20)	(-1.46)	(-1.31)
High Watermark		0.0221	0.138**	0.103**
		(0.43)	(2.45)	(2.05)
Hurdle Rate		0.161***	0.127**	0.113*
		(4.12)	(2.51)	(1.78)
R2				-2.450***
				(-12.34)
SDI				0.458***
				(3.21)
Constant	3.605***	2.076***	2.663***	4.615***
	(12.54)	(6.93)	(8.77)	(14.53)
Observations	391,149	477,013	320,145	316,091
Adjusted R^2	0.122	0.049	0.167	0.226

Table 6. *Fund Firm Idio Volatility vs. Equity Idio Volatility*

This table reports the results of Fama and MacBeth (1973) regressions of fund firm *i*'s idiosyncratic volatility in month *t+1* on fund firm *i*'s equity portfolio idiosyncratic volatility in month *t* controlling for different equity portfolio characteristics. As equity portfolio characteristcs, we include the number of assets in the fund firm's portfolio, the portfolio herfindahl index, the portfolio industry Herfindahl index, portfolio turnover, one-month and 12-month equity portfolio return, portfolio beta, portfolio skewness, portfolio kurtosis, average portfolio stock size, average portfolio book-to-market value, average portfolio illiquidity, average portfolio investment, average portfolio profitability, and average portfolio leverage. All control variables are defined in Panel C of Table A.1. Specifications (1) and (2) are related to the intersection of hedge fund firms from the Union Hedge Fund Database (constructed from combining the Eureka, HFR, Morningstar, and Lipper TASS databases) and firms that report 13F long equity holdings to the SEC. The sample period is from January 1997 to December 2017. Specifications (3) and (4) are related to the intersection of hedge fund firms from the Union Hedge Fund Database (constructed from combining the Eureka, HFR, Morningstar, and Lipper TASS databases) that report 13F long equity holdings to the SEC and that are providing portfolio transaction data to the brokerage firm Abel Noser (i.e., Abel Noser Data). The sample period is from January 1999 to September 2011. We use the Newey-West (1987) adjustment with 36 lags to adjust the standard errors for serial correlation. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

	Full Intersection		Intersection with Abel Noser	
	(1)	(2)	(3)	(4)
	Fund Firm Idio Vola	Fund Firm Idio Vola	Fund Firm Idio Vola	Fund Firm Idio Vola
Equity Idio Vola	0.262***	0.345***	0.168***	0.495**
	(14.49)	(7.69)	(4.73)	(2.30)
Number of Assets		-0.000351***		-0.00103**
		(-2.19)		(-2.34)
Herfindahl Index		1.386***		-0.907
		(3.08)		(-0.48)
Industry Herfindahl Index		-0.0945		-0.00321
		(-0.67)		(-0.31)
Portfolio Turnover		-0.772		0.725
		(-1.01)		(0.86)
Portfolio Beta		0.413***		0.940
		(5.85)		(0.95)
Equity 1m Portfolio Return		0.000836		-0.135
		(0.36)		(-1.31)
Equity 12m Portfolio Return		0.00579***		0.0200
		(2.89)		(1.01)
Portfolio Skewness		0.177		1.859
		(0.98)		(1.43)
Portfolio Kurtosis		0.0585		-1.953
		(1.12)		(-0.74)
Portfolio Stock Size		-0.0242*		-0.0991*
		(-1.87)		(-1.91)
Portfolio Book-to-Market		0.741***		0.324
		(2.93)		(1.08)
Portfolio Illiquidity		2.276***		0.141
		(5.09)		(0.06)
Portfolio Investment		0.00292		-0.000280
		(0.90)		(-0.51)
Portfolio Profitability		0.00113		0.00715
		(1.26)		(0.72)
Portfolio Leverage		-0.00849		0.0589
		(-0.72)		(0.16)
Constant	1.544***	-4.564***	1.721***	-1.637
	(10.03)	(-3.16)	(7.05)	(-1.63)
Observations	43,311	42,610	1,955	1,955
Adjusted R^2	0.088	0.228	0.164	0.587

Table 7. Stocks: *Idiosyncratic Volatility* and Future Returns

This table reports the results of univariate portfolio sorts and Fama and MacBeth (1973) regressions between idiosyncratic volatility in month *t* and the cross-section of average stock returns and Fung and Hsieh (2004) nine-factor alphas in month *t*+1. In Panel A we show the results of value-weighted univariate portfolio sorts for the time period from January 1997 to December2017. Specification (1) reports the results of portfolio sorts between idiosyncratic volatility in month *t* as well as average stock returns and Fung and Hsieh (2004) nine-factor alphas in month *t+1* for the whole cross-section of average stock returns. Specification (2) reports the results of portfolio sorts of stocks with high hedge fund ownership. To define the degree of hedge fund ownership for an individual stock, we compute the number of appearances of the stock in all fund firm portfolios and months. We classify hedge fund ownership of a stock *j* in month *t* as high, when hedge fund ownership of the stock is in the top half (in terms of number of hedge fund firms holding the stock in their long equity portfolio), conditional that there is at least one hedge fund firm holding the stock. We classify hedge fund ownership of a stock *j* in month *t* as low, when hedge fund ownership is in the bottom half (in terms of number of hedge funds holding the stock in their long equity portfolio), conditional that there is at least one hedge fund firm holding the stock, or no hedge fund firm is holding the stock at all. Specification (3) reports the results of sorts of stocks with low hedge fund ownership. We also report differences in average idiosyncratic volatility, returns, and alphas between portfolios of the high hedge fund ownership sample and the low hedge fund ownership sample. Panel B reports the results of the univariate portfolio sorts for the extended sample in the time period from January 1980 to December 2017. In Panel C we show the results of Fama and MacBeth (1973) regressions between idiosyncratic volatility in month *t* and returns in month *t*+1 for the whole cross-section of average stock returns, for the sample of stocks with high hedge fund ownership, and the sample of stocks with low hedge fund ownership in the time period from January 1980 to December 2017. As control variables, we include a stock's beta, one-month and 12-month excess return, skewness, kurtosis, size, book-to-market value, illiquidity, profitability, investment, and leverage. All control variables are defined in Panel D of Table A.1. Our sample covers the filtered sample of all U.S. common stocks traded on the NYSE / AMEX / NASDAQ. We use the Newey-West (1987) adjustment with 36 lags to adjust the standard errors for serial correlation. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

Panel A: Portfolio Sorts: 1997 – 2017

	(1) Cross-Section of Stock Returns (Value-Weighted)			(2) Stocks with High Hedge Fund Ownership			(3) Stocks with Low Hedge Fund Ownership			(4) Differences between High and Low HF Ownership Samples		
Portfolio	Idio Vola	Returns	Alphas	Idio Vola	Returns	Alphas	Idio Vola	Returns	Alphas	Idio Vola	Returns	Alphas
Q1	5.35%***	0.72%***	0.17%	5.16%***	0.36%**	-0.23%	5.67%***	1.05%***	0.45%*	-0.51%	-0.69%**	-0.68%*
Q2	8.00%***	0.73%***	0.18%	7.48%***	0.68%**	0.05%	8.08%***	0.92%**	0.35%	-0.60%	-0.24%	-0.30%
Q3	10.98%***	0.64%***	0.06%	9.87%***	0.72%***	0.16%	11.79%***	0.74%*	0.15%	-1.92%***	-0.02%	0.01%
Q4	14.90%***	0.58%***	0.02%	12.98%***	0.91%***	0.31%	16.11%***	0.48%	-0.07%	-3.13%***	0.43%*	0.38%
Q5	23.58%***	0.00%	-0.41%*	19.16%***	1.06%***	0.45%**	27.53%***	-0.48%*	-0.65%**	-8.37%***	1.54%***	1.10%***
Q5 – Q1	18.23%***	-0.72%*	-0.58%**	14.00%***	0.70%**	0.68%**	21.86%***	-1.53%***	-1.10%***	-7.86%***	2.23%***	1.78%***
		(-1.92)	(-2.01)		(2.29)	(2.43)		(-3.65)	(-3.25)	(-9.56)	(4.53)	(3.96)

Panel B: Portfolio Sorts: 1980 – 2017

	(1) Cross-Section of Stock Returns (Value-Weighted)			(2) Stocks with High Hedge Fund Ownership			(3) Stocks with Low Hedge Fund Ownership			(4) Differences between High and Low HF Ownership Samples		
Portfolio	Idio Vola	Returns	Alphas	Idio Vola	Returns	Alphas	Idio Vola	Returns	Alphas	Idio Vola	Returns	Alphas
Q1	5.24%***	0.87%***	0.33%	4.93%***	0.44%*	-0.20%	5.53%***	1.16%***	0.51%**	-0.60%	-0.72%**	-0.71%*
Q2	7.35%***	0.78%**	0.24%	6.92%***	0.79%**	0.12%	7.65%***	0.94%***	0.43%*	-0.73%*	-0.15%	-0.31%
Q3	10.81%***	0.67%*	0.13%	9.87%***	0.80%***	0.21%	11.50%***	0.65%*	0.15%	-1.63%**	0.15%	0.06%
Q4	14.49%***	0.55%*	0.00%	13.12%***	0.93%***	0.29%*	15.90%***	0.38%	-0.13%	-2.78%***	0.55%**	0.42%*
Q5	21.75%***	-0.17%	-0.52%**	17.14%***	1.34%***	0.65%**	24.28%***	-0.67%*	-1.04%***	-7.14%***	2.01%***	1.69%***
Q5 – Q1	16.51%***	-1.04%***	-0.85%**	12.21%***	0.90%***	0.85%***	18.75%***	-1.83%***	-1.55%***	-6.54%***	2.73%***	2.40%***
		(-3.46)	(-2.54)		(3.34)	(3.06)		(-5.49)	(-4.52)	(-9.23)	(6.02)	(5.42)

Panel C: Fama-MacBeth (1973) Regressions: 1980 – 2017

	(1) Cross-Section of Stock Returns, Future Return	(2) Stocks with High HF Ownership, Future Return	(3) Stocks with Low HF Ownership, Future Return
Idio Vola	-0.0225**	0.0408***	-0.0320***
	(-2.22)	(4.44)	(-3.01)
Beta	0.213**	-0.187	0.301***
	(2.40)	(-1.55)	(3.32)
1m Stock Return	-0.0443***	-0.0336***	-0.0485***
	(-8.06)	(-4.58)	(-8.97)
12m Stock Return	0.00865***	0.00684***	0.00938***
	(5.92)	(2.79)	(7.90)
Skewness	-0.00368	-0.186***	0.0716*
	(-0.11)	(-3.63)	(1.78)
Kurtosis	-0.0219	-0.0331	-0.0341**
	(-1.55)	(-1.04)	(-2.23)
Size	-0.0917***	-0.000659	-0.212***
	(-3.24)	(-0.01)	(-5.29)
Book-to-Market	1.515***	1.349***	1.565***
	(5.42)	(6.12)	(5.43)
Illiquidity	0.0103*	0.0306	0.00590
	(1.86)	(1.52)	(1.20)
Investment	0.000163***	0.000107***	0.000114***
	(5.80)	(5.07)	(5.45)
Profitability	0.00305***	0.00197***	0.00491***
	(4.20)	(3.07)	(5.64)
Leverage	-0.0385***	-0.0215***	-0.0443***
	(-3.21)	(-3.37)	(-4.01)
Constant	1.001**	-0.141	2.262***
	(2.01)	(-0.15)	(3.76)
Observations	1,419,397	522,338	897,059
Adjusted R^2	0.057	0.092	0.054

Table 8. *Idiosyncratic Volatility* of Stocks with High and Low Hedge Fund Ownership

Panel A of this table reports frequencies of stocks that are classified as stocks with high hedge fund ownership (column 1) and low hedge fund ownership (column 2) in portfolio sorts based on idiosyncratic volatility. To define the degree of hedge fund ownership for an individual stock, we compute the number of appearances of the stock in all fund firm portfolios and months. We classify hedge fund ownership of a stock *j* in month *t* as high, when hedge fund ownership of the stock is in the top half (in terms of number of hedge fund firms holding the stock in their long equity portfolio), conditional that there is at least one hedge fund firm holding the stock. We classify hedge fund ownership of a stock *j* in month *t* as low, when hedge fund ownership is in the bottom half (in terms of number of hedge funds holding the stock in their long equity portfolio), conditional that there is at least one hedge fund firm holding the stock, or no hedge fund firm is holding the stock at all. Column (3) reports the difference in frequencies between stocks with high and low hedge fund ownership per portfolio. In column (4), we compute a portfolio's adjusted frequency difference by summing up the value of column (3) with 26.34% (i.e., the difference in unconditional hedge fund ownership). In Panel B we show the results of Fama and MacBeth (1973) regressions between a stock's hedge fund ownership and idiosyncratic volatility as well as indicator variables that take the value of one if the stock is in idiosyncratic volatility quintile portfolio 2 (3, 4, 5) in month *t*. As control variables, we include a stock's beta, one-month and 12-month excess return, skewness, kurtosis, size, book-to-market value, illiquidity, profitability, investment, and leverage. All control variables are defined in Panel D of Table A.1. Our sample covers the filtered sample of all U.S. common stocks traded on the NYSE / AMEX / NASDAQ in the time period from 1980 to 2017. We use the Newey-West (1987) adjustment with 36 lags to adjust the standard errors for serial correlation. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

Panel A: Adjusted Frequencies

Portfolio	(1) High HF Ownership	(2) Low HF Ownership	(3) Differences: High - Low	(4) Adjusted Frequency Difference
Uncon- ditional	36.83%	63.17%	-26.35%*** (9.56)	-
Q1	47.71%	52.29%	-4.58%*** (-3.65)	+21.77%*** (12.56)
Q2	45.93%	54.07%	-8.14%*** (-6.13)	+18.21%*** (11.34)
Q3	40.56%	59.44%	-18.88%*** (-9.43)	+7.47%*** (9.11)
Q4	34.52%	65.48%	-30.96%*** (-15.06)	-4.61%*** (-3.56)
Q5	15.41%	84.59%	-69.18%*** (-38.32)	-42.83%*** (-26.83)
Average	36.83%	63.17%	-26.34%	+0.00%

Panel B: Fama-MacBeth (1973) Regressions

	(1) Hedge Fund Ownership	(2) Hedge Fund Ownership
Idio Vola	0.189***	
	(4.19)	
Idio Vola^2	-0.00203***	
	(-5.99)	
Idio Vola Portfolio Q2		0.159
		(0.62)
Idio Vola Portfolio Q3		0.617*
		(1.77)
Idio Vola Portfolio Q4		1.111***
		(2.86)
Idio Vola Portfolio Q5		-1.902***
		(-4.52)
Beta	-0.310*	-0.262
	(-1.89)	(-1.64)
1m Stock Return	-0.0235***	-0.0237***
	(-5.13)	(-5.11)
12m Stock Return	-0.00846***	-0.00826***
	(-4.37)	(-4.30)
Skewness	-0.137*	-0.107*
	(-1.95)	(-1.66)
Kurtosis	0.0468***	0.0720***
	(4.19)	(4.62)
Size	4.831***	4.817***
	(6.34)	(6.33)
Book-to-Market	2.038***	1.974***
	(6.71)	(6.82)
Illiquidity	0.177***	0.177***
	(4.08)	(4.09)
Investment	0.00191***	0.00190***
	(5.01)	(4.96)
Profitability	0.0320***	0.0320***
	(6.78)	(6.81)
Leverage	0.00607	0.00580
	(1.00)	(1.04)
Constant	-54.95***	-53.67***
	(-6.00)	(-5.99)
Observations	1,431,103	1,431,103
Adjusted R^2	0.696	0.697

Table 9. *Idiosyncratic Volatility* and *MAX* of Stocks with High and Low Hedge Fund Ownership

Panel A of this table reports the results of value-weighted univariate portfolio sorts between average idiosyncratic volatility in month *t* and average *MAX* over the past 12 months for the cross-section of average stock returns (column 1), for stocks with high hedge fund coverage (column 2), and for stocks with low hedge fund coverage (column 3). To define the degree of hedge fund ownership for an individual stock, we compute the number of appearances of the stock in all fund firm portfolios and months. We classify hedge fund ownership of a stock *j* in month *t* as high, when hedge fund ownership of the stock is in the top half (in terms of number of hedge fund firms holding the stock in their long equity portfolio), conditional that there is at least one hedge fund firm holding the stock. We classify hedge fund ownership of a stock *j* in month *t* as low, when hedge fund ownership is in the bottom half (in terms of number of hedge funds holding the stock in their long equity portfolio), conditional that there is at least one hedge fund firm holding the stock, or no hedge fund firm is holding the stock at all. We define *MAX* as the stock's maximum daily return over the past 12 months following Bali, Cakici, and Whitelaw (2011). Column (4) reports the results of differences in idiosyncratic volatilities and *MAX*s between stocks with high and low hedge fund ownership. Panel B of this table reports adjusted frequency differences of hedge fund ownership (see Section 6.2) for portfolios dependently double-sorted by a stock's *Idio Vola* and *MAX*. We also provide the average adjusted frequency differences across all double-sorted portfolios based on idiosyncratic volatility and *MAX* in the last column and row of the panel. In Panel C we show the results of Fama and MacBeth (1973) regressions between a stock's hedge fund ownership, idiosyncratic volatility, and *MAX*, as well as indicator variables that take the value of one if the stock is in idiosyncratic quintile portfolio 2 (3, 4, 5) and corresponding interactions with MAX in month *t*. As control variables, we include a stock's beta, one-month and 12-month excess return, skewness, kurtosis, size, book-to-market value, illiquidity, profitability, investment, and leverage. All control variables are defined in Panel D of Table A.1. Our sample covers the filtered sample of all U.S. common stocks traded on the NYSE / AMEX / NASDAQ in the time period from 1980 to 2017. We use the Newey-West (1987) adjustment with 36 lags to adjust the standard errors for serial correlation. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

Panel A: Portfolio Sorts

	(1) All Stocks		(2) High HF Ownership		(3) Low HF Ownership		(4) Differences: High - Low	
	Idio Vola	MAX	Idio Vola	MAX	Idio Vola	MAX	Idio Vola	MAX
Q1	5.24%***	3.82%***	4.93%***	3.74%***	5.53%***	3.89%***	-0.60%	-0.15%
2	7.35%***	5.70%***	6.92%***	4.99%***	7.65%***	6.39%***	-0.73%*	-1.40%**
3	10.81%***	7.74%***	9.87%***	6.40%***	11.50%***	8.64%***	-1.63%**	-2.24%***
4	14.49%***	10.39%***	13.12%***	8.22%***	15.90%***	11.64%***	-2.78%***	-3.42%***
Q5	21.75%***	15.38%***	17.14%***	9.01%***	24.28%***	19.90%***	-7.14%***	-10.89%***
Average	11.93%***	8.63%***	10.40%***	6.47%***	12.97%***	10.09%***	-2.58%***	-3.62%***

Panel B: Standardized Frequencies of High Hedge Fund Ownership

MAX		Idio Vola Q1	Idio Vola Q2	Idio Vola Q3	Idio Vola Q4	Idio Vola Q5	Average
Q1	High Ownership	+23.75%***	+21.94%	+18.21%***	+16.56%***	+9.57%***	+18.01%***
Q2	High Ownership	+17.89%***	+17.10%***	+12.52%***	+10.21%***	-1.57%*	+11.23%***
Q3	High Ownership	+13.43%***	+12.34%***	+4.28%***	-0.44%	-19.99%***	+1.92%*
Q4	High Ownership	+2.32%**	+1.44%*	-3.23%**	-8.17%***	-31.27%***	-7.78%***
Q5	High Ownership	-13.52%***	-14.72%***	-20.92%***	-26.05%***	-41.68%***	-23.38%***
Average	High Ownership	+8.77%***	+7.62%***	+2.17%**	-1.58%	-16.99%***	+0.00%

Panel C: Fama-MacBeth (1973) Regressions

	(1) Hedge Fund Ownership	(2) Hedge Fund Ownership
Idio Vola	0.175***	
	(3.66)	
Idio Vola^2	-0.00192***	
	(-2.74)	
MAX	-0.158**	
	(-2.46)	
Idio Vola × MAX	-0.00451***	
	(-3.61)	
Idio Vola Portfolio Q2		0.570
		(1.12)
Idio Vola Portfolio Q3		0.0223
		(0.04)
Idio Vola Portfolio Q4		0.625**
		(1.98)
Idio Vola Portfolio Q5		-1.185***
		(-3.12)
Idio Vola Portfolio Q1 × MAX		-0.00923
		(-0.89)
Idio Vola Portfolio Q2 × MAX		-0.0108**
		(-2.34)
Idio Vola Portfolio Q3 × MAX		-0.0394**
		(-2.42)
Idio Vola Portfolio Q4 × MAX		-0.0398***
		(-2.90)
Idio Vola Portfolio Q5 × MAX		-0.0529***
		(-4.37)
Controls	Yes	Yes
Constant	-55.03***	-53.37***
	(-5.99)	(-6.11)
Observations	1,431,103	1,431,103
Adjusted R^2	0.698	0.698

Table 10. *Idiosyncratic Volatility* and Mispricing of Stocks with High and Low Hedge Fund Ownership

Panel A of this table reports the results of value-weighted univariate portfolio sorts between average idiosyncratic volatility in month *t* and average mispricing (*MP*) for the cross-section of average stock returns (column 1), for stocks with high hedge fund coverage (column 2), and for stocks with low hedge fund coverage (column 3). To define the degree of hedge fund ownership for an individual stock, we compute the number of appearances of the stock in all fund firm portfolios and months. We classify hedge fund ownership of a stock *j* in month *t* as high, when hedge fund ownership of the stock is in the top half (in terms of number of hedge fund firms holding the stock in their long equity portfolio), conditional that there is at least one hedge fund firm holding the stock. We classify hedge fund ownership of a stock *j* in month *t* as low, when hedge fund ownership is in the bottom half (in terms of number of hedge funds holding the stock in their long equity portfolio), conditional that there is at least one hedge fund firm holding the stock, or no hedge fund firm is holding the stock at all. We define *MP* as a stock's composite rank as the arithmetic average of its ranks for 11 different asset pricing anomalies following Stambaugh, Yu, and Yuan (2015). Column (4) reports the results of differences in idiosyncratic volatilities and MPs between stocks with high and low hedge fund ownership. Panel B of this table reports adjusted frequency differences of hedge fund ownership (see Section 6.2) for portfolios dependently double-sorted by a stock's *Idio Vola* and *MP*. We also provide the average adjusted frequency differences across all double-sorted portfolios based on idiosyncratic volatility and *MP* in the last column and row of the panel. In Panel C we show the results of Fama and MacBeth (1973) regressions between a stock's hedge fund ownership, idiosyncratic volatility, and *MP*, as well as indicator variables that take the value of one if the stock is in idiosyncratic quintile portfolio 2 (3, 4, 5) and corresponding interactions with *MP* in month *t*. As control variables, we include a stock's beta, one-month and 12-month excess return, skewness, kurtosis, size, book-to-market value, illiquidity, profitability, investment, and leverage. All control variables are defined in Panel D of Table A.1. Our sample covers the filtered sample of all U.S. common stocks traded on the NYSE / AMEX / NASDAQ in the time period from 1980 to 2017. We use the Newey-West (1987) adjustment with 36 lags to adjust the standard errors for serial correlation. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

Panel A: Portfolio Sorts

	(1) All Stocks		(2) High HF Ownership		(3) Low HF Ownership		(4) Differences: High - Low	
	Idio Vola	MP	Idio Vola	MP	Idio Vola	MP	Idio Vola	MP
Q1	5.24%***	44.20***	4.93%***	42.16***	5.53%***	47.09***	-0.60%	-4.93***
2	7.35%***	45.37***	6.92%***	43.09***	7.65%***	48.44***	-0.73%*	-5.35***
3	10.81%***	47.76***	9.87%***	44.09***	11.50%***	49.49***	-1.63%**	-5.40***
4	14.49%***	50.47***	13.12%***	45.49***	15.90%***	54.84***	-2.78%***	-9.35***
Q5	21.75%***	53.64***	17.14%***	47.15***	24.28%***	57.29***	-7.14%***	-10.14***
Average	11.93%***	48.29***	10.40%***	44.40***	12.97%***	51.43***	-2.58%***	-7.03***

Panel B: Frequencies of High Hedge Fund Ownership

MP		Idio Vola Q1	Idio Vola Q2	Idio Vola Q3	Idio Vola Q4	Idio Vola Q5	Average
Q1	High Ownership	+25.78%***	+23.62%***	+14.46%***	+11.35%***	+3.02%**	+15.65%***
Q2	High Ownership	+17.00%***	+16.03%***	+10.65%***	+6.65%***	-10.61%***	+7.94%***
Q3	High Ownership	+10.09%***	+9.49%***	+7.32%***	+3.29%***	-15.83%***	+2.87%**
Q4	High Ownership	+1.10%*	+0.75%	-2.24%*	-5.79%***	-24.86%***	-6.21%***
Q5	High Ownership	-10.58%***	-12.11%***	-19.40%***	-23.22%***	-35.95%***	-20.25%***
Average	High Ownership	+8.68%***	+7.56%***	+2.16%*	-1.54%*	-16.85%***	+0.00%

Panel C: Fama-MacBeth (1973) Regressions

	(1) Hedge Fund Ownership	(2) Hedge Fund Ownership
Idio Vola	0.0661**	
	(2.02)	
Idio Vola^2	-0.00414***	
	(-4.95)	
MP	-0.119***	
	(-3.42)	
Idio Vola × MP	-0.00572***	
	(-2.90)	
Idio Vola Portfolio Q2		0.891
		(1.47)
Idio Vola Portfolio Q3		0.504
		(1.07)
Idio Vola Portfolio Q4		0.801***
		(3.03)
Idio Vola Portfolio Q5		-1.652***
		(-3.69)
Idio Vola Portfolio Q1 × MP		-0.161***
		(-3.77)
Idio Vola Portfolio Q2 × MP		-0.290***
		(-3.00)
Idio Vola Portfolio Q3 × MP		-0.400***
		(-3.59)
Idio Vola Portfolio Q4 × MP		-0.504***
		(-3.37)
Idio Vola Portfolio Q5 × MP		-0.814***
		(-6.24)
Controls	Yes	Yes
Constant	-56.51***	-53.08***
	(-6.27)	(-6.33)
Observations	1,072,529	1,072,529
Adjusted R^2	0.711	0.713

Table 11. Individual Derivative Positions and *Idiosyncratic Volatility*

Panel A of this table reports the results of Fama and MacBeth (1973) regressions between a stock's *derivative and confidential position hedge fund ownership* and idiosyncratic volatility in month *t*. Specifications (1) and (2) report regression specification (1) from Panel B of Table 8 with *call option hedge fund ownership* and *put option hedge fund ownership* as the dependent variables. To define the degree of *call option hedge fund ownership* for an individual stock, we compute the number of appearances of call options on the individual stock in all fund firm portfolios and months. To define the degree of *put option hedge fund ownership* for an individual stock, we compute the number of appearances of put options on the individual stock in all fund firm portfolios and months. Specifications (3) and (4) report regression specification (1) from Panel C of Table 9 with *call option hedge fund ownership* and *put option hedge fund ownership* as the dependent variables. Specifications (5) and (6) report specification (1) from Panel C of Table 10 with *call option hedge fund ownership* and *put option hedge fund ownership* as the dependent variables. As control variables, we include a stock's beta, one-month and 12-month excess return, skewness, kurtosis, size, book-to-market value, illiquidity, profitability, investment, and leverage. All control variables are defined in Panel D of Table A.1. Panel B repeats the same regressions on a smaller sample where we exclude the smallest 30% of stocks in the cross-section in each month *t*. All control variables are included in the regression, but surpressed for illustration purposes. Our sample covers the filtered sample of all U.S. common stocks traded on the NYSE / AMEX / NASDAQ in the time period from April 1999 to 2017. We use the Newey-West (1987) adjustment with 36 lags to adjust the standard errors for serial correlation. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

Panel A: Portfolio Sorts (Full Sample)

	(1) Call Option Hedge Fund Ownership	(2) Put Option Hedge Fund Ownership	(3) Call Option Hedge Fund Ownership	(4) Put Option Hedge Fund Ownership	(5) Call Option Hedge Fund Ownership	(6) Put Option Hedge Fund Ownership
Idio Vola	0.0680***	-0.0359**	0.0670***	-0.0344**	0.0784***	-0.0368**
	(4.14)	(-2.10)	(3.99)	(-2.01)	(3.71)	(-2.22)
Idio Vola^2	-0.000973***	0.000653***	-0.000978***	0.000598***	-0.00112***	0.000456***
	(-4.49)	(3.40)	(-4.12)	(3.17)	(-3.80)	(2.82)
MAX			-0.00282***	0.00347**		
			(-2.79)	(2.00)		
Idio Vola × MAX			-0.00137**	0.00286***		
			(-2.14)	(3.37)		
MP					-0.00451**	0.00418*
					(-2.00)	(1.82)
Idio Vola × MP					-0.00185**	0.00168**
					(-2.06)	(2.56)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Constant	-5.242***	-4.903***	-5.273***	-4.930***	-5.877***	-5.507***
	(-4.58)	(-4.60)	(-4.57)	(-4.60)	(-4.48)	(-4.50)
Observations	753,237	753,237	753,237	753,237	568,737	1,431,103
Adjusted R^2	0.456	0.440	0.457	0.441	0.473	0.455

Panel B: Portfolio Sorts (Reduced Sample)

	(1) Call Option Hedge Fund Ownership	(2) Put Option Hedge Fund Ownership	(3) Call Option Hedge Fund Ownership	(4) Put Option Hedge Fund Ownership	(5) Call Option Hedge Fund Ownership	(6) Put Option Hedge Fund Ownership
Idio Vola	0.103***	-0.0397***	0.101***	-0.0338**	0.103***	-0.0363**
	(4.26)	(-2.83)	(4.08)	(-2.16)	(3.90)	(-2.34)
Idio Vola^2	-0.00155***	0.00102***	-0.00152***	0.000755***	-0.00161***	0.000438***
	(-4.60)	(4.33)	(-4.09)	(3.12)	(-4.42)	(2.95)
MAX			-0.00215**	0.00524**		
			(-2.45)	(2.16)		
Idio Vola × MAX			-0.00112**	0.00143**		
			(-2.01)	(2.44)		
MP					-0.00333*	0.00398*
					(-1.99)	(1.86)
Idio Vola × MP					-0.00195**	0.00195***
					(-2.29)	(2.84)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Constant	-7.885***	-7.393***	-7.938***	-7.440***	-8.038***	-7.565***
	(-4.75)	(-4.75)	(-4.74)	(-4.75)	(-4.60)	(-4.61)
Observations	527,266	527,266	527,266	527,266	470,579	470,579
Adjusted R^2	0.482	0.467	0.483	0.468	0.494	0.477

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Albertus-Magnus-Platz
D-50923 cologne
Fon +49(0)221-470-6995
Fax +49(0)221-470-3992
kempf@cfr-cologne.de
www.cfr-cologne.de