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ABSTRACT

This paper examines idiosyncratic volatility of equity-oriented hedge funds and provides an explanation for why there exists a positive cross-sectional relation between funds' idiosyncratic volatility and their future returns, whereas higher idiosyncratic volatility predicts lower returns in the cross-section of individual stocks. We find that idiosyncratic volatility is a persistent hedge fund characteristic and positively linked to proxies for managerial incentives, discretion, and leverage. Moreover, funds with a greater value of long call options and confidential equity positions disclosed with a delay in their regulatory filings exhibit higher idiosyncratic volatility. We document a positive (negative) cross-sectional relation between idiosyncratic volatility and future returns on individual stocks with high (low) hedge fund ownership. The results indicate that hedge funds are able to solve the idiosyncratic volatility puzzle by successfully picking undervalued, high-volatility stocks that offer high future returns and shying away from overvalued, high-volatility and lottery-like stocks that offer low future returns.

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

JEL Classification Numbers: G11, G23

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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 2017 (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 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, 2018) with the joint 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) with regard to the Fung and Hsieh (2004) seven-factor model 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

[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) for default 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, Joenväärä, Kosowski, and Tolonen (2016) for fund size, Aggarwal and Jorion (2010) and Papageorgiou, Parwada, and Tan (2014) for manager experience, Li, Zhang, and Zhao (2011) for manager education, and Teo (2009a) for a fund's geographical location.

[2] We show in Section 4.3 that our results are robust when computing *Fund Idio Vola* with regard to other hedge fund risk factor models.

paper, we document that funds with high *Fund Idio Vola* outperform funds with low *Fund Idio Vola* and investigate potential trading channels that explain funds' outperformance based on this measure.

In our empirical analysis we estimate *Fund Idio Vola* based on a rolling horizon of 24 months for 6,281 equity-oriented hedge funds in the Union Hedge Fund Database (which consists of merged four major databases; Eureka, Hedge Fund Research (HFR), Morningstar, and Lipper TASS) for the period from January 1996 to December 2012.[3] We find that average *Fund Idio Vola* is 2.82% across all funds and months in the sample with a median of 2.16% and a standard deviation of 2.24%. Among the different strategies, *Fund Idio Vola* is lowest for Equity Market Neutral and Event Driven, while it is highest for Sector, Equity Long Only, and Equity Long-Short hedge funds. Moreover, we observe that *Fund Idio Vola* is a persistent attribute of a fund: Results from a transition matrix analysis indicate that funds sorted in the portfolio decile with the highest (lowest) *Fund Idio Vola* in month *t*-24 remain in this top (bottom) decile portfolio in month *t* with a likelihood of 58% (36%).

We show that *Fund Idio Vola* has significant predictive power for the cross-section of future hedge fund returns. Results from multivariate regressions of future fund returns and Fung and Hsieh (2004) seven-factor alphas in month *t*+1 on a fund's idiosyncratic volatility and additional fund characteristics (such as a fund's monthly return, size, age, delta of the incentive fee contract, a fund's management and incentive fee, minimum investment amount, the length of a fund's lockup and restriction period, and indicator variables that equal one if the fund employs leverage, is an offshore fund, has a hurdle rate and a high water mark, respectively, and zero otherwise) in month *t* indicate that *Fund Idio Vola* is a positive determinant. Depending on the specification, it has a coefficient estimate between 0.0562 and 0.0710 and is statistically significant at least at the 5% level with a Newey-West (1987) *t*-statistic between 2.11 and 2.71.

[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 positions in Section 5.1.

Our results 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 (correlation of -0.18 to *Fund Idio Vola*) and the Sun, Wang, and Zheng (2012)'s strategy distinctiveness index (SDI, correlation of 0.09 to *Fund Idio Vola*).

We confirm the results of a positive pricing effect of a fund's idiosyncratic volatility 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 0.55% per month with a Newey-West *t*-statistic of 2.16. When controlling for the widely used risk factors of the Fung and Hsieh (2004) seven-factor model, the risk-adjusted return spread only slightly reduces to 0.40% per month, again statistically significant at the 5% level. 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 5.60% = (6.31% – 0.71%). Multiplying this spread by the coefficient estimates between 0.0562 and 0.0710 in the multivariate regressions yields an estimated monthly premium between 31.5 and 39.8 basis points which translates into an annualized premium between 3.78% and 4.78%. We also show that this premium is robust to a large number of additional hedge fund risk factor models.

We conduct a number of robustness checks to show that our results are not sensitive to several choices we make in our empirical analysis. Our results are stable and qualitatively similar when we change the estimation horizon of *Fund Idio Vola*, estimate *Fund Idio Vola* using the Carhart (1997) four-factor model or the extended Fung and Hsieh (2004) eight-factor model, restrict our sample to funds with an equity long-short strategy, assign a delisting return to those hedge funds that leave the database, unsmooth fund returns using the Getmansky, Lo, and Makarov (2004) procedure, and use future two-month ahead and three-month ahead returns as the dependent variable in the multivariate regressions.

Which fund characteristics are associated with *Fund Idio Vola*? We document 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 is in line with Titman and Tiu (2011) and Sun, Wang, and Zheng (2012) who document that size is negatively (positively) correlated with a fund's R2 (SDI). *Fund Idio Vola* is positively associated with a fund manager's incentive structure (proxied by the management fee, incentive fee, and delta) and discretion (proxied by the lock-up and restriction period of a fund). Moreover, we observe a positive relationship between *Fund Idio Vola* and the leverage dummy, suggesting that high *Fund Idio Vola* funds are likely to employ derivative securities or engage in short-selling transactions.

After having examined different fund characteristics, we take a closer look at *actual trading channels* that affect a fund's idiosyncratic volatility. Particularly, we examine the impact of a fund's long equity portfolio holdings, derivative positions, and confidential holdings on a fund's idiosyncratic volatility. For this purpose, we merge the reported fund data from the Union Hedge Fund Database with the reported 13F equity portfolio holdings, option positions and confidential holdings (i.e., holdings that are reported with a delay, see Agarwal, Jiang, Tang, and Yang, 2013, and Aragon, Hertzel, and Shi, 2013) of hedge fund firms. Our results indicate a strong positive relationship between a fund firm's idiosyncratic volatility, *Fund Firm Idio Vola*, and a fund firm's value-weighted idiosyncratic volatility average of individual stocks (*Equity Idio Vola*). Moreover, we observe that the use of long call options and confidential holdings increase *Fund Firm Idio Vola*.

Finally, we relate our result of a positive effect of idiosyncratic volatility on the cross-section of average hedge funds with the seemingly contradicting result of a negative effect of idiosyncratic volatility on the cross-section of average 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 is significantly negative for stocks with low hedge fund ownership (spread of -1.61% per month with a *t*-statistic of -3.54), it is significantly positive for stocks with high hedge fund ownership (spread of 0.70% per month with a *t*-statistic of 2.95).

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. In particular, 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 et al., 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 with regard to eleven stock market anomalies. Hence, by investing in undervalued, high idiosyncratic volatility stocks, hedge funds profit from a positive idiosyncratic volatility – future return relationship. Thus, we conclude that – by picking high volatility stocks in a prudent way – hedge funds have solved the idiosyncratic volatility puzzle.

This paper is structured as follows. Section 2 provides a brief literature review. Section 3 describes the data used in the empirical analysis. Section 4 introduces the idiosyncratic volatility measure and analyzes its relationship with future hedge fund performance and fund characteristics. Section 5 investigates actual trading channels that affect a fund's idiosyncratic volatility and Section 6 disentangles the impact of idiosyncratic volatility on hedge fund returns from the impact of idiosyncratic volatility on stock returns. Section 7 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 average 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 (2016) 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 (2009a) 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 (2018) relate actual derivative positions and confidential holdings to a fund firm's unobserved performance, i.e., the risk-adjusted difference between a fund firm's reported returns and its 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, derivatives positions and confidential holdings.

Third, we extend the literature on the idiosyncratic volatility puzzle in the cross-section of individual stocks. The literature on this asset pricing puzzle 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 trying to explain the puzzle: Among others, potential explanation 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 reversal (Fu, 2009), average variance beta (Chen and Petkova, 2012), and retail trading proportion (Han and Kumar, 2013).[4] Hou and Loh (2016) evaluate a large number of different 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 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. Finally, 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 as well as long equity

[4] In addition, there are studies who show 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.

positions that are disclosed with a delay (referred to as *confidential* by Agarwal, Jiang, Tang, and Yang, 2013).

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 65% of the funds only report to one database. We display the overlap between the four databases in Figure A.1 in the Appendix. The Union Hedge Fund Database includes data for 25,732 funds for the period from 1994 to 2012.

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 24 monthly return observations. We filter out all funds that are denoted 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', 'Equity Market Neutral', 'Short Bias' or 'Sector' as equity-oriented. Finally, our main variable of interest, *Fund Idio Vola* (see Section 4.1), is estimated based on a rolling window of 24 monthly return observations which uses the first two years of our sample. This filtering process leaves us with a final sample of 6,281 equity-oriented hedge funds for the period from January 1996 to December 2012.

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.

[Insert Table 1 around here]

Summary statistics are calculated over all funds and months in our sample period and show that the average (median) excess return amounts to 0.62% (0.52%) 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 and the SEC EDGAR database are provided in Section 5 of the paper.

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 return of hedge fund *i* in month *t* on the risk factors of the Fung and Hsieh (2004) seven-factor model using a rolling estimation window of 24 months:

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

where $r_{i,t}$ denotes fund i's reported return in month *t*, and $S\&P_t$, $SCMLC_t$, $BD10RET_t$, $BAAMTSY_t$, $PTFSBD_t$, $PTFSFX_t$, and $PTFSCOM_t$ denote the risk factors of the Fung and Hsieh (2004) seven-factor model.[5] 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 24 monthly residuals of the regression in eq. (1):

$$FUND\ IDIO\ VOLA_{i,t} = STDEV(\varepsilon_{i,t}). \quad (2)$$

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) seven-factor model. Hence, hedge funds with high *Fund Idio Vola* conduct investment strategies

[5] In Section 4.3 we perform a robustness check and compute *Fund Idio Vola* using the risk factors of the Fama-French-Carhart four-factor model and an extended eight-factor model (Fung and Hsieh seven-factor model extended with an emerging equity markets factor). Our main results are robust across different factor models.

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 2.82% across all funds and months in the sample with a median of 2.16% and a standard deviation of 2.24%. Among the different strategies, *Fund Idio Vola* is lowest for Equity Market Neutral and Event Driven, while it is highest for Sector, Equity Long Only, and Equity Long-Short hedge funds. For the two remaining strategies, Emerging Markets and Short Bias, *Fund Idio Vola* is close to the overall sample mean (2.82%). 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 total volatility and systematic volatility, return, a manager's delta, management fee, as well as a fund's offshore location and leverage. It is negatively related to a fund's size, age, and minimum investment. 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 persistence 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* decile portfolio i in month t given that it was in *Fund Idio Vola* decile portfolio j in month t-24 during our sample period from January 1996 to December 2012.

[Insert Table 2 around here]

If there were no persistence in *Fund Idio Vola*, all frequencies would be 10% because high (low) *Fund Idio Vola* in month t-24 should have no predictive ability about high (low) *Fund Idio Vola* in month t. Instead we find evidence of substantial persistence in *Fund Idio Vola*: Funds which are sorted into portfolio 10 (1) in month t-24 show up again in portfolio 10

(1) with a likelihood of 58% (36%). 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 deciles 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 four years. Figure 1 displays the results.

[Insert Figure 1 around here]

We observe that funds in decile portfolio 10 (i.e., funds with high *Fund Idio Vola*) consistently show higher *Fund Idio Vola* in the following years than funds in decile portfolio 1 (i.e., fund firms with low *Fund Idio Vola*). Hence, our results indicate that *Fund Idio Vola* is indeed a long-term persistent attribute of hedge funds which is likely to have an impact on fund performance. We will investigate this idea 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 relate fund returns and alphas in month *t*+1 to *Fund Idio Vola* measures in month *t*. In particular, we run Fama and MacBeth (1973) regressions of future fund returns and alphas in month *t*+1 on fund total volatility, fund idiosyncratic volatility, and fund systematic volatility as well as additional fund characteristics as control variables in month *t*:

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

where $r_{i,t+1}$ denotes fund *i*'s reported return in month *t*+1, $FV_{i,t}$ a fund's total volatility, $FIV_{i,t}$ a fund's idiosyncratic volatility, $FSV_{i,t}$ a fund's systematic volatility, and $X_{i,t}$ is a vector of fund characteristics, such as a fund's monthly return, size, age, delta of the incentive fee contract, a fund's management and incentive fee, minimum investment amount, the length of a fund's lockup and restriction period, and indicator variables that equal one if the fund employs leverage, is an offshore fund, has a hurdle rate and a high water mark, respectively, and zero otherwise. To adjust standard errors for potential serial correlation in monthly slope coefficients, we use the Newey and West (1987) adjustment with 24 lags. As additional fund characteristics, all variables defined in Table A.1 of the Appendix are included in the cross-sectional regressions. Panel A of Table 3 presents the results.

[Insert Table 3 around here]

In regression (1), we include a fund's volatility as the only explanatory variable. As in Bali, Brown, and Caglayan (2012), we find that the total volatility of a fund is a positive predictor for the cross-section of future hedge fund returns. It is statistically significant at the 5% level with a *t*-statistic of 2.13.

When we decompose the total volatility of a fund into an idiosyncratic component and a systematic component in regression (2), we find that only the idiosyncratic part of fund volatility, i.e., *Fund Idio Vola*, is priced, whereas the systematic part is not.[6]

In regressions (3) and (4), we include additional fund characteristics, such as a fund's past one-month return, size, age, delta of the incentive fee contract, a fund's management and incentive fee, minimum investment amount, the length of a fund's lockup and restriction period, and indicator variables that equal one if the fund employs leverage, is an offshore fund, has a hurdle rate and a high water mark, respectively, and zero otherwise. 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, Teo, 2009b, and Joenväärä, Kosowski, and Tolonen, 2016) has a negative

[6] This finding contradicts with the empirical results reported in Bali, Brown, and Caglayan (2012). The differences in results are due to three discrepancies in the empirical setup: First, Bali, Brown, and Caglayan (2012) investigate the impact of systematic and idiosyncratic variance on future hedge fund returns, whereas our paper uses systematic and idiosyncratic volatility (standard deviation) as predictors to be consistent with the idiosyncratic volatility literature (e.g., Ang et al., 2006). Second, our paper works with a larger sample size; while Bali, Brown, and Caglayan (2012) solely use the Lipper TASS database in the empirical analysis, this paper takes advantage of the Union Hedge Fund Database – consisting of merged Eureka, Hedge Fund Research (HFR), Morningstar, and Lipper TASS databases – which results in extended hedge fund coverage. Finally, this paper uses a 3-year longer sample period, i.e. asset pricing tests are evaluated over the period from 1996 to 2012, while Bali, Brown, and Caglayan (2012) investigate the time period from 1997 to 2010.

impact. More importantly in our context, our results indicate that the inclusion of control variables does not affect the positive and statistically significant impact of fund total volatility in regression (3) and fund idiosyncratic volatility in regression (4).

In regression (5), we repeat regression set up (4) but use Fung and Hsieh (2004) seven-factor alphas instead of fund raw returns as the independent variable. We compute a fund's individual Fung and Hsieh (2004) seven-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 with regard to the Fung and Hsieh (2004) risk factors estimated over the time period from month t-24 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. Finally, regression (6) also controls for the impact of other activeness measures, as we include Titman and Tiu (2011)'s R2 measure and Sun, Wang, and Zheng (2012)'s strategy distinctiveness index (SDI) in the setup. We again find that the impact of *Fund Idio Vola* remains statistically strong.[7]

In addition to fund-level Fama-MacBeth regressions, we provide evidence from univariate portfolio sorts. For each month t from January 1996 to December 2012, 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 B of Table 3 shows the average *Fund Idio Vola*, the next month average return in month t+1, and the Fung and Hsieh (2004) seven-factor alpha for each quintile. The last row in Panel B of Table 3 displays the average return and 7-factor alpha differences between quintiles 5 and 1 along with the Newey-West t-statistics in parentheses.

[7] At the same time, we confirm 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.

Moving from quintile 1 to quintile 5, we observe that average raw returns on the *Fund Idio Vola* portfolios increase monotonically from 0.28% to 0.83% per month. This indicates a monthly average raw return difference of 0.55% between quintiles 5 and 1 (i.e., high *Fund Idio Vola* vs. low *Fund Idio Vola* quintiles) with a *t*-statistic of 2.16, suggesting that this positive return difference is economically and statistically significant. Hence, hedge funds in the highest *Fund Idio Vola* quintile generate about 6.60% higher annual returns compared to funds in the lowest *Fund Idio Vola* quintile. We also find that the seven-factor alpha difference between quintiles 5 and 1 is 0.40% with a *t*-statistic of 2.25, 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 seven-factor alphas of quintile 1 vs. quintile 5. Panel B of Table 3 shows that the average return and the seven-factor alpha of quintile 1 are 0.28% and 0.17% per month with *t*-statistics of 1.39 and 1.21, 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 seven-factor alpha of quintile 5 are 0.83% and 0.57% per month with *t*-statistics of 2.75 and 3.20, 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. We display the cumulative returns of a hypothetical trading strategy based on *Fund Idio Vola* in Figure 2.

[Insert Figure 2 around here]

To implement the strategy, we go long (short) the quintile of hedge funds with the highest (lowest) *Fund Idio Vola* and apply monthly rebalancing without accounting for trading costs. We observe that an investment of $100 at the beginning of 1996 (i.e., at the end of the first estimation of *Fund Idio Vola* based on a horizon of 24 months) grows to $237.62 at the end of the year 2012.[8]

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. As discussed earlier, the average return and alpha spreads between quintiles 5 and 1 are 0.55% and 0.40%, respectively. The economic magnitude of the associated effect from fund-level Fama-MacBeth regressions is similar. Specifically, the spread in average *Fund Idio Vola* between quintiles 5 and 1 is approximately 5.60% = (6.31% – 0.71%), and multiplying this spread by the average slope coefficients between 0.0562 and 0.0710 in Panel A of Table 3 yield estimated monthly premia ranging from 31.5 to 39.8 basis points. This translates into a range of annualized fund-specific volatility premia between 3.78% and 4.78%.

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 C 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 an 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, and the Gao, Gao, and Song (2018). Hence, these additional asset pricing factors are not able to explain the *Fund Idio Vola* spread.

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

[8] We acknowledge that it is not feasible to short hedge funds. Nevertheless, since the *Fund Idio Vola* spread is due to outperformance by the high idiosyncratic volatility funds, the profit of the strategy can be also realized by long-only investments.

significant determinant even when we control for a standard set of hedge fund risk factors and a large number of fund characteristics.

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 robustness checks are conducted. To do so, we investigate the robustness of our results by (i) estimating *Fund Idio Vola* using a rolling estimation window of 36 months instead of 24 months, (ii) estimating *Fund Idio Vola* using the Fama-French-Carhart four-factor model and the extended Fung and Hsieh (2004) eight-factor model (extension by an emerging equity market factor), (iii) restricting our sample to hedge fund firms with an equity long-short strategy, (iv) assigning a delisting return of –1.61% as in Hodder, Jackwerth, and Kolokolova (2014) to those hedge funds that leave the database, (v) applying the correction method of Getmansky, Lo, and Makarov (2004) to unsmooth hedge fund returns, and (vi) use 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 Table 3) of future fund firm returns on *Fund Idio Vola* and different fund characteristics measured in month *t*.

[Insert Table 4 around here]

We only report the average slope coefficient estimate for *Fund Idio Vola*. Other control variables are included in the regressions, but suppressed in the table. For ease of comparison, we report in the first column of Table 4 the baseline results from model (4) in Table 3. Across all robustness checks, we continue to find a positive and statistically significant effect of *Fund Idio Vola* on future fund firm returns.

4.4. Idiosyncratic Volatility and Fund Characteristics

Sections 4.2 and 4.3 document that *Fund Idio Vola* is a robust variable to predict 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 the following regression 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. As fund characteristics, all variables defined in Table A.1 of the Appendix are included. We adjust standard errors for autocorrelation using the Newey and West (1987) correction method with 24 lags. Table 5 reports the results.

[Insert Table 5 here]

In model (1), we include time-varying fund characteristics, such as a fund's monthly return, size, fund age, and a manager's delta as 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 which is in line with Titman and Tiu (2011) and Sun, Wang, and Zheng (2012) who show that smaller hedge funds have lower R^2 values with regard to hedge fund factor models and have higher strategy distinctiveness in their investment strategies, respectively.

Model (2) includes time-invariant fund characteristics such as a fund's management and incentive fee, minimum investment, lockup and restriction period, as well as indicator variables for 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. We also observe that higher management and incentive fees enhance *Fund Idio Vola* which is consistent with the notion that better incentivized managers engage in investment strategies that are not easily replicable by traditional systematic risk factors.

Finally, model (3) includes all fund characteristics together. We continue to observe that *Fund Idio Vola* exhibits a significant positive assocation with a fund's monthly return, lockup period, and management fee, as well as a negative relationship with fund size and minimum investment. We also find significant correlations of *Fund Idio Vola* with a fund manager's delta, offshore domicile, leverage usage, high watermark, and hurdle rate.

To summarize, we provide evidence that a fund's idiosyncratic volatility is significantly related to certain fund characteristics. In particular, we find that smaller funds, funds with higher discretion, funds with higher incentive structures, and funds with higher leverage show high *Fund Idio Vola*.

5. Determinants of Idiosyncratic Volatility: Evidence from Actual Holdings

So far, we have examined which fund characteristics are associated with a fund's idiosyncratic volatility. We now delve into *actual trading channels* that lead to high idiosyncratic volatility in a fund's reported return. Specifically, we look at *Fund Idio Vola* induced by idiosyncratic volatility from a fund's long equity portfolio holdings (Section 5.1), derivative positions (Section 5.2), and confidential holdings (Section 5.3).

5.1. Equity Positions

In this section we analyze whether high idiosyncratic volatility in a fund's reported return can be related to investments in stocks with high idiosyncratic volatility. Specifically, we examine whether we can find direct evidence of the sources of *Fund Idio Vola* using their disclosed 13F portfolio holdings that include long positions in equities.

To establish direct evidence 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 5,536 institutional investors during the period from 1980 to 2012. 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.[9] We end up with a sample of 1,694 unique hedge fund firms among the 13F filing institutions holding a total value of $2.52 trillion of long equity positions in 2012, which is equivalent to 88% of the size of the hedge fund industry in the year 2012 (according to HFR).

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 24 overlapping periods of data from both data sources. We end up with 675 hedge fund firms managing 2,316 distinct funds during the period from 1996 to 2012.

Since portfolio holdings are reported only at the hedge fund firm level, we first compute a fund firm's idiosyncratic volatility, *Fund Firm Idio Vola*, in month t as the value-weighted average of *Fund Idio Vola* of the firm's individual funds. Second, using the portfolio information of the 13F equity holdings, we compute a fund firm's equity portfolio idiosyncratic volatility, *Equity Idio Vola* in month t. We do so as follows: To obtain a series of monthly equity return observations, we make the assumption 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.[10] We then regress the return of stock j in fund firm portfolio i at month t on the risk factors of the four-factor model of Fama-French (1993) and Carhart (1997) using a rolling estimation window of 24 months:

[9] 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.

[10] 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.

$$s_{j,t} = \alpha_{i,t} + \beta_{1,j,t} MARKET_t + \beta_{2,j,t} SMB_t + \beta_{3,j,t} HML_t + \beta_{4,j,t} UMD_t + \varepsilon_{j,t}\,, \tag{5}$$

where $s_{j,t+1}$ denotes stock *j'*s return in month *t*, and $MARKET_t$, SMB_t, HML_t, and UMD_t denote the risk factors of the Fama-French-Carhart four-factor model. All risk factors are defined in Panel B of Table A.1 in the Appendix. Finally, we compute a stock's idiosyncratic volatility based on a rolling estimation of 24 months as the standard deviation of the residuals of the regression in eq. (5),

$$STOCK\ IDIO\ VOLA_{i,t} = STDEV(\varepsilon_{j,t}), \tag{6}$$

and compute fund firm *i*'s *Equity Idio Vola* in month *t* as the value-weighted average of *Stock Idio Vola* of the firm's individual stocks.

To examine the relation between a fund firm's idiosyncratic volatility and equity portfolio idiosyncratic volatility, we estimate Fama and MacBeth (1973) regressions. We regress *Fund Firm Idio Vola* of hedge fund firm *i* in month *t* on its *Equity Idio Vola* in month *t* controlling for different equity portfolio risk characteristics using the Newey and West (1987) adjustment with 24 lags:

$$FFIV_{i,t} = \alpha + \beta_1 EIV_{i,t} + \beta_2 Y_{i,t} + \varepsilon_{i,t}\,, \tag{7}$$

where $FFIV_{i,t}$ denotes a fund firm's idiosyncratic volatility in month *t*, $EIV_{i,t}$ denotes equity portfolio idiosyncratic volatility in month *t*, and $Y_{i,t}$ is a vector of equity portfolio risk characteristics. As control variables, we include the number of assets in the portfolio, the portfolio herfindahl index, portfolio turnover, portfolio beta, portfolio skewness, portfolio kurtosis, portfolio size, portfolio book-to-market, portfolio illiquidity, portfolio r&d expenses, portfolio profitability, and portfolio leverage.[11] Table 6 presents the results.

[Insert Table 6 here]

In model (1), we use *Equity Idio Vola* as the only explanatory variable. It shows a positive impact (coefficient of 0.167) and is highly statistically significant at the 1% level. 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 additional equity portfolio risk 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 turnover as well as average stock characteristics such as book-to-market, r&d, and profitability. 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 an even higher coefficient estimate of 0.276, indicating that a one standard deviation rise in *Equity Idio Vola* leads to an increase in *Fund Firm Idio Vola* of $0.249 \times 1.97\% = 0.54\%$. Hence, a fund firm's idiosyncratic volatility is strongly positively related to its equity portfolio idiosyncratic volatility.

5.2. Derivative Positions

In addition to idiosyncratic volatility induced from long equity holdings, we now inspect another plausible channel through which a fund firm’s idiosyncratic volatility can be affected: derivative usage via long call and put options.

[11] Portfolio beta, portfolio skewness, portfolio kurtosis, portfolio size, portfolio book-to-market, portfolio illiquidity, portfolio r&d expenses, portfolio profitability, and portfolio leverage are computed as the value-weighted average of the individual stock characteristics in a fund firm's portfolio and are defined in Panel C of Table A.1 in the Appendix.

To empirically investigate this channel, we apply long call and put option holdings data from 13F filings in the SEC EDGAR database for the sample period from April 1999 to December 2012.[12] During this period 47.9% of fund firms (i.e., 323 of 675 firms) file at least one long option position. To merge 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 hedge fund firm *i* in month *t*, the number of different stocks on which funds hold call and put positions, the equivalent number of equity shares underlying these positions (in millions), and the equivalent value of equity shares underlying these positions (in millions) are computed.[13] To mitigate the influence of outliers, we winsorize the number and value of equity shares at the 1% level. We find that the average number of different stocks on which call (put) positions are held is 3.21 (3.28), the number of equity shares underlying the put (call) positions is 1.45 (1.49) million, and the value of equity shares underlying the put (call) positions is $15.75 (16.17) million.

We regress *Fund Firm Idio Vola* of hedge fund firm *i* in month *t* on its option holdings in month *t* using the Newey and West (1987) adjustment with 24 lags:

$$FFIV_{i,t} = \alpha + \beta_1 NDC_{i,t} + \beta_2 NDP_{i,t} + \beta_3 EDC_{i,t} + \beta_4 EDP_{i,t} + \beta_5 VDC_{i,t} + \beta_6 VDP_{i,t} + \varepsilon_{i,t}, \qquad (8)$$

where $FFIV_{i,t}$ again denotes a fund firm's idiosyncratic volatility in month *t*, $NDC_{i,t}$ and $NDP_{i,t}$ denote the number of different stocks on which funds hold call and put positions, $EDC_{i,t}$ and $EDP_{i,t}$ denote the log of one plus the equivalent number of equity shares underlying these

[12] All 13F filing institutions must report long call and put option position holdings on individual 13F securities. We again merge the hedge fund firms in the SEC EDGAR database with reported fund firm data in the Union Hedge Fund database.

[13] To illustrate these measures, we provide the following example: A fund firm holds call options on 10,000 shares of stock A that trades at $20 and 5,000 shares of stock B that trades at $30. It holds put options on 20,000 shares of stock C that trades at $40. Then, the number of stocks on which call options are held is 2 and the number of stocks on which put options are held is 1, the equivalent number of equity shares underlying the call options is 15,000 and the equivalent number of equity shares underlying the put options is 20,000, and the equivalent value of equity shares underlying the call options is $350,000 and the equivalent value of equity shares underlying the put options is $800,000.

positions (in millions), and $VDC_{i,t}$ and $VDP_{i,t}$ denote the log of one plus the equivalent value of equity shares underlying these positions (in millions). The results are presented in Table 7.

[Insert Table 7 here]

In specifications (1) through (4), *Fund Firm Idio Vola* is regressed on the different measures of option holdings activity. We find that, in a multivariate setting including all variables, the number and value of equity shares underlying the call positions significantly increase a fund firm's idiosyncratic volatility, whereas the number of put positions decreases *Fund Firm Idio Vola*. In terms of economic significance, we find that a one standard deviation increase in the number (value) of equity shares underlying the call positions enhances a fund firm’s idiosyncratic volatility by 0.09% (0.06%), whereas a one standard deviation increase in the number of put options decreases *Fund Firm Idio Vola* by -0.10%. Overall, these results provide evidence that derivative usage of hedge fund firms is an important channel that affects a fund firm’s idiosyncratic volatility.

5.3. Confidential Holdings

Another channel through which a fund firm’s idiosyncratic volatility can be potentially influenced is by *confidential holding* positions. 13F filing institutions can request confidential treatment from the SEC for certain holdings when delaying disclosure is *necessary or appropriate in the public interest or for the protection of investors*. If such a request is denied, or after the approval period of confidentiality expires, the filers must reveal these holdings by filing *amendments* to their original Form 13F. We refer to these amendments as confidential holdings. Agarwal, Jiang, Tang, and Yang (2013) and Aragon, Hertzel. And Shi (2013) find that these amendments are disproportionally associated with information-sensitive events, greater information assymmetry and higher volatility. Hence, it is likely that fund firms with a large number and value of confidential holdings display high *Fund Firm Idio Vola*.

Confidential holdings data are retrieved from the 13F filings in the SEC EDGAR database for the sample period from April 1999 to December 2012 and merged with the Union hedge fund database. During this time period, 15.26% of firms (i.e., 103 of 675 firms) file at least one confidential holdings position. In the same way as for derivative holdings, we apply the convention that dislosed positions in month *t* are carried forward for the subsequent months *t*+1 to *t*+3. We compute for hedge fund firm *i* in month *t*, the number of different confidential positions, the equivalent number of equity shares underlying these positions (in millions), and the equivalent value of equity shares underlying these positions (in millions).[14] To mitigate the influence of outliers, we winsorize the number and value of equity shares at the 1% level. We obtain an average number of confidential positions of 0.49, an average number of equity shares underlying the confidential positions of 0.23 million, and an average value of equity shares underlying the confidential positions of $6.55 million.[15]

We regress *Fund Firm Idio Vola* of hedge fund firm *i* in month *t* on its confidential positions in month *t* using the Newey and West (1987) adjustment with 24 lags:

$$FFIV_{i,t} = \alpha + \beta_1 NCP_{i,t} + \beta_2 NES_{i,t} + \beta_3 VES_{i,t} + \varepsilon_{i,t}, \tag{9}$$

where $FFIV_{i,t}$ denotes a fund's idiosyncratic volatility in month *t*, $NCP_{i,t}$ denotes the number of different confidential positions, $NES_{i,t}$ denotes the log of one plus the equivalent number of equity shares underlying these positions (in millions), and $VES_{i,t}$ denotes the log of one plus the equivalent value of equity shares underlying these positions (in millions). We report the results in Table 8.

[Insert Table 8 here]

[14] To illustrate these measures, we provide the following example: A fund firm files confidential positions on 10,000 shares of stock A that trades at $20 and 20,000 shares of stock B that trades at $30. Then, the number of different confidential positions is 2, the equivalent number of equity shares underlying these positions is 30,000, and the equivalent value of equity shares underlying these positions is $800,000.

[15] These averages are computed over all hedge fund firms and months in the sample period. Conditionally that a fund firm is filing confidentially, the average number of confidential positions is 30.54, the number of equity shares underlying the confidential positions is 11.75 million, and the value of equity shares underlying the confidential positions is $156.51 million.

Specifications (1) through (3) investigate the univariate relationships between *Fund Firm Idio Vola* and the number of different confidential positions, the equivalent number of equity shares underlying these positions, and the equivalent value of equity shares underlying these positions. Our results indicate that, in a univariate setting, all three measures of confidentiality significantly increase a fund firm's idiosyncratic volatility, respectively. In model (4) we perform a regression of *Fund Firm Idio Vola* on all three explanatory variables and find that the number of different confidential positions and the equivalent value of equity shares underlying the confidential positions remain statistically significant. In terms of economic significance, a one standard deviation increase in the number of different confidential positions (the equivalent value of equity shares underlying the confidential positions) enhances *Fund Firm Idio Vola* by 0.04% (0.10%). Hence, we obtain direct empirical evidence that confidential holdings are an important channel that influences a fund firm's idiosyncratic volatility.

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

Sections 4 and 5.1 document that a fund's idiosyncratic volatility has a positive impact on the cross-section of future hedge fund returns and that a fund's idiosyncratic volatility is strongly connected to idiosyncratic volatility stemming from its long equity positions. Now, we investigate this link closer and relate it to the impact of idiosyncratic volatility on the cross-section of average stock returns, a relationship widely known as the *idiosyncratic volatility puzzle*.

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) who 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 stock 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 asset pricing 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 this analysis by examining the impact of idiosyncratic volatility in the cross-section of average stock returns using univariate portfolio sorts. Our stock sample covers all U.S. common stocks traded on the NYSE/AMEX/NASDAQ in our main sample period from January 1996 to December 2012. For each month *t*, we sort all stocks into quintile portfolios based on their idiosyncratic volatility (computed as described in Section 5.1) in increasing order. We then compute TNA-value-weighted monthly returns of these portfolios in month t+1. Panel A of Table 9 reports the results.

[Insert Table 9 here]

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 difference amounts to -0.53% per month and is statistically different from zero at the 10% significance level with a *t*-statistic of -1.78. We then go on and analyze the effect of idiosyncratic volatility for stocks with high hedge fund ownership and low hedge fund ownership in specifications (2) and (3). 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 (low), when hedge fund ownership of the stock (in terms of number of hedge funds holding the stock in their long equity holdings) is in the two top (bottom) quartiles among all stocks in month *t*. Our results are striking: While we continue to find a significantly negative relationship between idiosyncratic volatility and future returns with low hedge fund ownership, the relationship reverses for stocks with high hedge fund ownership. Specifically, the monthly average return spread is -1.00% for stocks with low hedge fund ownership, whereas it is +0.45% for stocks with high hedge fund ownership.

Specifications (4) to (6) repeat specifications (1) to (3) for a longer sample period from 1980 – 2012.[16] We find similar results as before, but the magnitudes of the return spreads for stocks with high and low hedge fund ownership are widening: In the extended sample period, we document a monthly average return spread of -1.61% (*t*-statistic of -3.54) for stocks with low hedge fund ownership, and a monthly average return spread of 0.80% (*t*-statistic of 2.95) for stocks with high hedge fund ownership. Hence, differences in the relationship between idiosyncratic volatility and future returns become even larger when extending the overall sample period.

Panel B of Table 9 reports the results in a multivariate context using Fama and MacBeth (1973) regressions controlling for different stock characteristics. We obtain very similar results as in the case of univariate portfolio sorts: The impact of idiosyncratic volatility on future returns is significantly negative for stocks with low hedge fund coverage, while it is significantly positive for stocks with high hedge fund coverage.

How can we rationalize these empirical findings? In the following sections we provide evidence that hedge funds pick stocks wisely in the sense that their investments in high volatility stocks are not affected by low future returns. In particular, we show that hedge funds (i) do not invest in stocks with the highest idiosyncratic volatility, (ii) do not invest in high volatility

[16] We can expand the sample period since Thomson Reuters 13F equity portfolio holdings data goes back to 1980 and we do not require variables from the Union Hedge Fund Database in this analysis.

stocks with strong lottery characteristics, and (iii) do not invest in high volatility stocks that are overvalued.

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

The results in specification (4) of Panel A in Table 9 document that future returns of stocks monotonically decrease in their level of idiosyncratic volatility, i.e., stocks in the portfolio with the highest idiosyncratic volatility underperform the most with an average monthly return of -0.42%. Hence, the first explanation of the positive (negative) relation between idiosyncratic volatility and future returns for stocks with high (low) hedge fund ownership could be that hedge funds shy away from stocks with the highest idiosyncratic volatility. We investigate this explanation in Table 10.

[Insert Table 10 here]

Specifications (1) to (3) of Panel A in Table 10 repeat the findings of a negative (positive) relation between stocks' idiosyncratic volatilities and future returns. However, in this table we concentrate on the level of idiosyncratic volatility and display differences in idiosyncratic volatility between the quintile portfolios of stocks with high and low hedge fund ownership. Consistent with our conjecture, we observe that the average level of idiosyncratic volatility is 2.57% for the stocks with high hedge fund ownership, whereas it is 4.33% for the stocks with low hedge fund ownership. The average difference, thus, amounts to -1.76% and is statistically significant at the 1% level. We also investigate the differences in idiosyncratic volatility for the individual portfolios. Interestingly, the spread in idiosyncratic volatility between high and low hedge fund ownership is monotonically decreasing in portfolios: while the spread is a moderate -0.57% for portfolio 1, the spread becomes a large -3.59% for portfolio 5. Hence, this analysis reveals that hedge funds particularly shy away from stocks with the highest idiosyncratic volatility in the cross-section of stock returns.

We confirm this pattern in Panel B of Table 10, where we look at the frequency of stocks with high and low hedge fund ownership in the cross-section of average stock returns. In line with our results in Panel A, we find that stocks with high hedge fund ownership are overrepresented in the portfolios with low idiosyncratic volatility (i.e., portfolios 1 shows a relationship of 75.74% stocks with high hedge fund ownership vs. 24.26% with low hedge fund ownership), while they are underrepresented in the portfolios with high idiosyncratic volatility (i.e., portfolio 5 displays a relationship of 21.90% of stocks with high hedge fund ownership vs. 78.10% with low hedge fund ownership). Note that these findings also hold when we additionally control for other stock characteristics such as size, book-to-market, or the liquidity of a stock; results of these additional tests are available from the authors upon request.

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

Bali, Cakici, and Whitelaw (2011) find that stocks with lottery-like payoffs, approximated by their past maximum daily return, *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 11. In line with Bali, Cakici, and Whitelaw (2011) and our prior analysis with hedge fund data, we define *MAX* as the stock's maximum daily return over the past 12 months.

[Insert Table 11 here]

In Panel A of Table 11 we report the results of average *MAX* across the idiosyncratic volatility portfolios for stocks with high and low hedge fund coverage. As in the case for idiosyncratic volatility, we find that average *MAX* is positively increasing in the portfolios and is higher for stocks with low hedge fund ownership.[17] More importantly, we find that the average spread in *MAX* between stocks with high and low 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 5.29 ($= \frac{3.59\% - 0.57\%}{0.57\%}$), the corresponding relative change in *MAX* is 20.96 ($= \frac{42.16\% - 1.92\%}{1.92\%}$). 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 11, where we perform bivariate portfolio sorts based on a stock's idiosyncratic volatility and *MAX*. Our results reveal that, given a stock is characterized as a high volatility *and* high *MAX* stock (i.e., it is sorted into idiosyncratic volatility portfolio 5 and *MAX* portfolio 5), the likelihood that a stock has high (low) hedge fund ownership is 7.48% (92.52%). To the contrary, given a stock is characterized as a high volatility *and* low *MAX* stock (i.e., it is sorted into idiosyncratic volatility portfolio 5 and *MAX* portfolio 1), the likelihood that a stock has high (low) hedge fund ownership is 76.26% (23.74%). Thus, we find compelling evidence that hedge funds shy away from stocks with lottery-like payoffs (i.e., high *MAX* stocks), in particular when they also show high idiosyncratic volatility, to be not affected by the abnormal low future returns for this subset of stocks.

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

Stambaugh, Yu, and Yuan (2015) show that the relationship between a stocks' 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

[17] The strong link between idiosyncratic volatility and *MAX* is not surprising since both measures are significantly positively related with a correlation of 0.65 at the individual stock level in our sample.

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 return anomalies in the cross-section of average stock returns.[18] The lower MP, the more underpriced the respective stock is. The results are reported in Table 12.

[Insert Table 12 here]

Panel A of Table 12 illustrates the results of average *MP* across the idiosyncratic volatility portfolios for stocks with high and low hedge fund coverage. In line with our findings for a stock's *MAX*, we document that average *MP* is increasing in the idiosyncratic volatility portfolios and 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.

We confirm these empirical findings in Panel B of Table 12, where we conduct bivariate portfolio sorts based on a stock's idiosyncratic volatility and *MP*. We find that, given a stock is characterized as a high volatility *and* high *MP* stock (i.e., it is sorted into idiosyncratic volatility portfolio 5 and *MP* portfolio 5), the likelihood that a stock has high (low) hedge fund ownership is 11.91% (88.09%). To the contrary, given a stock is characterized as a high volatility *and* low *MP* stock (i.e., it is sorted into idiosyncratic volatility portfolio 5 and *MP* portfolio 1), the likelihood that a stock has high (low) hedge fund ownership is 51.51% (48.49%). Hence, we provide compelling evidence that hedge funds shy away from overvalued equity. This is particularly true for stocks in the high idiosyncratic volatility domain: hedge funds do not invest

[18] 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).

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. 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 statistically and economically significant 6.6% 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 dig 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 leverage are positively associated with a fund's idiosyncratic volatility. Moreover, actual trading strategies involving long equity positions with high idiosyncratic volatility, long call options, and confidential holdings enhance a fund's idiosyncratic volatility.

Finally, we contribute to the well-documented idiosyncratic volatility puzzle in the cross-section of stock returns, 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.

Appendix

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

The Union Hedge Fund Database contains a sample of 25,732 hedge funds created by merging four commercial databases: 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.

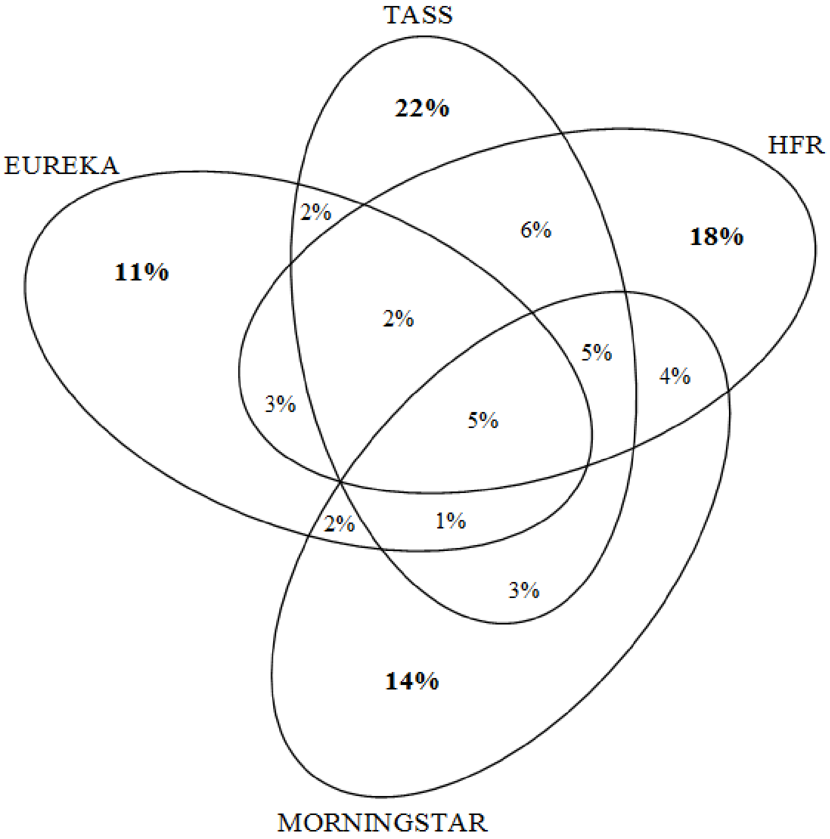

Table A.1. Definitions and Data Sources of Main Variables

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) KF: Kenneth French Data Library, (iii) DH: David A. Hsieh's webpage, (iv) FRS: Data library of the Federal Reserve System, (v) CRSP: CRSP Stocks Database, and (vi) 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 1-month T-Bill rate is used.	UNION, KF, EST
Fund Vola	Standard Deviation of a hedge fund’s reported returns over the past 24 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 with regard to the Fung and Hsieh (2004) seven-factor model as detailed in Section 3.1.	UNION, EST
Fund Systematic Vola	Systematic component of a hedge fund's volatility. Computed as the difference between a fund's volatility and a fund's idiosyncratic volatility as detailed in Section 3.1.	UNION, 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).	Agarwal, Daniel, and Naik (2009)
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
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 Fung and Hiseh (2004) seven-factor model estimated based on the past 24 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 24 months.	UNION, EST

Panel B: Hedge Fund Risk Factors

Variable Name	Description	Source
MARKET	The CRSP US value-weighted monthly market return,	KF
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
MSCI EM	The MSCI Emerging Market index monthly total return.	DH
SMB	Monthly return on Fama and French (1993) small-minus-big size factor.	KF
HML	Monthly return on Fama and French (1993) high-minus-low value factor.	KF
UMD	Monthly return on Carhart (1997) momentum factor.	KF

Panel C: Equity Portfolio Characteristics

Variable Name	Description	Source
Fund Firm Idio Vola	A hedge fund firm's idiosyncratic volatility. Computed as the value-weighted average of Fund Idio Vola of the fund firm's individual funds as detailed in Section 4.1.	UNION, KF, EST
Equity Idio Vola	A hedge fund firm's equity portfolio idiosyncratic volatility. Computed as detailed in Section 4.1.	CRSP, KF, EST
Number of Assets	The number of different stocks in a hedge fund firm's portfolio.	EST
Herfindahl Index	The herfindahl index computed based on assets under management of different portfolio positions in a hedge fund firm's portfolio.	EST
Portfolio Turnover	Turnover of a hedge fund firm's portfolio from quarter t to quarter $t+1$	EST
Portfolio Beta	The value-weighted average of stock betas in a hedge fund firm's portfolio.	CRSP
Portfolio Skewness	The value-weighted average of stocks' skewness in a hedge fund firm's portfolio.	CRSP
Portfolio Kurtosis	The value-weighted average of stocks' kurtosis in a hedge fund firm's portfolio.	CRSP
Portfolio Size	Natural logarithm of the hedge fund's asset under management of equity portfolio positions.	CRSP
Portfolio Book-to-Market	The value-weighted average of stocks' book-to-market ratios in a hedge fund firm's portfolio.	CRSP, Compustat
Portfolio Illiquidity	The value-weighted average of stocks' illiquidity in a hedge fund firm's portfolio measured by the Amihud (2002) illiquidity ratio.	CRSP
Portfolio R&D	The value-weighted average of firms' r&d expenses in a hedge fund firm's portfolio.	CRSP, Compustat
Portfolio Profitability	The value-weighted average of firms' profitability in a hedge fund firm's portfolio.	CRSP, Compustat
Portfolio Leverage	The value-weighted average of firms' leverage in a hedge fund firm's portfolio.	CRSP, Compustat

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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*+24, *t*+48, *t*+72, and *t*+96. 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 1996 to December 2012. All variables are defined in the Appendix.

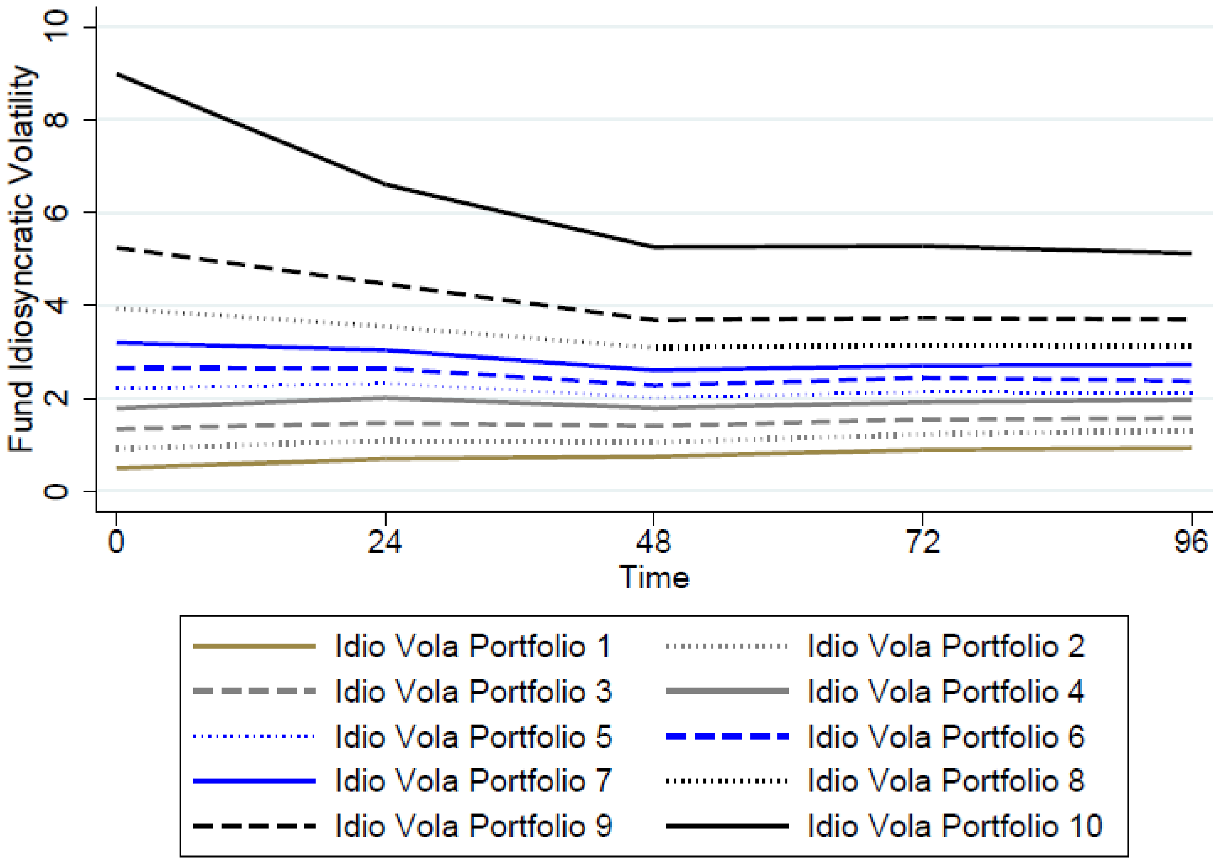

Figure 2. Cumulative Returns

This figure displays the temporal variation of the cumulative monthly returns for the hypothetical long-short investment strategy based on *Fund Idio Vola*. For this strategy we go long the quintile of hedge funds with the highest realizations of *Fund Idio Vola* and go short the quintile with the lowest realizations of *Fund Idio Vola* and apply monthly rebalancing without accounting of trading costs. We assume an investment of USD 100 at the beginning of of our sample period (i.e., at the end of the first estimation of *Fund Idio Vola* metrics based on a horizon of 24 months). Our sample covers hedge fund firms from the Union Hedge Fund Database constructed from combining the Eureka, HFR, Morningstar, and Lipper TASS databases who report 13F long equity holdings to the SEC. The sample period is from January 1996 to December 2012.

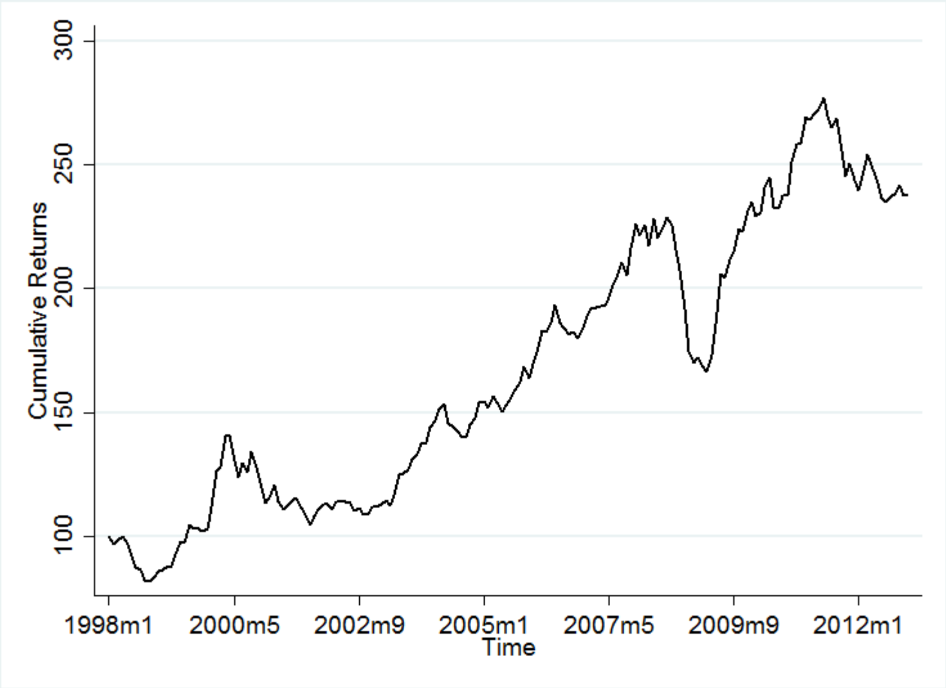

Table 1. Summary Statistics

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 1996 to December 2012. All variables are defined in Table A.1.

Panel A: Returns and Fund Characteristics

Variable	Mean	25%	Median	75%	StdDev
Fund Return	0.62%	-1.40%	0.52%	2.64%	6.14
Fund Vola	4.54%	2.09%	3.53%	5.81%	3.80%
Fund Idio Vola	2.82%	1.33%	2.16%	3.59%	2.24%
Fund Systematic Vola	1.73%	0.51%	1.14%	2.36%	2.14%
Size	3.36	2.20	3.42	4.58	1.83
Age (in months)	64.72	23.00	49.00	92.00	56.19
Delta (in $100 thousands)	1.84	0.07	0.37	1.49	4.18
Management Fee (in %)	1.41	1.00	1.50	1.75	0.52
Incentive Fee (in %)	18.17	20.00	20.00	20.00	5.51
Min Investment (in $100 thousands)	10.91	1.50	5.00	10.00	94.40
Lockup Period (in years)	0.41	0.00	0.00	1.00	0.61
Restriction Period (in years)	0.34	0.16	0.33	0.38	0.29
Offshore	0.52	0.00	1.00	1.00	0.49
Leverage	0.59	0.00	1.00	1.00	0.49
HWM	0.80	1.00	1.00	1.00	0.39
Hurdle Rate	0.27	0.00	0.00	1.00	0.44

Panel B: *Fund Idio Vola*

Strategy	Number of Fund Firms	Mean	25%	Median	75%	StdDev
Emerging Markets	531	2.62%	2.25%	3.65%	5.40%	2.62%
Event Driven	852	1.93%	0.83%	1.38%	2.28%	1.81%
Equity Long-Short	3,736	2.88%	1.46%	2.26%	3.58%	2.17%
Equity Long Only	331	3.32%	1.61%	2.65%	4.37%	2.46%
Equity Market Neutral	515	1.68%	0.87%	1.34%	2.05%	1.33%
Short Bias	66	2.77%	1.50%	2.18%	3.37%	1.90%
Sector	250	3.52%	1.70%	2.77%	4.61%	2.52%
All	6,281	2.82%	1.33%	2.16%	3.59%	2.24%

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

	Fund Return	Fund Vola	Fund Idio Vola	Fund Systematic Vola	Size	Age	Delta	Management Fee	Incentive Fee	Min Investment	Lockup Period	Restriction Period	Offshore	Leverage	HWM	Hurdle Rate
Fund Return	+1.00															
Fund Vola	+0.05	+1.00														
Fund Idio Vola	+0.06	+0.87	+1.00													
Fund Systematic Vola	+0.04	+0.97	+0.76	+1.00												
Size	-0.01	-0.20	-0.20	-0.18	+1.00											
Age	-0.03	-0.00	-0.05	+0.01	+0.29	+1.00										
Delta	+0.03	+0.08	+0.09	+0.07	+0.57	+0.27	+1.00									
Mgmt. Fee	+0.00	+0.03	+0.07	+0.02	+0.05	-0.10	+0.04	+1.00								
Inc. Fee	+0.00	-0.02	-0.00	-0.04	-0.01	-0.07	+0.10	+0.01	+1.00							
Min Inv	+0.00	-0.02	-0.02	-0.02	+0.06	+0.01	+0.05	+0.02	+0.00	+1.00						
Lockup	+0.01	+0.03	+0.00	+0.03	+0.00	-0.01	-0.01	-0.04	+0.15	+0.06	+1.00					
Restriction	+0.01	-0.04	+0.02	-0.03	+0.08	+0.08	+0.10	-0.12	+0.12	+0.04	+0.34	+1.00				
Offshore	-0.01	+0.01	+0.04	-0.00	+0.14	-0.09	+0.07	+0.21	-0.04	-0.04	-0.28	-0.33	+1.00			
Leverage	-0.00	+0.00	+0.04	-0.01	+0.01	-0.02	+0.03	+0.03	+0.17	-0.04	+0.04	+0.03	+0.02	+1.00		
HWM	+0.00	+0.03	+0.03	+0.05	+0.01	-0.08	+0.05	+0.05	+0.37	+0.01	+0.14	+0.08	-0.06	+0.14	+1.00	
Hurdle Rate	+0.01	+0.01	+0.03	+0.02	-0.08	+0.07	-0.06	-0.12	+0.03	-0.00	+0.14	+0.16	-0.50	+0.01	-0.04	+1.00

Table 2. Transition Matrix

This table reports the results of a 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*-24. 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 1996 to December 2012.

Portfolios	1 (month *t*)	2 (month *t*)	3 (month *t*)	4 (month *t*)	5 (month *t*)	6 (month *t*)	7 (month *t*)	8 (month *t*)	9 (month *t*)	10 (month *t*)
1 (month *t*-24)	0.36	0.27	0.16	0.08	0.06	0.03	0.02	0.01	0.01	0.00
2 (month *t*-24)	0.10	0.23	0.23	0.16	0.11	0.07	0.04	0.02	0.01	0.01
3 (month *t*-24)	0.04	0.13	0.19	0.20	0.16	0.12	0.08	0.04	0.02	0.01
4 (month *t*-24)	0.02	0.07	0.14	0.19	0.18	0.17	0.11	0.06	0.04	0.01
5 (month *t*-24)	0.01	0.05	0.09	0.16	0.19	0.18	0.15	0.10	0.05	0.02
6 (month *t*-24)	0.01	0.03	0.06	0.11	0.17	0.19	0.18	0.15	0.08	0.03
7 (month *t*-24)	0.00	0.01	0.04	0.08	0.12	0.17	0.20	0.19	0.13	0.05
8 (month *t*-24)	0.00	0.01	0.02	0.04	0.07	0.12	0.18	0.23	0.21	0.11
9 (month *t*-24)	0.00	0.00	0.01	0.02	0.04	0.06	0.12	0.21	0.30	0.23
10 (month *t*-24)	0.00	0.00	0.01	0.01	0.01	0.02	0.05	0.09	0.24	0.58

Table 3. *Fund Idio Vola* and Future Returns

Panel A of this table reports the results of Fama and MacBeth (1973) regressions of excess returns and Fund and Hsieh (2004) alphas in month *t*+1 on a fund's volatility, idiosyncratic volatility, systematic volatility and different fund characteristics in month *t*. For fund characteristics, we include a fund's monthy return, size, age, delta of the incentive fee contract, a fund's 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 employs leverage, is an offshore fund, has a hurdle rate and a high water mark, respectively, and zero otherwise. Panel B 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 equally-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-7-Factor" report the monthly alpha using the Fung and Hsieh (2004) seven-factor model. In Panel C, 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) seven-factor model presented in the first column, an 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 the Buraschi, Kosowski, and Trojani (2014) correlation risk factor (*Return CORR*), and the Gao, Gao, and Song (2018) RIX factor (*Return RIX*). 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 1996 to December 2012. We use the Newey-West (1987) adjustment with 24 lags to adjust the standard errors for serial correlation. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

Panel A: Fama-MacBeth (1973) Regressions

	(1) Future Fund Return	(2) Future Fund Return	(3) Future Fund Return	(4) Future Fund Return	(5) Fung and Hsieh Alpha	(6) Fung and Hsieh Alpha
Fund Vola	0.0607**		0.0574**			
	(2.13)		(2.16)			
Fund Idio Vola		0.0688**		0.0710***	0.0562**	0.0578**
		(2.11)		(2.71)	(2.14)	(2.23)
Fund Systematic Vola		0.0303		0.0216	0.0134	0.0167
		(0.77)		(0.67)	(0.58)	(0.92)
Fund Return			0.0981***	0.101***	0.076***	0.069***
			(8.82)	(8.08)	(6.43)	(5.29)
Size			-0.0630***	-0.0605***	-0.0743***	-0.0791***
			(-3.27)	(-2.68)	(-3.43)	(-4.52)
Age			-0.00102**	-0.000947**	-0.00121***	-0.00102**
			(-2.56)	(-2.11)	(-2.83)	(-2.18)
Delta			0.0207***	0.0177***	0.0189***	0.0217***
			(3.75)	(4.60)	(3.63)	(3.42)
Management Fee			0.0103	0.00378	0.00542	0.00113
			(0.26)	(0.09)	(0.25)	(0.12)
Incentive Fee			-0.000930	-0.00214	-0.00142	0.00056
			(-0.20)	(-0.49)	(-0.38)	(0.27)
Minimum Investment			0.00197**	0.00222**	0.00245**	0.00191
			(2.25)	(2.28)	(2.41)	(1.42)
Lockup Period			0.0808**	0.0769*	0.0967**	0.0712*
			(2.01)	(1.67)	(2.39)	(1.78)
Restriction Period			0.144*	0.127	0.098	0.145**
			(1.86)	(1.49)	(0.93)	(1.98)
Offshore			-0.00308	0.0108	0.0195	-0.0145
			(-0.04)	(0.16)	(0.43)	(-1.33)
Leverage			0.0104	0.00179	0.0291	0.0157
			(0.27)	(0.04)	(0.87)	(1.29)
High Watermark			0.138***	0.137***	0.102*	0.067
			(3.11)	(2.81)	(1.74)	(0.93)
Hurdle Rate			0.105***	0.103***	0.0672**	0.0799**
			(3.15)	(3.12)	(2.08)	(2.21)
R2						-0.178*
						(-1.75)
SDI						0.236*
						(1.80)
Constant	0.280***	0.189**	0.275**	0.224*	0.189*	0.114
	(3.15)	(2.24)	(2.42)	(1.80)	(1.73)	(1.09)
Observations	419536	385502	194896	179804	168654	168654
Adjusted R^2	0.079	0.101	0.160	0.180	0.164	0.175

Panel B: Univariate Portfolio Sorts

Quintiles	Average *Fund Idio Vola*	Return	FH-7-Factor
Q1	0.71%	0.28%	0.17%
		(1.39)	(1.21)
Q2	1.43%	0.35%**	0.23**
		(2.26)	(2.34)
Q3	2.17%	0.44%**	0.30**
		(2.16)	(2.40)
Q4	3.23%	0.51%***	0.35%***
		(2.68)	(3.12)
Q5	6.31%	0.83%***	0.57%***
		(2.75)	(3.20)
Q5 - Q1	5.60%	0.55%**	0.40%**
t-statistic		(2.16)	(2.25)

Panel C: 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
S&P	0.438***	0.0250	-0.288**	0.438***	0.406***	0.446***	-0.160**	0.439***
	(10.92)	(0.56)	(-5.83)	(10.90)	(9.00)	(11.12)	(-2.52)	(10.94)
SCMLC	0.303***	0.153***	-0.0455	0.301***	0.284***	0.301***	0.115***	0.296***
	(5.94)	(3.90)	(-1.21)	(5.87)	(5.42)	(5.93)	(2.66)	(5.75)
BD10RET	-0.109	-0.104	-0.00549	-0.106	-0.107	-0.0775	-0.0257	-0.0945
	(-1.13)	(-1.48)	(-0.09)	(-1.10)	(-1.12)	(-0.80)	(-0.34)	(-0.97)
BAAMTSY	0.279***	0.135*	0.0488	0.263***	0.329***	0.309***	0.0253	0.302***
	(2.99)	(1.95)	(0.82)	(2.77)	(3.35)	(3.28)	(0.33)	(3.15)
PTFSBD	0.0163	0.0237***	0.0121	0.0162	0.0113	0.0215*	0.00605	0.0135
	(1.34)	(2.67)	(1.61)	(1.34)	(0.90)	(1.74)	(0.64)	(1.08)
PTFSFX	0.0224**	0.0172**	0.0144**	0.0229**	0.0237**	0.0196*	0.0143*	0.0226**
	(2.07)	(2.18)	(2.17)	(2.12)	(2.20)	(1.80)	(1.70)	(2.09)
PTFSCOM	0.0187	0.0233**	0.0258***	0.0192	0.0176	0.0210	0.0227**	0.0184
	(1.38)	(2.35)	(3.09)	(1.41)	(1.30)	(1.55)	(2.16)	(1.36)
EM		0.365***						
		(12.32)						
Senti			0.690***					
			(16.96)					
PS Liqui				0.0386				
				(0.91)				
BAB					-0.0708			
					(-1.56)			
Return Macro						0.0771*		
						(1.81)		
Return CORR							0.652***	
							(10.81)	
Return RIX								0.0438
								(1.04)
Constant	0.401**	0.291**	0.420***	0.373**	0.414**	0.318*	0.292**	0.362**
	(2.25)	(2.23)	(3.82)	(2.06)	(2.33)	(1.74)	(2.12)	(1.99)
Observations	180	180	178	180	180	180	180	180
Adjusted R^2	0.563	0.769	0.838	0.565	0.569	0.571	0.740	0.566

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 excess returns in month *t*+1. We investigate the robustness when we estimate a fund's idiosyncratic volatility using a rolling estimation horizon of 36 months instead of 24 months, estimate a fund's idiosyncratic volatility using the four-factor model of Fama-French-Carhart and the extended Fung and Hsieh (2004) eight-factor model (instead of the Fung and Hsieh (2004) seven-factor model), restrict our sample to hedge funds with an equity long-short strategy, 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, 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 Table 3 of future excess returns 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 excess returns (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 1996 to December 2012. We use the Newey-West (1987) adjustment with 24 lags to adjust the standard errors for serial correlation. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

	(1) Baseline	(2) 36 months	(3) Carhart (1997)	(4) Fung and Hsieh 8-Factor	(5) Equity Long-Short Funds	(6) Delisting Return	(7) Return Smoothing	(8) 2 months ahead	(9) 3 months ahead
Fund Idio Vola	0.0710***	0.0768***	0.0695***	0.0695**	0.1106**	0.0718***	0.0614**	0.1254**	0.1743**
	(2.71)	(3.27)	(2.54)	(2.46)	(2.49)	(2.78)	(2.02)	(2.41)	(1.99)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.180	0.162	0.178	0.179	0.193	0.180	0.167	0.178	0.162

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 incentive fee contract, a fund’s 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 employs leverage, is an offshore fund, has a hurdle rate and a high water mark, respectively, and zero otherwise 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 1996 to December 2012. We use the Newey-West (1987) adjustment with 24 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
Fund Return	0.0258**		0.0251**
	(2.36)		(2.24)
Size	-0.277***		-0.307***
	(-4.99)		(-5.39)
Age	-0.000147		0.000749
	(-0.16)		(0.79)
Delta	0.0114		0.0223**
	(1.41)		(2.51)
Management Fee		0.281***	0.292***
		(13.46)	(20.68)
Incentive Fee		0.00631***	0.00183
		(3.98)	(0.88)
Minimum Investment		-0.0124***	-0.00454***
		(-5.47)	(-6.39)
Lockup Period		0.242***	0.254***
		(6.05)	(8.07)
Restriction Period		0.563	0.315
		(0.32)	(1.04)
Offshore		0.155	0.298***
		(1.45)	(3.64)
Leverage		0.0705	0.112***
		(1.29)	(2.84)
High Watermark		0.0566	0.118**
		(1.46)	(2.24)
Hurdle Rate		0.0794	0.0894***
		(1.38)	(3.18)
Constant	3.596***	2.393***	2.885***
	(9.34)	(7.71)	(7.00)
Observations	281375	258387	190260
Adjusted R^2	0.131	0.035	0.167

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* on fund firm *i*'s equity portfolio idiosyncratic volatility in month *t* controlling for different portfolio characteristics. As control variables, we include the number of assets in the portfolio, the portfolio herfindahl index, the portfolio turnover, portfolio beta, portfolio skewness, portfolio kurtosis, stock size, book-to-market, stock illiquidity, r&d expenses, profitability, and portfolio leverage. All portfolio characteristics are computed as the value-weighted average of the individual stock characteristics in a fund firm's portfolio. Our sample is 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 1996 to December 2012. We use the Newey-West (1987) adjustment with 24 lags to adjust the standard errors for serial correlation. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

	(1) Fund Firm Idio Vola	(2) Fund Firm Idio Vola
Equity Idio Vola	0.167***	0.276***
	(11.16)	(10.08)
Number of Assets		-0.000786**
		(-2.56)
Herfindahl Index		2.764***
		(3.37)
Portfolio Turnover		-0.380**
		(-2.33)
Portfolio Beta		0.724***
		(2.76)
Portfolio Skewness		0.0896
		(1.22)
Portfolio Kurtosis		-0.165
		(-0.71)
Portfolio Size		-0.0477***
		(-3.17)
Portfolio Book-to-Market		-0.664
		(-1.07)
Portfolio Illiquidity		-0.0268
		(-0.22)
Portfolio R&D		4.018***
		(2.68)
Portfolio Profitability		2.203***
		(3.70)
Portfolio Leverage		0.823
		(1.45)
Constant	1.716***	1.978***
	(11.69)	(11.03)
Observations	37860	33865
Adjusted R^2	0.052	0.222

Table 7. *Fund Firm Idio Volatility* and Derivative Positions

This table reports the results of Fama and MacBeth (1973) regressions of fund firm *i*'s idiosyncratic volatility in month *t* on hedge fund firm *i*'s long positions in call and put options in month *t*. We compute a hedge fund firm *i*'s number of different stocks on which call positions are held (*Number of Different Call Positions*), number of different stocks on which put positions are held (*Number of Different Put positions*), the number of equity shares underlying the call positions (*Number of Equity Shares Underlying the Call Positions*, in millions), the number of equity shares underlying the put positions (*Number of Equity Shares Underlying the Put Positions*, in millions), the value of equity shares underlying the call positions (*Value of Equity Shares Underlying the Call Positions*, in millions of dollars), and the value of equity shares underlying the put positions (*Value of Equity Shares Underlying the Put Positions*, in millions of dollars). Our sample is 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 long call and put positions to the Securities and Exchange Commission in their 13F filings. The sample period is from April 1999 to December 2012. We use the Newey-West (1987) adjustment with 24 lags to adjust the standard errors for serial correlation. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

Derivatives holdings–based variables	(1) Fund Firm Idio Vola	(2) Fund Firm Idio Vola	(3) Fund Firm Idio Vola	(4) Fund Firm Idio Vola
Number of Different Call Positions	0.00743*			0.00293
	(1.68)			(1.15)
Number of Different Put Positions	-0.00328			-0.00401*
	(-0.30)			(-1.69)
log(1 + Number of Equity Shares Underlying the Call Positions)		0.0887*		0.0894**
		(1.92)		(2.37)
log(1 + Number of Equity Shares Underlying the Put Positions)		-0.0475		-0.0508
		(-0.39)		(-1.22)
log(1 + Value of Equity Shares Underlying the Call Positions)			0.0300***	0.0635**
			(2.91)	(2.23)
log(1 + Value of Equity Shares Underlying the Put Positions)			-0.0144	-0.0238
			(-0.44)	(-1.44)
Constant	2.105***	2.097***	2.097***	2.100***
	(10.63)	(10.59)	(10.65)	(10.65)
Observations	36,967	36,967	36,967	36,967
Adjusted R^2	0.010	0.010	0.016	0.036

Table 8. *Fund Firm Idio Volatility* and Confidential Holdings

This table reports the results of Fama and MacBeth (1973) regressions of regressions of fund firm *i*'s idiosyncratic volatility in month *t* on hedge fund firm *i*'s confidential 13F positions in month *t*. Confidential holdings are quarter-end equity holdings that are disclosed with a delay through amendments to form 13F. We compute a hedge fund firm *i*'s number of different confidential holding stocks (*Number of Different Confidential Holdings*), the number of equity shares underlying the confidential holdings (*Number of Equity Shares Underlying the Confidential Holdings*, in millions), and the value of equity shares underlying the confidential holdings positions (*Value of Equity Shares Underlying the Confidential Holdings*, in millions of dollars). Our sample is 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 confidential holdings to the Securities and Exchange Commission in their 13F filing amendments. The sample period is from April 1999 to December 2012. We use the Newey-West (1987) adjustment with 24 lags to adjust the standard errors for serial correlation. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

Confidential holdings variable	(1) Fund Firm Idio Vola	(2) Fund Firm Idio Vola	(3) Fund Firm Idio Vola	(4) Fund Firm Idio Vola
Number of Different Confidential Holdings	0.00624**			0.00423**
	(2.31)			(2.09)
Log (1 + Number of Equity Shares Underlying the Confidential Holdings)		0.0811**		0.0686
		(2.33)		(1.59)
Log (1 + Value of Equity Shares Underlying the Confidential Holdings)			0.0763***	0.1970***
			(4.91)	(2.79)
Constant	2.117***	2.119***	2.118***	2.118***
	(37.56)	(37.66)	(37.66)	(37.72)
Observations	24948	24948	24948	24948
Adjusted R^2	0.004	0.003	0.003	0.008

Table 9. Stock Returns: *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 in month *t+1*. In Panel A we show the results of univariate portfolio sorts, with specifications (1) – (3) displaying results in the sample period from January 1996 to December 2012. Specification (1) reports the results of value-weighted portfolio sorts between idiosyncratic volatility in month *t* and average stock returns in month *t+1*. Specification (2) reports the results of value-weighted portfolio sorts of stocks with high hedge fund ownership. 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 (in terms of number of hedge funds holding the stock in their long equity holdings) is in the two top quartiles among all stocks in month *t*. Specification (3) reports the results of value-weighted portfolio sorts of stocks with low hedge fund ownership. We classify hedge fund ownership of a stock *j* in month *t* as low, when hedge fund ownership of the stock is in the two bottom quartiles among all stocks in month *t*. Specifications (4) – (6) report the corresponding results of models (1) – (3) in the extended sample period from January 1980 to December 2012. In Panel B we show the results of Fama and MacBeth (1973) regressions between idiosyncratic volatility in month *t* and the cross-section of average stock returns in month *t+1* as in Panel A of this table. As control variables we also include a fund's average portfolio beta, skewness, kurtosis, size, book-to-market, illiquidity, R&D expenses, profitability, and firm leverage in month *t*. Specifications (1) – (3) report the results in the sample period from January 1996 to December 2012, specifications (4) – (6) report the results in the sample period from January 1980 to December 2012. Our sample covers all U.S. common stocks traded on the NYSE / AMEX / NASDAQ. We use the Newey-West (1987) adjustment with 24 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

	January 1996 to December 2012						January 1980 to December 2012					
	(1) Cross-Section of Stock Returns (Value-Weighted)		(2) Stocks With High Hedge Fund Ownership (Value-Weighted)		(3) Stocks With Low Hedge Fund Ownership (Value-Weighted)		(4) Cross-Section of Stock Returns (Value-Weighted)		(5) Stocks With High Hedge Fund Ownership (Value-Weighted)		(6) Stocks With Low Hedge Fund Ownership (Value-Weighted)	
	Equity Idio Vola	Returns	Equity Idio Vola	Returns	Equity Idio Vola	Returns	Equity Idio Vola	Returns	Equity Idio Vola	Returns	Equity Idio Vola	Returns
Q1	1.35%	0.55%	1.32%	0.40%	1.85%	0.75%	1.27%	0.64%	1.18%	0.25%	1.75%	0.86%
2	2.14%	0.49%	1.93%	0.50%	2.92%	0.52%	2.06%	0.63%	1.79%	0.35%	2.81%	0.62%
3	2.96%	0.51%	2.54%	0.63%	4.05%	0.07%	2.86%	0.53%	2.29%	0.50%	3.85%	0.10%
4	4.03%	0.28%	3.36%	0.64%	5.42%	0.10%	3.90%	0.09%	3.09%	0.68%	5.13%	0.ß1%
Q5	6.17%	0.02%	5.17%	0.85%	8.46%	-0.25%	6.11%	-0.42%	4.50%	1.05%	8.09%	-0.75%
5-1	4.82%***	-0.53%*	3.85%	0.45%*	7.61%	-1.00%*	4.84%***	-1.06%**	3.32%***	0.80%***	6.34%***	-1.61%***
		(-1.78)		(1.88)		(-1.76)		(-2.39)		(2.95)		(-3.54)

Panel B: Fama-MacBeth (1973) Regressions

	January 1996 to December 2012			January 1980 to December 2012		
	(1) Future Stock Return in the Cross-Section of Stock Returns	(2) Future Stock Return with High Hedge Fund Coverage	(3) Future Stock Return with Low Hedge Fund Coverage	(4) Future Stock Return in the Cross-Section of Stock Returns	(5) Future Stock Return with High Hedge Fund Coverage	(6) Future Stock Return with Low Hedge Fund Coverage
Equity Idio Vola	-0.119*	0.261*	-0.211**	-0.160**	0.301***	-0.387***
	(-1.71)	(1.72)	(-2.20)	(-2.19)	(2.82)	(-3.46)
Beta	-0.130	-0.379	-0.0578	-0.235*	0.145	-0.314*
	(-0.58)	(-1.08)	(-0.28)	(-1.80)	(0.97)	(-1.76)
Skewness	-0.119*	-0.0913	-0.0925	-0.00338	-0.104*	0.00312
	(-1.83)	(-1.55)	(-1.24)	(-0.06)	(-1.89)	(0.67)
Kurtosis	0.00340*	0.00322*	0.00288	0.00196*	0.00214	0.00156
	(1.96)	(1.96)	(1.56)	(1.72)	(1.18)	(1.31)
Size	-0.0297	-0.183**	-0.868***	0.00985	-0.137	0.00467
	(-0.40)	(-2.05)	(-5.96)	(0.20)	(-1.44)	(0.29)
Book to Market	1.927***	1.939***	1.659***	1.841***	1.639***	1.788***
	(9.13)	(9.00)	(7.35)	(12.03)	(5.41)	(6.00)
Equity Return	-4.880***	-3.575***	-5.911***	-6.743***	-2.112**	-5.112***
	(-6.18)	(-4.41)	(-6.98)	(-10.07)	(-2.13)	(-3.04)
Past Yearly Equity Return	0.0802	0.226	0.115	0.450***	0.426**	0.589***
	(0.34)	(0.75)	(0.55)	(2.62)	(2.35)	(2.95)
Illiquidity	0.0371	0.514	-0.00936	0.0158	0.0514	-0.0632
	(1.39)	(1.42)	(-0.49)	(1.37)	(0.67)	(-0.98)
R&D expenses	6.170***	6.529***	5.878***	7.553***	6.529***	8.123**
	(5.99)	(4.00)	(7.22)	(8.41)	(3.56)	(2.43)
Profitability	5.580***	6.134***	5.001***	6.622***	7.452***	4.582
	(11.45)	(8.58)	(11.38)	(9.64)	(7.54)	(1.01)
Firm Leverage	0.0432	0.512	-0.760*	-0.0766	-0.0132	-0.0309
	(0.09)	(0.96)	(-1.79)	(-0.25)	(-0.45)	(-0.59)
Constant	-1.876	0.176	7.464***	-2.372***	-1.467*	4.691***
	(-1.50)	(0.13)	(4.22)	(-3.24)	(-1.84)	(4.64)
Observations	456,469	152,156	152,156	775,297	258,432	258,432
Adjusted R^2	0.080	0.107	0.079	0.076	0.100	0.078

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

Panel A of reports the results of value-weighted univariate portfolio sorts between average idiosyncratic volatility in month *t* and average stock returns in month *t+1* 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). Column (4) reports the results of differences in idiosyncratic volatilities and returns between stocks with high and low hedge fund ownership. 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 (low), when hedge fund ownership of the stock (in terms of number of hedge funds holding the stock in their long equity holdings) is in the two top (bottom) quartiles among all stocks in month *t*. Panel B provides the frequency of stocks that are classified as stocks with high hedge fund ownership and low hedge fund ownership in portfolio sorts based on idiosyncratic volatility. We also provide differences in the frequencies between high hedge fund and low hedge fund ownership in the last column of the panel. The sample period is from January 1980 to December 2012. Our sample covers all U.S. common stocks traded on the NYSE / AMEX / NASDAQ. We use the Newey-West (1987) adjustment with 24 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) Cross-Section of Stock Returns (Value-Weighted)		(2) Stocks With High Hedge Fund Ownership (Value-Weighted)		(3) Stocks With Low Hedge Fund Ownership (Equal-Weighted)		(4) Differences: High - Low	
	Equity Idio Vola	Returns	Equity Idio Vola	Returns	Equity Idio Vola	Returns	Equity Idio Vola	Returns
Q1	1.27%	0.64%	1.18%	0.25%	1.75%	0.86%	-0.57%***	-0.61%*
2	2.06%	0.63%	1.79%	0.35%	2.81%	0.62%	-1.02%***	-0.27%
3	2.86%	0.53%	2.29%	0.50%	3.85%	0.10%	-1.56%***	+0.40%
4	3.90%	0.09%	3.09%	0.68%	5.13%	0.01%	-2.04%***	+0.67%*
Q5	6.11%	-0.42%	4.50%	1.05%	8.09%	-0.75%	-3.59%***	+1.80%***
Average	3.24%	0.29%	2.57%	0.57%	4.33%	0.17%	-1.76%***	+0.40%**

Panel B: Frequencies

	(1) All Stocks	High HF Ownership	(2) Low HF Ownership	(3) Differences: High - Low
	Equity Idio Vola	Frequency	Frequency	Frequency
Q1	1.27%	75.74%	24.26%	+51.48%***
2	2.06%	65.85%	34.15%	+31.70%***
3	2.86%	56.51%	43.49%	+13.02%***
4	3.90%	44.40%	55.60%	-11.20%***
Q5	6.11%	21.90%	78.10%	-56.20%***
Average	3.24%	50.00%	50.00%	0.00%

Table 11. *Idiosyncratic Volatility* and *MAX* of Stocks with High and Low Hedge Fund Ownership

Panel A of 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). 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 MAXs between stocks with high and low hedge fund ownership. Panel B provides the frequency of stocks that are classified as stocks with high hedge fund ownership in portfolio double-sorts based on idiosyncratic volatility and MAX. We also provide average differences in the frequencies between high hedge fund and low hedge fund ownership for each idiosyncratic volatility sorted colomn in the last row of the panel. The sample period is from January 1980 to December 2012. Our sample covers all U.S. common stocks traded on the NYSE / AMEX / NASDAQ. We use the Newey-West (1987) adjustment with 24 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) Cross-Section of Stock Returns (Value-Weighted)		(2) Stocks With High Hedge Fund Ownership (Value-Weighted)		(3) Stocks With Low Hedge Fund Ownership (Equal-Weighted)		(4) Differences: High - Low	
	Equity Idio Vola	MAX	Equity Idio Vola	MAX	Equity Idio Vola	MAX	Equity Idio Vola	MAX
Q1	1.27%	6.44%	1.18%	5.61%	1.75%	7.53%	-0.57%***	-1.92%***
2	2.06%	10.54%	1.79%	8.03%	2.81%	12.65%	-1.02%***	-4.62%***
3	2.86%	15.08%	2.29%	10.44%	3.85%	21.08%	-1.56%***	-10.64%***
4	3.90%	20.96%	3.09%	12.01%	5.13%	29.54%	-2.04%***	-17.53%***
Q5	6.11%	36.47%	4.50%	12.38%	8.09%	54.54%	-3.59%***	-42.16%***
Average	3.24%	17.89%	2.57%	9.69%	4.33%	25.07%	-1.76%***	-15.37%***

Panel B: Frequencies of High Hedge Fund Ownership

		Equity Idio Vola Q1	Equity Idio Vola Q2	Equity Idio Vola Q3	Equity Idio Vola Q4	Equity Idio Vola Q5	Average
MAX Q 1	High Ownership	84.86%	81.04%	78.42%	77.40%	76.26%	79.59%
MAX Q 2	High Ownership	81.99%	74.39%	61.35%	52.31%	46.13%	63.23%
MAX Q 3	High Ownership	75.22%	60.36%	47.21%	34.87%	20.11%	47.55%
MAX Q 4	High Ownership	65.42%	42.76%	32.95%	23.63%	12.05%	35.36%
MAX Q 5	High Ownership	41.48%	33.30%	23.84%	15.26%	7.48%	24.27%
Average	High Ownership	69.79%	56.37%	48.75%	40.69%	32.41%	50.00%

Table 12. *Idiosyncratic Volatility* and Mispricing of Stocks with High and Low Hedge Fund Ownership

Panel A of reports the results of value-weighted univariate portfolio sorts between average idiosyncratic volatility in month *t* and average mispricing (MP) in month *t* 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). 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). The higher the rank, the greater the relative degree of overpricing. Column (4) reports the results of differences in idiosyncratic volatilities and MPs between stocks with high and low hedge fund ownership. Panel B provides the frequency of stocks that are classified as stocks with high hedge fund ownership in portfolio double-sorts based on idiosyncratic volatility and MP. We also provide average differences in the frequencies between high hedge fund and low hedge fund ownership for each idiosyncratic volatility sorted colomn in the last row of the panel. The sample period is from January 1980 to December 2012. Our sample covers all U.S. common stocks traded on the NYSE / AMEX / NASDAQ. We use the Newey-West (1987) adjustment with 24 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) Cross-Section of Stock Returns (Value-Weighted)		(2) Stocks With High Hedge Fund Ownership (Value-Weighted)		(3) Stocks With Low Hedge Fund Ownership (Equal-Weighted)		(4) Differences: High - Low	
	Equity Idio Vola	MP	Equity Idio Vola	MP	Equity Idio Vola	MP	Equity Idio Vola	MP
Q1	1.27%	41.99	1.18%	40.52	1.75%	44.32	-0.57%***	-3.80***
2	2.06%	45.22	1.79%	41.98	2.81%	51.16	-1.02%***	-9.19***
3	2.86%	48.17	2.29%	44.95	3.85%	52.02	-1.56%***	-7..07***
4	3.90%	51.45	3.09%	47.34	5.13%	55.08	-2.04%***	-7.74***
Q5	6.11%	55.67	4.50%	49.87	8.09%	60.68	-3.59%***	-10.81***
Average	3.24%	13.68	2.57%	9.35	4.33%	16.36	-1.76%***	-7.01***

Panel B: Frequencies

		Equity Idio Vola Q1	Equity Idio Vola Q2	Equity Idio Vola Q3	Equity Idio Vola Q4	Equity Idio Vola Q5	Average
MP Q 1	High Ownership	82.48%	80.59%	66.12%	65.63%	51.51%	69.27%
MP Q 2	High Ownership	76.18%	70.05%	61.36%	53.81%	41.41%	60.56%
MP Q 3	High Ownership	64.85%	56.43%	47.87%	42.86%	33.93%	49.19%
MP Q 4	High Ownership	53.00%	41.03%	38.30%	31.99%	21.66%	36.96%
MP Q 5	High Ownership	53.86%	42.09%	37.09%	24.02%	11.91%	34.04%
Average	High Ownership	66.07%	58.04%	50.15%	43.66%	32.08%	50.00%