Volatility of Aggregate Volatility and Hedge Fund Returns

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This version: July 26, 2016

Abstract

This paper investigates empirically whether uncertainty about equity market volatility can explain hedge fund performance both in the cross section and over time. We measure uncertainty via volatility of aggregate volatility (VOV) and construct an investable version through returns on lookback straddles on the VIX index. We find that VOV exposure is a significant determinant of hedge fund returns. After controlling for fund characteristics, we document a robust and significant negative risk premium for VOV exposure in the cross section of hedge fund returns. We corroborate our results using statistical and parameterized proxies of VOV over a longer sample period.

JEL Classification: G10; G11; C13

Keywords: Uncertainty; volatility of volatility; hedge funds; performance

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We are grateful to the editor, Bill Schwert, and an anonymous referee for their extremely helpful comments and suggestions. We thank Yacine Aït-Sahalia, Gurdip Bakshi, Turan Bali, Andrea Buraschi, Antonio Gargano, Alexey Malakhov, Scott Murray, Emre Ozdenoren, Sebastien Pouget, and Christophe Spaenjers for their insightful comments and constructive suggestions. We benefited from the comments received at presentations at the Financial Research Workshop at IIM Kolkata, 7th Annual Hedge Fund Research Conference, Dauphine-Amundi Asset Management Workshop, 5th FEBS Conference, HEC Paris, 2015 FMA Annual Meetings, IFSID 4th Conference on Derivatives, and 2016 AFA Annual Meetings. The authors acknowledge financial support from Dauphine-Amundi Foundation Chair in Asset Management.

1. Introduction

In an economy with time-varying investment opportunities, uncertainty about aggregate volatility can have important implications for pricing and portfolio decisions. Although there is a well-established literature on time-variation in aggregate volatility, less is known about the stochastic nature of this variation and how uncertainty about aggregate volatility is related to the portfolio decisions and in turn to the cross section of hedge fund returns.[1] Stochastic volatility has become an important feature of macro-finance models that seek to explain the stylized facts in macroeconomics and asset pricing.[2] Uncertainty about volatility of the market portfolio can also be an important source of risk for hedge funds who take state-contingent bets in the market and who pursue dynamic strategies relating to unexpected changes in economic circumstances. For example, a shock to the economy that suddenly increases uncertainty about volatility of the market portfolio can result in difficult-to-assess situations and create challenges in assigning subjective (or objective) probabilities to events that investors are unfamiliar with. This can result in a widespread withdrawal of investments by uncertainty-averse investors from the markets, and can have strong implications for the performance of different hedge fund strategies.[3]

Our paper contributes to the extant literature by first modeling uncertainty about market volatility in terms of a forward-looking measure based on volatility of aggregate volatility (VOV), and second by examining how this uncertainty is related to the cross section of hedge fund returns. The paper closest in spirit to our investigation is by Baltussen et al.

[1] The time-series relation between aggregate stock market volatility and expected returns has been documented extensively by French, Schwert, and Stambaugh (1987), Schwert (1989), Campbell and Hentschel (1992), Glosten, Jagannathan, and Runkle (1993), Braun, Nelson, and Sunier (1995), Bekaert and Wu (2000), Ang et al. (2006), and Bali (2008).

[2] Bansal and Yaron (2004) show the importance of stochastic volatility in consumption growth for explaining the equity premium and the dynamic dependencies in returns over long horizons. Bansal, Khatchatrian, and Yaron (2005), Lettau, Ludvigson, and Wachter (2008), Bekaert, Engstrom, and Xing (2009), Bollerslev, Tauchen, and Zhou (2009), Drechsler and Yaron (2011), Bansal and Shaliastovich (2013), and Bansal, Kiku, Shaliastovich and Yaron (2014) document the importance of stochastic volatility for asset prices and the macroeconomy

[3] Caballero and Krishnamurthy (2008), Routledge and Zin (2009), Uhlig (2009), and Guidolin and Rinaldi (2010) provide models that study policy implications of uncertainty in different financial market settings, such as bank runs, liquidity shortages, flight to quality, and market breakdowns.

(2015) who document that volatility of volatility of *individual stocks* is an important factor in the cross section of stock returns. Arguably, since hedge funds invest in a portfolio of stocks, one would expect the individual stock-specific risk to get diversified away and funds' trading strategies to be primarily exposed to the systematic or the *market* risk. Therefore, in this paper, we examine the implications of the uncertainty about market volatility for the cross section of hedge fund returns.

To test our hypotheses, in the spirit of Fung and Hsieh (2001), we employ a forward-looking option-based *investable* strategy to measure market's perception of uncertainty about market volatility. Our measure of uncertainty, which we proxy by volatility of aggregate volatility (VOV), is monthly returns on a lookback straddle strategy written on the VIX index (hereafter *LBVIX*).[4] The VIX index, which is also referred to as the "investor fear gauge", measures market's overall expectation regarding the evolution of near-term aggregate volatility. The payoff on a lookback straddle is path dependent, and allows its holder to benefit from large deviations in the VIX index and offers a payoff, which equals the range of the VIX index during the lifetime of the option.[5] The payoff on *LBVIX* provides us with an instrument to investigate the relation between uncertainty about the aggregate volatility and returns earned by different hedge fund strategies.[6] In particular, our measure helps us to test how different hedge fund strategies performed during the recent financial crisis, a period when the perceived uncertainty about risk and return dynamics of the market portfolio increased significantly (Bernanke, 2010; Caballero and Simsek, 2013).[7]

[4] We also use two different non-investable statistical measures of VOV, which are monthly range of the VIX index, and monthly standard deviation of the VIX index. The results are very comparable. Although statistical measures of VOV have the advantage of extending the sample period back to 1990, an investable and forward-looking VOV measure is more relevant to evaluate funds' risk exposures and to even replicate the funds' returns.

[5] *VVIX* index (implied volatility of VIX) is an alternative measure that summarizes market's expectations regarding the evolution of VIX volatility over the next month. However *VVIX* is not investable, while *LBVIX* is investable.

[6] Fung and Hsieh (1997, 2001, 2004), Mitchell and Pulvino (2001), Agarwal and Naik (2004), Hasanhodzic and Lo (2007), and Fung et al. (2008) show option-like characteristics of hedge fund returns. Fung and Hsieh (2001, 2004) use returns on lookback straddles on different assets as systematic factors to explain fund returns.

[7] In most models of uncertainty, the effect of uncertainty aversion is shown to be stronger when the perceived level of uncertainty is high (e.g., Dimmock, Kouwenberg, and Wakker, 2016).

To the best of our knowledge, ours is the first investigation to examine whether uncertainty about market volatility is priced in the cross section of hedge fund returns. Previous work has looked at uncertainty in other contexts. For example, Zhang (2006) studies uncertainty about the quality of information, and finds that information uncertainty enhances price continuation anomalies. Cremers and Yan (2016), and Pástor and Veronesi (2003) study uncertainty about the future profitability of a firm, and find that it affects asset valuations. Bansal and Shaliastovich (2013) investigate long-run risk in bond markets to show that the bond risk premium changes with the uncertainty about expected growth and inflation. Our VOV measure is calculated from option prices and measures variation in the expectations about the equity market volatility, whereas dispersion statistics in the prior literature are computed from analysts' forecasts and capture variation in aggregate earnings forecasts.

Our research is related to the well-established strand of literature in option pricing with stochastic volatility. It is common in option pricing models to assume stochastic volatility for the dynamics of the underlying asset.[8] For example, Buraschi and Jiltsov (2007) argue that stochastic volatility in option pricing models can be rationalized by the presence of heterogeneous agents who are exposed to model uncertainty and have different beliefs regarding expected returns. Bakshi, Madan, and Panayotov (2015) show that if investors have heterogeneity in beliefs about volatility outcomes, they maximize their utility by choosing volatility-contingent cash flows, such as VIX options. Drechsler and Yaron (2011) draw a link between uncertainty and investors' demand for compensation against stochastic volatility. Buraschi, Trojani, and Vedolin (2014) study the link between market-wide uncertainty, difference of opinions, and comovement of stock returns and show that this link explains the dynamics of equilibrium volatility and correlation risk. Using volatility of volatility implied by a cross section of the VIX options (*VVIX*), Park (2013) shows that model-free risk-neutral

[8] For example, Bakshi, Cao, and Chen (1997) document that option pricing models which incorporate stochastic volatility (as in Hull and White (1987) and Heston (1993)) perform better in terms of internal consistency, yield lower out-of-sample pricing errors, and most notably perform better in hedging.

VVIX index has forecasting power for future tail-risk hedge returns. Huang and Shaliastovich (2014) show that volatility-of-volatility risk (measured by *VVIX*) is priced in the cross section of option returns. Buraschi, Porchia, and Trojani (2010) find that optimal portfolios include distinct hedging components against both stochastic volatility risk and correlation risk. Our VOV measure is similar to the stochastic volatility parameter that captures volatility in aggregate volatility dynamics as a separate source of risk.

Our research complements the recent work of Bali, Brown, and Caglayan (2014) and Buraschi, Kosowski, and Trojani (2014) who respectively show that hedge fund returns are related to macroeconomic uncertainty and correlation risk. Our research differs as we examine the effect of uncertainty about future movements of market volatility on fund performance, which is an uncertainty mechanism distinct from both macroeconomic risk and correlation risk.

Using monthly *LBVIX* returns as an investable measure of volatility of aggregate volatility, our findings can be summarized as follows. During the sample period from April 2006 to December 2012, funds have a negative exposure to VOV both at the index and individual fund level. The negative exposure of funds to VOV is much more prominent especially during the turbulent crisis period ending in March 2009. Using Dow Jones Credit Suisse hedge fund indexes, we find that the aggregate hedge fund index as well as the strategy-specific indexes (convertible arbitrage, event driven, global macro, long/short equity, managed futures, and multi strategy) all exhibit significant and negative VOV betas.[9] The relation is robust to inclusion of liquidity risk factor of Sadka (2010), correlation risk factor of Buraschi, Kosowski, and Trojani (2014), macroeconomic uncertainty risk factor of Bali, Brown, and Caglayan (2014), and aggregate volatility and jump risk factors of Cremers, Halling, and Weinbaum (2015). Stepwise regressions and variable selection tests also show

[9] We also pool the eight fund indexes together and estimate panel regressions on the pooled sample. We allow both the intercepts and factor loadings to vary with the indexes as well as allow them to be the same for each index. The results confirm a negative VOV loading over the full sample period and during the financial crisis.

significance and high explanatory power of VOV in explaining index returns. The findings are robust to the use of alternative databases of fund indexes from the Center for International Securities and Derivatives Markets (CISDM), Eurekahedge, and Hedge Fund Research (HFR).

We next investigate whether VOV is a systematic risk factor for individual hedge funds, and if so, what are the pricing implications of this factor in the cross section of hedge fund returns. To address these questions, we use a comprehensive database created by combining four hedge fund databases (Eurekahedge, HFR, Lipper TASS, and Morningstar) that cover a large portion of the fund universe. We start with examining the relation between funds' VOV exposures and future returns. To that end, we first estimate the VOV betas of individual funds each month using 36-month rolling windows. Next, we form quintile portfolios each month by sorting funds according to their VOV betas. We then examine *out-of-sample* average quintile returns for the following month to investigate whether funds' VOV exposures explain the cross-sectional dispersion in next month's fund returns. Univariate portfolio sorts indicate that funds in the highest VOV beta quintile underperform funds in the lowest VOV beta quintile by 1.62% per month. This result is robust to controlling for factors that have been shown to be important determinants of fund returns, using 24-month rolling windows to estimate VOV betas, and controlling for backfilling bias. The difference in risk-adjusted returns (8-factor alphas) of portfolios with highest and lowest exposures to VOV is negative and statistically significant.

It is now well documented that aggregate volatility risk is priced in the cross section of stock returns and is negative.[10] To ensure that our proposed measure of aggregate uncertainty (*LBVIX*) is not simply capturing market volatility risk premium, we conduct bivariate portfolio sorts based on funds' volatility (VOL) betas and VOV betas. In particular, we use

[10] Ang et al. (2006), Bali and Engle (2010), and Cremers, Halling, and Weinbaum (2015) document a negative market volatility risk premium in the cross section of stock returns.

monthly change of the VIX index as a proxy of aggregate volatility risk. The bivariate sort exercise essentially helps disentangle the effect of aggregate volatility risk (VOL) from volatility of aggregate volatility risk (VOV) captured by *LBVIX*. The bivariate portfolio sorts further confirm the negative relation between VOV beta and fund returns. Regardless of VOL beta ranking of a portfolio, funds in the highest VOV beta quintile underperform funds in the lowest VOV beta quintile ranging from 1.43% to 1.95% per month. Furthermore, multivariate Fama and MacBeth (1973) cross-sectional regressions consistently yield negative and significant average coefficients on VOV betas across different specifications even after controlling for different fund-level characteristics and aggregate volatility risk. This evidence indicates that VOV is a systematically and distinct priced risk factor in hedge funds.

We next investigate whether the significant relation between VOV betas and fund returns over the 2006–2012 period using the tradable *LBVIX* factor can be extended to periods prior to the availability of VIX option data. We use two statistical non-traded proxies of VOV, i.e., monthly standard deviation of the VIX (*SDVIX*) and monthly range of VIX (*RVIX*). We also employ a parameterized stochastic volatility process by fitting a Heston (1993) type diffusion process to the S&P 500 index return dynamics during the 2006–2013 period. We estimate the parameters of this bivariate diffusion model using Aït-Sahalia and Kimmel's (2007) methodology. Using the parameter values obtained in the first step, we interpolate the stochastic volatility process (*SVOL*) to the period prior to the availability of the option data. Using non-traded proxies of VOV helps in extending the sample period back to 1994 when survivorship-bias-free data on fund returns became available. Extending the analysis over the 1994–2013 period also enables us to analyze another period of high uncertainty that covers both the Long Term Capital Management (LTCM) crisis and the dotcom bubble.

The time-series results at the index level confirm our previous finding that most funds have significant negative exposure to VOV over 1994–2013 period and this negative exposure is mainly driven by the two crisis periods when uncertainty about volatility of the market portfolio is high. Furthermore, the univariate portfolio sorts corroborate the negative relation between VOV exposure and fund returns in the cross section. Finally, using both the statistical and the parameterized proxies of VOV, we document a significant and negative VOV risk premium in the cross section of hedge fund returns over the longer 1994–2013 period.

The remainder of the paper is organized as follows. Section 2 presents data and details the construction of *LBVIX*, our investable proxy for uncertainty about volatility of the market measured by the VOV. Sections 3 and 4 conduct time-series and cross-sectional analysis of fund performance, respectively, to examine the relation between VOV exposure and fund performance. Section 5 extends the analysis to periods prior to the availability of VIX option data by using statistical and parameterized proxies of VOV. Section 6 concludes.

2. Data and variable construction

In this section, we first describe the hedge fund data used in our analysis. Next, we present risk factors that have been shown to be important in explaining hedge fund performance. Finally, we explain the construction of our VOV measure, *LBVIX*.

2.1. Hedge fund database

Index level data for our baseline analyses is from Dow Jones Credit Suisse. We also use CISDM, Eurekahedge, and HFR indexes for robustness checks. We obtain data on individual hedge funds by merging four commercial hedge fund databases: Eurekahedge, HFR, Lipper TASS, and Morningstar. The union of these four databases (henceforth "*union database*") contains net-of-fee returns, assets under management, and other fund characteristics such as management and incentive fees, lockup, notice, and redemption periods, minimum investment amount, inception dates, and fund strategies. The availability of four databases enables us to create a comprehensive sample that is more representative of the hedge fund industry. After filtering out funds that have assets under management less than $5 million, we have 13,283 funds in our sample, which form the basis of our analyses at the individual fund level.

2.2. Hedge fund risk factors

The factors that we use in our analysis follow the standard 7-factor model of Fung and Hsieh (2004).These seven factors have been shown to have considerable explanatory power for hedge fund returns in the literature. Specifically, the seven factors comprise the three trend-following risk factors constructed using portfolios of lookback straddle options on currencies (*PTFSFX*), commodities (*PTFSCOM*), and bonds (*PTFSBD*); two equity-oriented risk factors constructed using excess S&P 500 index returns (*SNPMRF*), and the return difference of Russell 2000 index and S&P 500 index (*SCMLC*); two bond-oriented risk factors constructed using 10-year Treasury constant maturity bond yields (*BD10RET*), and the difference in yields of Moody's *Baa* bonds and 10-year Treasury constant maturity bonds (*BAAMTSY*), all yields adjusted for the duration to convert them into returns.[11]

Throughout our analysis, we test the robustness of our results after including three other risk factors that have also been documented as important in explaining hedge fund returns. In particular, we use the liquidity risk factor (*LIQ*) of Sadka (2010), correlation risk factor (*CR*) of Buraschi, Kosowski, and Trojani (2014), and macroeconomic uncertainty risk factor (*UNC*) of Bali, Brown, and Caglayan (2014). Furthermore, VOV can also be related to jump and volatility risks at the aggregate level, which have been shown to be important factors in explaining the cross section of stock returns by Cremers, Halling, and Weinbaum

[11] Bond, commodity and currency trend following factors are obtained from David A. Hsieh's data library available at https://faculty.fuqua.duke.edu/~dah7/HFRFData.htm. Equity-oriented risk factors are from *Datastream*. Bond-oriented risk factors are from the Board of Governors of the Federal Reserve System.

(2015). We further test the robustness of VOV against aggregate jump (*JUMP)* and aggregate volatility (*VOL)* risk factors and report the results in Appendix B.[12]

2.3. Construction of VOV factor

Our main proxy to capture the uncertainty risk in fund returns is VOV. Our hypothesis is that if funds are exposed to VOV and incorporate this risk factor in models, such a factor should explain both the time series and the cross section of hedge fund returns. To be able to estimate funds' exposure to VOV, we follow methodology outlined in Goldman, Sosin, and Gatto (1979) and implemented in Fung and Hsieh (2001) to create a lookback straddle written on the VIX index (*LBVIX*). Our starting point is the VIX index because it is a forward-looking measure of near-term aggregate volatility. Following its success in tracking market volatility and investors' sentiment, CBOE introduced VIX options on February 24, 2006. VIX options offer a powerful tool for investors to get exposure to (or to protect from) VOV by buying and selling VIX volatility directly, without having to deal with the other risk factors that would otherwise have an impact on the value of an option position on the market. Hence, if funds are exposed to VOV, this exposure can be replicated by the maximum possible return to a VOV trend-following strategy based on the respective underlying asset, i.e., the VIX. Using a cross section of VIX options, we create our proxy for the VOV factor, *LBVIX*, as follows.

VIX index options started trading on February 24, 2006. We obtain data on VIX options from Market Data Express (*MDX*) of Chicago Board Options Exchange (*CBOE*). Our analysis starts in April 2006 allowing for market participants to learn about the newly introduced VIX options for the first two months, and ensuring that the trading volume and open interest in VIX option contracts is sufficiently large for the market prices to be reliable. Starting from April 2006, at the beginning of each month, we create two long positions in at-the-money (ATM) VIX straddles, i.e., two calls and two puts with the same strike price and

[12] We would like to thank Turan Bali, Martijn Cremers, Robert Kosowski, and Ronnie Sadka for the factor data.

same maturity written on the VIX index.[13] We define one of the straddles as "up straddle", and the other as the "down straddle." We denote the initial date as $t = 0$, and the initial strike price of the max straddle as $K_{up}(0)$, and that of the down straddle as $K_{down}(0)$.

First, we describe the trading strategy for the up straddle. Suppose on the next trading day, denoted by $t = 1$, VIX rises more than half the distance between two adjacent strike prices.[14] In this case, we roll the up straddle to the higher strike price, selling the put and call at the existing strike price of $K_{up}(0)$ and buying a new straddle that is ATM with respect to the current VIX, $K_{up}(1) > K_{up}(0)$. In contrast, if the VIX does not rise more than half the distance between two adjacent strike prices on the next trading day, then we hold on to our existing position, i.e. $K_{up}(1) = K_{up}(0)$. By following this strategy during the calendar month, we are guaranteed to hold an up straddle position which is always nearest-to-the-money in case of up moves in the VIX, with a strike price that is nearest to the maximum value of VIX attained in a given month.

Next, we describe the trading strategy for the down straddle. Suppose at $t = 1$, the VIX falls more than half the distance between two adjacent strike prices. In this case, we roll the straddle to the lower strike price, selling the existing straddle and buying a new straddle that is ATM with respect to the current VIX, $K_{down}(1) < K_{down}(0)$. In contrast, if the VIX does not fall more than half the distance between two adjacent strike prices on the next trading day, then we hold on to our existing position, i.e. $K_{down}(1) = K_{down}(0)$. This strategy ensures that we hold a down straddle position which is always nearest-to-the-money in case of down moves in the VIX, with a strike price that is nearest to the minimum value of VIX attained in a given month.

[13] We choose VIX options maturing in the next calendar month as they are the most actively traded contracts among various maturities. If there is no option that expires in the next calendar month, we choose the one that expires in two calendar months. For moneyness level, we choose the VIX option which is nearest-to-the-money.
[14] The rebalancing is based on the end-of-day VIX levels.

Combining the up and down straddles, *LBVIX* strategy grants its owner the right to *sell* at the *highest* level of VIX during that month (by exercising the put leg of the up straddle), and the right to *buy* at the *lowest* level of VIX during that month (by exercising the call leg of the down straddle). On last trading day of the month, we liquidate the options that construct the *LBVIX* strategy, and compute the return to the strategy. We repeat this exercise next month.

Monthly returns on *LBVIX* straddles from April 2006 to December 2012 as described above form the basis of our main tests to examine whether i) hedge funds have VOV exposure at the index and individual fund level; ii) VOV can explain time series and cross section of hedge fund returns; and iii) VOV is a priced factor in the cross section of hedge fund returns.

<<Insert Table 1 about here>>

Table 1 presents summary statistics of *LBVIX* and its correlation with other risk factors. *LBVIX* strategy on average earned 1.10% per month during the sample period. However, looking at the subsamples in Panel A, we can observe that this positive return is attributable to the turbulent period of subprime crisis and European sovereign debt crisis when uncertainty peaked globally, and the health of financial system was threatened.[15] During the crisis sub-period, *LBVIX* strategy earned an average of 11.19% per month, consistent with our expectations that investors that were long VOV were able to avoid uncertainty about expected market returns with a long position in an *LBVIX* strategy. In contrast, during the second sub-period, *LBVIX* strategy lost on average 6.97% per month as aggregate uncertainty was easing down following U.S. government's interventions in the financial system, monetary easing programs implemented by the U.S. Federal Reserve Bank (FED), Bank of England (BoE),

[15] Our definition of sub-periods is based on Edelman et al. (2012), who identify March 2009 as a structural break associated with the end of credit crisis. Our results are robust to alternative sub-periods ranging from September 2008 to February 2009. In particular, VOV risk exposure becomes important from September 2008 onwards.

interventions by the European Central Bank (ECB), the strike of a Greek debt haircut deal, and austerity measures undertaken by troubled Eurozone countries to handle the debt crisis.[16]

We note the high correlations between $LBVIX$ with return on VIX (*RetVIX*) and correlation risk factor (*CR*) of Buraschi, Kosowski, and Trojani (2014), both of which are 0.74. *RetVIX* is defined as the monthly return of the VIX index that captures a strategy with volatility exposure. One would naturally expect that the two proxies for exposures to aggregate volatility (*RetVIX*) and volatility of aggregate volatility ($LBVIX$) to be highly correlated. Buraschi, Trojani, and Vedolin (2014) show that in a Lucas orchard with heterogeneous beliefs, there is a link between market-wide uncertainty and comovement of stock returns. In their model, greater subjective uncertainty and a higher disagreement on the market-wide signal imply a larger correlation of beliefs, a stronger comovement of stock returns, and a substantial correlation risk premium generated by the endogenous optimal risk sharing among investors. Therefore, $LBVIX$ and *CR* are expected to share a common component. To isolate the confounding effects of correlation risk and aggregate volatility risk factors with our VOV measure, we use the orthogonalized versions of *RetVIX* and *CR* in the remainder of the analysis.

3. Time-series analysis of hedge fund performance

We start with time-series analysis of returns on fund indexes, and examine their exposures to VOV. Our starting benchmark is the Fung and Hsieh (2004) seven-factor model, in which a fund's excess returns $r_{i,t}$ can be decomposed into a risk-adjusted performance component(α_i), and exposures to each risk factor, (β_i^k). To capture the links between hedge fund index returns, hedge fund strategies, and their exposure to VOV, we extend the seven-factor model to an eight-factor model incorporating the VOV factor ($LBVIX$):

[16] These findings are also in line with Barnea and Hogan (2012) who show a negative variance risk premium in VIX options.

$$r_{i,t} = \alpha_i + \beta_i^1 PTFSBD_t + \beta_i^2 PTFSFX_t + \beta_i^3 PTFSCOM_t + \beta_i^4 BD10RET_t + \beta_i^5 BAAMTSY_t + \beta_i^6 SNPMRF_t + \beta_i^7 SCMLC_t + \beta_i^8 LBVIX_t + \varepsilon_{i,t}\ , \tag{1}$$

where $r_{i,t}$ is the monthly return on hedge fund index i in excess of one-month T-bill return, and other variables are as described in the previous section.[17] All returns with the exception of those for *BAAMTSY* and *SCMLC* factors are in excess of the risk-free rate.

3.1. Analysis for the whole sample period

We use the 8 indexes from Dow Jones Credit Suisse database. We focus on Hedge Fund Index, Convertible Arbitrage, Equity Market Neutral, Event Driven, Global Macro, Long/Short Equity, Managed Futures, and Multi-Strategy indexes, which cover the major hedge fund strategies.[18] Table 2 presents loadings on the eight risk factors in Eq. (1) for the above indexes as well as for the pooled sample of the indexes during the full sample period.

<<Insert Table 2 about here>>

The adjusted R^2's of the 8-factor model range from 16.62% for the global macro index to 73.32% for the event driven index. With the exception of equity market neutral strategy, seven of the eight indexes exhibit significantly negative VOV loadings over our sample period from April 2006 to December 2012. Furthermore, panel regressions also indicate a negative VOV exposure providing further evidence that funds are significantly exposed to the VOV factor, and VOV is a critical determinant of fund returns at the index level.[19]

As noted in the previous section, VOV factor can be related to the jump and volatility risk factors of Cremers, Halling, and Weinbaum (2015), and correlation risk factor of Buraschi, Kosowski, and Trojani (2014). Furthermore, Sadka (2010) finds that liquidity risk is

[17] *LBVIX* is by construction non-normal as it is bounded below by −100%. To investigate the potential impact of non-normality of *LBVIX*, we test the normality of residuals from the time-series regressions. We find that residuals are normally distributed in most of the specifications.
[18] There are originally 14 indexes covered by Dow Jones Credit Suisse. We omit emerging market and three sub categories of event driven strategies, dedicated short bias, and fixed income strategies as they are either covered by the chosen strategies or do not have significant amount of assets under management.
[19] The *t*-statistics in panel regression are adjusted for heteroskedasticity and cross-correlations in error terms. Our results are robust to allowing for AR(1) error terms.

important in explaining the cross section of fund returns. Recently, Bali, Brown, and Caglayan (2014) show that exposure to macroeconomic risk is a significant determinant of cross-sectional differences in fund returns. To check the robustness of our results with respect to these factors, we further extend the 8-factor model to a 12-factor model:

$$\begin{aligned} r_{i,t} = \alpha_i &+ \beta_i^1 PTFSBD_t + \beta_i^2 PTFSFX_t + \beta_i^3 PTFSCOM_t + \beta_i^4 BD10RET_t \\ &+ \beta_i^5 BAAMTSY_t + \beta_i^6 SNPMRF_t + \beta_i^7 SCMLC_t + \beta_i^8 LBVIX_t \\ &+ \beta_i^9 RetVIX_t + \beta_i^{10} LIQ_t + \beta_i^{11} CR_t + \beta_i^{12} UNC_t + \varepsilon_{i,t}\,, \end{aligned} \tag{2}$$

where $r_{i,t}$ and the first eight factors are explained in Eq. (1), *RetVIX* is the orthogonalized version of monthly return on VIX, *LIQ* is the permanent-variable price impact component of Sadka (2006) liquidity measure, *CR* is the orthogonalized version of correlation risk factor in Buraschi, Kosowski, and Trojani (2014), and *UNC* is the economic uncertainty index in Bali, Brown, and Caglayan (2014) to capture funds' macroeconomic risk exposure.[20]

As can be seen from Table 3, once again with the exception of equity market neutral strategy, seven out of eight indexes exhibit significantly negative VOV loadings, even after controlling for volatility, correlation, liquidity, and macroeconomic risk factors. Further, pooled panel regressions confirm the previously documented negative VOV exposure for funds. Overall, our results show that VOV factor is an important determinant of fund returns at the index level.

<<Insert Table 3 about here>>

3.2. Sub-period analysis

Are hedge funds' VOV exposures constant throughout the sample period, or do they exhibit time-series variation? Given the increase in uncertainty about expected returns during the financial crisis, it is important to investigate if and how funds' VOV exposures change during the crisis and post-crisis periods. For this purpose, we divide the sample period into

[20] Due to the availability of *correlation* risk factor up to June 2012, we conduct our empirical analyses of the 12-factor model over the period from April 2006 to June 2012.

two sub-periods using March 2009 as the structural break point for the end of financial crisis as in Edelman et al. (2012). We then estimate the 12-factor model loadings in the two sub-periods.

<<Insert Table 4 about here>>

As can be seen from Panels A and B of Table 4, the significance of funds' VOV exposures is essentially driven by the crisis (subprime and European sovereign debt crises) period during which uncertainty about risk of the market portfolio peaked and the health of the global economic system was put under question. Our full sample results are mostly driven by this period of extreme uncertainty. None of the other factors has an explanatory power in explaining fund returns as powerful as the VOV factor, which exhibits robustly negative and significant loadings for seven of the eight indexes during the first sub-period from April 2006 to March 2009. In contrast, the explanatory power of VOV factor disappears in the second sub-period as there was less uncertainty in the market following reassurances from the U.S. and European governments about the health of the financial system with ambitious buyback programs for the troubled banks and insurance companies, the resolution of the Greek debt crisis, and the implementation of austerity programs throughout troubled Eurozone economies, as well as monetary easing programs by the FED, BoE, and the ECB.

We conclude our time-series analyses at the index level by testing the explanatory power of the 12 factors in explaining the time-series variation in index returns. We conduct three different variable selection tests. The first test is a forward recursive variable selection method with the objective of identifying variables that achieve the highest improvement in adjusted R^2.[21] The second and third tests are based on stepwise regressions, in which we impose 10% significance level condition for a variable to be selected by the model. We

[21] More details about the variable selection test could be found in Lindsey and Sheather (2010).

implement this condition both in forward stepwise and backward stepwise regressions.[22] For the sake of brevity, we only present results of variable selection tests based on improvement in adjusted R^2's.[23] The results in Table A1 in Appendix A provide us information about the factors that are more important in explaining index returns. The tests are repeated for the full sample and the two sub-periods. A value of 1 indicates if a factor is selected in the model. The bottom row reports the percentage of times a variable is selected among the 8 indexes, and the third last column reports the number of variables selected to explain the corresponding index return.

Consistent with the earlier results for the time-series regressions, VOV factor shows up as an important variable in explaining hedge fund index returns as it is associated with a significant improvement in the explanatory power of the model. During the full sample period, VOV factor is selected 87.50% of the time (i.e., for seven out of the eight indexes), and this result seems to be largely driven by the first sub-period (VOV is selected 87.50% in the first sub-period compared to no significance in the second sub-period). Market risk, correlation risk, and bond spread are also important risk factors in explaining hedge fund index returns, all being selected for more than half of the indexes during the full sample.

Taken together, these findings show that during the crisis when aggregate uncertainty is high and VOV factor returns are positive, hedge funds perform poorly due to their negative VOV exposures. However, these negative exposures pay off during periods of low VOV when uncertainty is diminished. It is important to note that fund styles are heterogeneous and can exhibit significant cross-sectional variation. Thus, even though time-series analysis at the index level points towards VOV being an important risk factor, explanatory power might

[22] Given some of the potential issues such as multicollinearity and instability of results that might exist when a large set of variables is used in stepwise regressions, we also test two alternative variable selection procedures proposed in the literature. The first test is the least angle regression and shrinkage (LARS) method of Efron et al. (2004) based on least absolute shrinkage and selection operator (LASSO) method of Tibshirani (1996). The second test is based on Bayesian Information Criterion (BIC) proposed by Raftery (1995) and Raftery, Madigan, and Hoeting (1997). The results of both tests are very similar and are included in the Appendix A.

[23] The results for forward and backward stepwise regressions are very similar and are available upon request.

result from other characteristics of fund styles. In the next section, we examine if cross-sectional differences in funds' risk-return profiles are attributable to VOV, and if VOV is a priced risk factor.

4. Cross-sectional analysis of hedge fund performance

In this section, we conduct parametric and nonparametric tests to examine the relation between VOV exposures and hedge fund returns. We start with univariate and bivariate portfolio level analyses. Next, we present multivariate cross-sectional regressions controlling for several fund characteristics. Before going into the details of the analysis at the individual fund level, Table 5 presents summary statistics of several fund characteristics over the full sample period from April 2006 to December 2012.

<<Insert Table 5 about here>>

Despite a turbulent period of financial crisis, hedge funds earned an average of 0.58% per month during the sample period. Another noteworthy observation is the disparity between mean and median assets under management, which points to an industry dominated by a few large funds. Average fund age is 4.52 years. Average management and incentive fees are also very close to the 2-20 typical fee structure in the hedge fund industry.

4.1. Univariate VOV beta sorts

We start with examining whether funds' VOV exposures can predict the cross-sectional differences in their returns. We estimate funds' monthly VOV betas via time-series regressions over 36-month rolling windows:

$$r_{i,t} = \alpha_{i,t} + \beta_{i,t}^{LBVIX} LBVIX_t + \varepsilon_{i,t} \,, \tag{3}$$

where $r_{i,t}$ is the excess return on fund *i* in month *t*, $LBVIX_t$ is the excess return on a lookback straddle written on the VIX index, and $\beta_{i,t}^{LBVIX}$ is the VOV beta for fund *i* in month *t*.[24]

[24] Given the short time span of our sample period, we also use 24-month rolling window regressions to estimate funds' VOV exposures. The results are essentially similar and available upon request.

We next conduct portfolio-level analysis to investigate cross-sectional predictive power of $\beta_{i,t}^{LBVIX}$. For each month, from March 2009 to December 2012, funds are sorted into quintile portfolios based on their $\beta_{i,t}^{LBVIX}$. Our portfolio formation exercise uses information available only as of the formation date to avoid look-ahead bias in the estimation of VOV betas. Quintile 1 (5) contains funds with the lowest (highest) VOV betas. We calculate next month's post-ranking value-weighted portfolio returns and repeat the procedure each month.[25] Table 6 reports average VOV betas, next month's returns, and 8-factor alphas of VOV beta-sorted quintiles.

<<Insert Table 6 about here>>

Univariate portfolio sorts indicate a monotone and negative relation between the VOV betas and next month's average returns. Portfolio of funds with lowest VOV betas (portfolio 1) earns 1.70% per month, whereas return on the portfolio of funds with highest VOV betas (portfolio 5) is 0.08% per month. The spread portfolio which is long in the highest VOV beta funds and short in the lowest VOV beta funds (high $\beta_{i,t}^{LBVIX}$– low $\beta_{i,t}^{LBVIX}$) loses on average 1.62% per month with a *t*-statistic of –2.38. Table 6 also presents next month's risk-adjusted returns (8-factor alphas) for $\beta_{i,t}^{LBVIX}$sorted quintiles. We observe a similar pattern in alphas that decrease monotonically from the highest VOV beta portfolios to the lowest VOV beta portfolios, with a significant and negative alphas of –1.89% for the spread portfolio.[26]

Note that pre-ranking average VOV betas range from –0.09 to 0.02. Hence a negative VOV beta is, on average, associated with superior returns. When we investigate the source of this significant and negative return differential between high $\beta_{i,t}^{LBVIX}$ and low $\beta_{i,t}^{LBVIX}$funds, we find that the difference is attributable to the outperformance of funds in the lowest (most

[25] Value-weighting scheme is based on funds' assets under management. We also use equally-weighted sorts, and sorts without backfill bias by omitting funds' first 24 months of return data after their inception (Fung and Hsieh (2000) provide a good discussion of data biases). The results are essentially similar and available upon request.
[26] Negative and significant relation between *LBVIX* beta sorted portfolios and next month's risk-adjusted returns is robust after controlling for jump, volatility, and correlation risk factors.

negative) VOV beta quintile. For example, when we compare returns of portfolios 1 and 5, we observe that funds in the lowest $\beta_{i,t}^{LBVIX}$ quintile exhibit significantly positive returns, whereas returns on funds in the highest $\beta_{i,t}^{LBVIX}$ are not significant. The results provide evidence that the negative and significant return difference between high $\beta_{i,t}^{LBVIX}$ and low $\beta_{i,t}^{LBVIX}$ funds is due to outperformance of funds in the lowest $\beta_{i,t}^{LBVIX}$ quintile, i.e., funds that have the most negative VOV exposure, and not due to underperformance of funds in the highest $\beta_{i,t}^{LBVIX}$ quintile.

4.2. Bivariate VOL-VOV beta sorts

Aggregate volatility risk has been documented to be an important risk factor in explaining the cross section of stock returns (see e.g., Ang et al., 2006; Bali and Engle, 2010; Cremers, Halling, and Weinbaum, 2015). To ensure that our *LBVIX* measure is not simply picking up aggregate volatility risk, we further sort hedge funds with respect to their volatility risk (VOL) and VOV exposures.[27] We estimate each fund's volatility risk exposure by estimating the following time-series regressions over 36-month rolling windows:

$$r_{i,t} = \alpha_{i,t} + \beta_{i,t}^{MKT} MKT_t + \beta_{i,t}^{VOL} VOL_t + \varepsilon_{i,t}\ , \tag{4}$$

where $r_{i,t}$ is the excess return on fund *i* in month *t*, MKT_t is the monthly excess market return, and VOL_t is the monthly change in the VIX index.

For each month, from March 2009 to December 2012, we sort funds into 25 (5x5) portfolios based on their VOL ($\beta_{i,t}^{VOL}$), and VOV ($\beta_{i,t}^{LBVIX}$) exposures. Quintile 1 (5) contains funds with the lowest (highest) VOL and VOV betas. We calculate next month's post-ranking value-weighted portfolio returns, and repeat the procedure each month. Table 7 reports next month's average return and 8-factor alphas for the 25 VOL-VOV beta sorted portfolios.

<<Insert Table 7 about here>>

[27] *LBVIX* essentially captures volatility of aggregate volatility risk (VOV) and is different from the monthly change in the VIX index that captures the aggregate volatility risk (VOL).

Bivariate portfolio sorts confirm the negative relation between VOV betas and next month's average fund returns. Regardless of the portfolios' VOL exposures, the five spread portfolios that are long in the highest VOV beta funds and short in the lowest VOV beta funds (high $\beta_{i,t}^{LBVIX}$– low $\beta_{i,t}^{LBVIX}$) always exhibit significantly negative next-month returns, with losses ranging from 1.43% to 1.95%. The 8-factor alphas indicate even greater losses for the spread portfolios, ranging from –1.66% to –2.49%. In contrast, controlling for VOV betas, VOL-beta-sorted spread portfolios do not exhibit returns significantly different from zero. Overall, the results from the non-parametric tests indicate a strong negative link between VOV exposure and fund performance, with a strong cross-sectional dispersion in next month's average fund returns.

However, since our analysis is at the portfolio level, it may potentially suffer from the aggregation effect due to omission of information in the cross section. For example, the funds in the lowest $\beta_{i,t}^{LBVIX}$quintile may have different characteristics compared to the funds in the highest $\beta_{i,t}^{LBVIX}$quintile. To mitigate the effects of aggregation, and to control for potential effects of fund characteristics, we conduct multivariate analysis in the next section.

4.3. Multivariate cross-sectional regressions

We estimate the following Fama and MacBeth (1973) regressions at the individual fund level after controlling for a large set of fund characteristics:

$$\begin{aligned} r_{i,t+1} = {} & \lambda_{0,t} + \lambda_{LBVIX,t}\beta_{i,t}^{LBVIX} + \lambda_{r,t}r_{i,t} + \lambda_{Size,t}Size_{i,t} + \lambda_{Age,t}Age_{i,t} \\ & + \lambda_{MgmtFee,t}MgmtFee_{i,t} + \lambda_{IncFee,t}IncFee_{i,t} \\ & + \lambda_{Redemption,t}Redemption_{i,t} + \lambda_{MinInv,t}MinInv_{i,t} + \lambda_{Lockup,t}Lockup_{i,t} \\ & + \lambda_{Delta,t}Delta_{i,t} + \lambda_{Vega,t}Vega_{i,t} + \lambda_{VOL,t}\beta_{i,t}^{VOL} + \varepsilon_{i,t+1}\ , \end{aligned} \tag{5}$$

where $r_{i,t+1}$ is the excess return on fund *i* in month *t+1*, $\beta_{i,t}^{LBVIX}$is the VOV beta of fund *i* in month *t*, $r_{i,t}$ is the one-month excess return on fund *i* in month *t*, *Size* is the monthly AUM (in billions of dollars), *Age* is the number of months since fund's inception, *MgmtFee* is a fixed fee as a percentage of AUM, *IncFee* is a fixed percentage fee of the fund's net annual profits above a pre-specified hurdle rate, *Redemption* is the minimum number of days an investor needs to notify the fund before she can redeem the invested amount from the fund, *MinInv* is the minimum initial investment amount (in millions of dollars) that the fund requires from its investors, *Lockup* is the minimum number of days that the investor has to wait before she can withdraw her investment, *Delta* is the expected dollar change in the manager's compensation for a 1% change in the fund's net asset value (NAV), *Vega* is the expected dollar change in the manager's compensation for a 1% change in the volatility of fund's NAV, and $\beta_{i,t}^{VOL}$ is the VOL beta of fund *i* in month *t* estimated using Eq. (4).[28]

<<Insert Table 8 about here>>

Table 8 reports the average intercept and time-series averages of the slope coefficients from the monthly cross-sectional regressions of one-month ahead fund excess returns on VOV betas, as well as different fund characteristics for the period from March 2009 to December 2012 after allowing for the first 36 months of data from April 2006 for the estimation of first set of VOV betas. The *t*-statistics reported in parentheses are adjusted for autocorrelation and heteroskedasticity as well as potential errors-in-variables (EIV) problem that may result from the fact that betas are estimated (hence are measured with error) in the first pass.[29] The first specification examines the cross-sectional relation between the VOV beta and one-month-ahead fund returns without any controls. Consistent with our findings in nonparametric tests of portfolio sorts in the previous sections, column 1 shows a significantly negative relation between $\beta_{i,t}^{LBVIX}$ and future returns, with an average slope of –0.1770 and a *t*-statistic of –2.15.

[28] Agarwal, Daniel, and Naik (2009) describe the computation of hedge fund's delta and vega.

[29] The fact that betas in the first pass are estimated with error has potential consequences in two-step least squares procedure. First, if standard errors do not include information that betas are measured with error, the implied *t*-statistics might overstate the precision of the risk premium estimates. Second, least squares estimators of risk premiums in the second step might be biased in finite samples in presence of the EIV problem. To mitigate these issues, we follow Shanken (1992) to adjust the standard errors and *t*-statistics.

Having confirmed the significant negative relation at the individual fund level via univariate Fama and MacBeth (1973) regressions, we next control for individual fund characteristics and aggregate volatility risk to investigate whether this relation persists in the presence of different fund characteristics. We test six alternative specifications. As funds' delta and vega are closely related to their management and incentive fees, to avoid a potential multicollinearity problem, we do not include management fees and incentive fees in the second specification. The third specification excludes delta and vega but includes the two types of fees. The fourth specification incorporates all fund-specific characteristics. The fifth specification examines the robustness of VOV factor in the presence of volatility risk factor (VOL), and the sixth specification tests the full model presented in Eq. (5).

Consistent with prior studies of Aragon (2007) and Agarwal, Daniel, and Naik (2009), we find significant and positive relation between both lockup period and delta with funds' future returns. Furthermore, the results indicate a negative relation between a fund's size and its future returns. Regardless of the control variables used, all the five specifications show a robust and significant negative relation between a fund's VOV beta and its future return, confirming our previous results that a fund's VOV exposure has a significant predictive power to explain its future returns. Having established a robust negative relation between VOV betas and hedge fund returns both in the time series and in the cross section over the 2006–2012 period, we next investigate if and whether the results are robust to the use of alternative proxies of VOV.

5. Statistical and parameterized proxies of VOV

Although our traded VOV proxy, *LBVIX*, has the advantage of being investable, the major challenge to using *LBVIX* is the short time span due to availability of VIX option data only after 24 February 2006. To test if our results can be generalized over and above the sample period, we extend our analysis to period prior to 2006 by using non-traded proxies of VOV. In particular, we use two statistical proxies and one parameterized proxy of VOV.

5.1. Statistical proxies of VOV

The first statistical VOV proxy is the monthly range of the VIX index defined as:

$$RVIX_t = ln[Max\{VIX_\tau\}] - ln[Min\{VIX_\tau\}],\ \tau = 1, 2, \dots, T \qquad (6)$$

where τ denotes trading days in a given month, and t denotes months.[30]

The second statistical proxy for VOV is monthly standard deviation of the VIX index:

$$SDVIX_t = \sqrt{\frac{1}{T}\sum_{\tau=1}^{T}(VIX_\tau - \overline{VIX}_t)^2},\ \tau = 1, 2, \dots, T \qquad (7)$$

τ denotes trading days in a given month, t denotes months, and $\overline{VIX}_t$ is the average VIX.

5.2. Parameterizing VOV using Aït-Sahalia and Kimmel (2007) methodology

It is well-documented that volatility is stochastic and option pricing models that incorporate stochastic volatility in the underlying asset price process perform better in pricing (Hull and White, 1987; Stein and Stein, 1991; Heston, 1993; Bakshi, Cao and Chen, 1997). Although estimating parameters of the stochastic volatility models is challenging, Aït-Sahalia and Kimmel (2007) provide closed-form solutions to maximum likelihood estimation of stochastic volatility processes. To parameterize stochastic volatility, we follow Aït-Sahalia and Kimmel (2007) methodology and assume a Heston (1993) type stochastic volatility process for the return on the market portfolio. In particular, we estimate the parameters of the following bivariate diffusion model over the sample period of April 2006 – December 2013:

$$d\begin{bmatrix} S_t \\ Y_t \end{bmatrix} = \begin{bmatrix} a + bY_t \\ \kappa(\gamma - Y_t) \end{bmatrix} dt + \begin{bmatrix} \sqrt{(1-\rho^2)Y_t} & \rho\sqrt{Y_t} \\ 0 & \sigma\sqrt{Y_t} \end{bmatrix} d\begin{bmatrix} W_1(t) \\ W_2(t) \end{bmatrix} \qquad (8)$$

[30] This definition of range-based volatility assumes a driftless volatility process as in Bali and Weinbaum (2005). Our results are also robust to defining monthly range of VIX as $RVIX_t = Max\{VIX_\tau\} - Min\{VIX_\tau\}$.

where s_t is the logarithm of the S&P 500 index, and Y_t is its stochastic variance. In the above bivariate diffusion process, $a = r - d$, b= $\lambda_1(1-\rho^2) + \lambda_2\rho - \frac{1}{2}$, r is the instantaneous risk-free interest rate, d is the dividend yield, λ_1 and λ_2 are the two components of market prices of risk of the stochastic volatility state variable, ρ is the correlation coefficient between the two Wiener processes that drive the uncertainty in market returns and its stochastic variance, κ is the speed of mean reversion of stochastic variance, γ is the long-term value of variance, and σ is the VOV parameter, our variable of interest.

We follow Aït-Sahalia and Kimmel (2007) and use the VIX index as a proxy for Y_t. When VIX series is used as the volatility proxy, i.e., when the volatility state variable is observable, we assume that the second component of market price of risk for the unobservable volatility state variable λ_2 is zero. Hence, Eq. (8) can be rewritten as:

$$d\begin{bmatrix} s_t \\ Y_t \end{bmatrix} = \begin{bmatrix} r - d + \left(\lambda_1(1-\rho^2) - \frac{1}{2}\right)Y_t \\ \kappa(\gamma - Y_t) \end{bmatrix} dt + \begin{bmatrix} \sqrt{(1-\rho^2)Y_t} & \rho\sqrt{Y_t} \\ 0 & \sigma\sqrt{Y_t} \end{bmatrix} d\begin{bmatrix} W_1(t) \\ W_2(t) \end{bmatrix} \tag{9}$$

which requires the maximum likelihood estimation of the parameter set θ = [κ, γ, σ, ρ, λ_1].[31] Using daily log returns on the S&P 500 index and daily VIX data, we present below the results of the parameter estimates of Eq. (9) during April 2006 – December 2013:

κ	γ	σ	ρ	λ_1
5.1189	0.0512	0.4323	-0.8175	6.9611

The estimated parameters are very similar to those obtained in Table 6 of Aït-Sahalia and Kimmel (2007) over the period 1990–2003. In line with the literature, the correlation between the innovations to stock price and stochastic volatility is strongly negative (–0.82). The long-term value of volatility of the market portfolio $\gamma^{1/2}$ is estimated to be 23% with a speed of mean reversion of approximately 5. We observe a larger risk premium, which is

[31] We would like to thank to Yacine Aït-Sahalia for making publicly available the MATLAB codes for maximum likelihood estimation of various diffusion processes on his website at http://www.princeton.edu/~yacine/closedformmle.htm. Model B6 corresponds to the bivariate Heston (1993) diffusion model, and forms the basis of our estimation.

expected given the large uncertainty about the volatility of the market portfolio, i.e., the VIX, over the sample period.[32]

Having estimated the parameters of the stochastic volatility process during the April 2006 – December 2013 period, we next interpolate these results to back up the volatility-of-volatility parameter (σ) during the period January 1994 – December 2013. In particular, we use the discrete time equivalent for the second component of the diffusion equation in Equation (9) and interpolate the parameters of the stochastic volatility process such that:

$$\Delta VIX_t = 5.1189(0.0512 - VIX_t)\Delta t + \sigma\sqrt{VIX_t}\Delta W_2(t) \tag{10}$$

where ΔVIX_t is the daily change in the VIX index, $\Delta t = 1/252$, and $W_2(t)$ is a standard Wiener process. We use 500 simulations of the Wiener process, and define the average of the 500 σ parameters resulting from Equation (10) as the σ parameter in day *t*. We then calculate the monthly averages of σ_t to estimate the interpolated values of the stochastic volatility process based on the parameters of the Heston (1993) type bivariate diffusion model and the MLE methodology in Aït-Sahalia and Kimmel (2007). This procedure results in a monthly time-series of stochastic volatility parameter (*SVOL*).

<<Insert Table 9 about here>>

Table 9 presents the summary statistics of the three non-traded VOV proxies over the extended sample period from January 1994 to December 2013. The correlations in Panel B show that our investable VOV proxy, *LBVIX*, is highly correlated with the three non-traded proxies, ranging from 0.49 to 0.76 over the common sample period from April 2006 to December 2012. Further, the correlations in Panels C and D imply that the three non-traded proxies are highly correlated among themselves both over the extended sample period of

[32] The large uncertainty for the risk premium estimate is not surprising given that the estimation period is only 7 years long, and that risk premiums are typically poorly estimated even in longer samples (Aït-Sahalia and Kimmel, 2007; Aït-Sahalia, Amengual, and Manresa, 2015). Since the risk premium estimate does not enter into the volatility diffusion equation, this does not affect the precision of the parameterization of the stochastic volatility process. In contrast, diffusion parameters, such as vol-of-vol are estimated with much higher precision since their asymptotics depends on the sampling frequency (Δt = 1/252).

January 1994–December 2013, and over the period prior to the availability of VIX option data (i.e., prior to April 2006), with pairwise correlations ranging from 0.59 to 0.81. High correlations with statistical and parameterized proxies of VOV show that our investable *LBVIX* proxy successfully captures the dynamics of volatility of aggregate volatility. Next section presents the time-series results at the hedge fund index level using *SVOL* as our VOV proxy.[33]

5.3. Time-series analysis over January 1994–December 2013 period

We use the Fung and Hsieh (2004) seven-factor model augmented with *SVOL*:

$$\begin{aligned} r_{i,t} = \alpha_i + \beta_i^1 PTFSBD_t + \beta_i^2 PTFSFX_t + \beta_i^3 PTFSCOM_t + \beta_i^4 BD10RET_t \\ + \beta_i^5 BAAMTSY_t + \beta_i^6 SNPMRF_t + \beta_i^7 SCMLC_t + \beta_i^8 SVOL_t + \varepsilon_{i,t}\,, \end{aligned} \tag{11}$$

where $r_{i,t}$ is the monthly return on fund index *i* in excess of one-month T-bill return, and other variables and fund indexes are as described in the previous section. Table 10 presents the loadings on the eight risk factors in Eq. (11) for the fund indexes as well as for the pooled sample of the indexes during the extended sample period of January 1994 – December 2013.

<<Insert Table 10 about here>>

The adjusted R^2's of the 8-factor model range from 13.24% for the global macro index to 62.73% for the event driven index. With the exception of multi-strategy index, seven out of eight indexes exhibit significant VOV loadings over the sample period from January 1994 to December 2013. Panel regressions also show a negative VOV exposure providing further evidence that funds are significantly exposed to the VOV factor, and VOV is a critical determinant of fund returns at the index level over the extended 20-year period. These results are consistent with our earlier findings using an investable VOV factor over the 2006–2012 period, and show that VOV factor is an important determinant of fund returns at the index level.

[33] We present the results based on the two statistical proxies of VOV, *RVIX* and *SDVIX* in Appendix C.

5.3.1. Sub-period analysis

Time-series analysis in Section 3 reveals that the significance of VOV factor is mainly driven by the financial crisis period of 2007–2008, a significant event associated with huge uncertainty about market volatility. The ability to extend the sample period back to 1994 enables comparing and contrasting of results for the recent financial crisis with another period of high uncertainty spanning the LTCM crisis and dotcom bubble.

<<Insert Table 11 about here>>

As can be seen from Panels A and B of Table 11, 5 and 6 out of 8 hedge fund indexes exhibit negative VOV exposures over the first sub-period corresponding to the LTCM crisis and dotcom bubble, and second sub-period that includes the recent financial crisis, respectively.[34] The results are comparable to the significance of VOV exposures at the index level using *LBVIX* as the VOV proxy (Table 4). Although the LTCM and the dotcom events were much more localized compared to the scale of the financial crisis, we confirm our initial finding that the negative and significant VOV exposure of funds magnifies and becomes more significant in crisis periods when uncertainty about market risk peaks.[35]

Taken together, time-series analyses at the index level over the extended period indicate that funds exhibit a significantly negative VOV exposure. We find that funds' VOV exposures are time-varying and are mostly driven by periods of extreme uncertainty about market risk. During crisis when uncertainty about market volatility is high, funds perform poorly due to their negative VOV exposures. In particular, equity driven strategies such as Convertible Arbitrage, Event Driven, and Long Short Equity are most negatively exposed to VOV risk during crisis.

[34] The results for non-crisis periods that are reported in the Appendix C are mostly insignificant for the January 1994–June 1998, and April 2000–March 2006 periods (see Table C1).
[35] Using CISDM indexes, we find 7 out of 11 indexes exhibit significantly negative VOV exposures over the LTCM crisis and dotcom bubble.

5.4. Cross-sectional analysis over January 1994–December 2013 period

In this section, we examine the robustness of the negative relation between VOV exposures and hedge fund returns by extending the previous parametric and nonparametric tests conducted during the 2006–2012 period using the investable and tradable VOV proxy, *LBVIX*, to a longer sample period using the parameterized and non-traded version of VOV, i.e., *SVOL*.[36]

5.4.1. Univariate SVOL beta sorts

We examine whether funds' *SVOL* exposures can predict the cross-sectional differences in their returns over the extended 1994–2013 period. We estimate funds' monthly *SVOL* betas via time-series regressions over 24-month rolling windows:

$$r_{i,t} = \alpha_{i,t} + \beta_{i,t}^{SVOL} SVOL_t + \varepsilon_{i,t}\ , \qquad (12)$$

where $r_{i,t}$ is the excess return on fund i in month t, $SVOL_t$ is the parameterized and interpolated VOV proxy calculated via estimating the parameters of Heston (1993) type stochastic volatility process in Eq. (9) over 2006–2013 period using the methodology in Aït-Sahalia and Kimmel (2007), and interpolating the estimated model to the 1994–2013 period using Eq. (10), and $\beta_{i,t}^{SVOL}$is the VOV beta proxy for fund i in month t.[37]

For each month between January 1994 and December 2013, we sort the funds into quintile portfolios based on their $\beta_{i,t}^{SVOL}$. Quintile 1 (5) contains funds with the lowest (highest) *SVOL* betas. We then calculate next month's post-ranking equally-weighted portfolio returns, and repeat the procedure each month.[38] Table 12 reports the results.

<<Insert Table 12 about here>>

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[36] The results are similar for the two statistical proxies of VOV, i.e., *RVIX* and *SDVIX* (see Appendix C).
[37] We also use 36-month rolling window regressions to estimate funds' VOV exposures, and find similar results.
[38] We also conduct value-weighted sorts, and sorts without backfill bias by omitting funds' first 24 months of return data after their inception. The results are qualitatively similar and available upon request.

Consistent with the results obtained for the 2009–2012 period using the investable VOV proxy (*LBVIX*), univariate portfolio sorts using the parameterized VOV proxy (*SVOL*) indicate a monotonically negative relation between the *SVOL* betas and next month's average returns over the 1994–2013 period. Funds with lowest *SVOL* betas (portfolio 1) earn 1.31% per month, whereas return on funds with highest *SVOL* betas (portfolio 5) is 0.61% per month. The spread portfolio that is long in highest *SVOL* beta funds and short in the lowest *SVOL* beta funds (high $\beta_{i,t}^{SVOL}$– low $\beta_{i,t}^{SVOL}$) loses on average 0.70% per month with a *t*-statistic of –1.83. We observe a similar pattern in risk-adjusted returns (8-factor alphas) that decrease monotonically from the highest *SVOL* beta portfolio to the lowest *SVOL* beta portfolio, with a significantly negative alpha of –0.70% (*t*-stat –2.09) for the spread portfolio.[39]

5.4.2. Multivariate cross-sectional regressions with SVOL betas

This section presents the results of following Fama and MacBeth (1973) regressions conducted at the individual fund level after controlling for fund characteristics:

$$\begin{aligned} r_{i,t+1} = {} & \lambda_{0,t} + \lambda_{SVOL,t}\beta_{i,t}^{SVOL} + \lambda_{r,t}r_{i,t} + \lambda_{Size,t}Size_{i,t} + \lambda_{Age,t}Age_{i,t} \\ & + \lambda_{MgmtFee,t}MgmtFee_{i,t} + \lambda_{IncFee,t}IncFee_{i,t} \\ & + \lambda_{Redemption,t}Redemption_{i,t} + \lambda_{MinInv,t}MinInv_{i,t} + \lambda_{Lockup,t}Lockup_{i,t} \\ & + \lambda_{Delta,t}Delta_{i,t} + \lambda_{Vega,t}Vega_{i,t} + \lambda_{VOL,t}\beta_{i,t}^{VOL} + \varepsilon_{i,t+1}\,, \end{aligned} \tag{13}$$

where $r_{i,t+1}$ is the excess return on fund *i* in month *t+1*, $\beta_{i,t}^{SVOL}$is the *SVOL* beta of fund *i* in month *t*, and other variables are as defined earlier in Eq. (5).

<<Insert Table 13 about here>>

Table 13 presents the average intercept and time-series averages of the slope coefficients from the monthly cross-sectional regressions of one-month ahead fund excess returns on VOV betas, as well as different fund characteristics for the period from January 1994 to December 2013. The first specification examines the cross-sectional relation between

[39] We also conduct bivariate *VOL-SVOL* beta sorts to ensure that the results are not due to the volatility risk exposure of funds. We find that the negative relation between *SVOL* beta and next-month return persists regardless of the volatility risk exposure of funds. These results are available upon request.

the *SVOL* beta and one-month-ahead fund excess returns without any controls. Consistent with our findings in nonparametric tests of portfolio sorts and multivariate cross-sectional regressions using the investable VOV proxy, *LBVIX*, column 1 shows a significantly negative relation between $\beta_{i,t}^{SVOL}$ and future fund excess returns, with an average slope of –0.0352 and a *t*-statistic of –2.10.

We then control for fund characteristics and aggregate volatility risk to investigate whether the negative relation between VOV exposure and fund returns persists. Regardless of the control variables, all five specifications show a robust and significantly negative relation between a fund's *SVOL* beta and its future return, confirming our previous results that a fund's VOV exposure has a significant predictive power to explain fund's future returns.

6. Concluding remarks

We investigate whether uncertainty about the volatility of the market portfolio can explain the cross section of hedge fund returns. We measure this uncertainty with volatility of volatility (VOV) of the equity market returns. Using the returns on lookback straddles written on the VIX index to construct an investable proxy for the VOV, we document several findings.

First, we find that hedge funds have a negative and significant VOV exposure at the index level. The negative relation between VOV exposure and fund returns is most prominent during the financial crisis when uncertainty is very high. The results are robust to using a variety of hedge fund indexes and inclusion of a wide range of risk factors that prior literature has shown to be important in explaining hedge fund returns.

Second, we find that funds' VOV betas have significant explanatory power in predicting funds' one-month ahead excess returns. Sorting individual funds into quintile portfolios based on their VOV betas, we find that funds with low (more negative) VOV betas outperform funds with high (less negative or positive) VOV betas. The significant return differential is attributed to funds' outperformance in low VOV beta quintile. The negative relation between funds' VOV betas and future returns is robust to use of risk-adjusted returns (8-factor alphas), an alternative weighting scheme (equally-weighted), an alternative estimation window (24-month rolling window), a sample without backfill bias, and controlling for volatility risk. Multivariate Fama and MacBeth (1973) regressions that control for fund characteristics further corroborate our findings and confirm the negative relation between VOV exposures and hedge fund returns.

Although *LBVIX* has the advantage of being investable and is therefore more suitable to replicate the funds' exposures to VOV risk factor, it covers a relatively short sample period due to the availability of VIX options data. To mitigate potential limitations of short time span of *LBVIX*, we construct three alternative non-traded VOV proxies, the monthly range of the VIX index (*RVIX*), the monthly standard deviation of the VIX index (*SDVIX*), and a parameterized process based on Heston (1993) model (*SVOL*). Using both the statistical as well as the parameterized proxies of VOV, we show that the negative relation between VOV exposures and hedge fund returns is robust over the extended sample period from January 1994 to December 2013, and that VOV is a priced risk factor in the cross section of hedge fund returns.

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Table 1
Summary statistics and correlations among factors

Panel A reports summary statistics of our VOV measure, *LBVIX*, during the full sample period (April 2006 – December 2012), and the two sub-periods (April 2006 – March 2009 and April 2009 – December 2012), where *LBVIX* is defined as the monthly returns on a lookback straddle written on the VIX index. Panel B reports correlations between the 12 factors used in the analysis over the full sample period. *PTFSBD*, *PTFSFX*, and *PTFSCOM* are the bond, currency and trend following factors as defined in Fung and Hsieh (2004), *BD10RET* is the monthly change in the 10-year treasury constant maturity bond yields, *BAAMTSY* is the monthly change in the difference between Moody's Baa rated bond and 10-year treasury constant maturity bond yields, *SNPMRF* is the monthly S&P 500 excess return, *SCMLC* is the difference between returns on the Russell 2000 index and S&P 500 index, *RetVIX* is the monthly return on the VIX index, *CR* is the correlation risk factor as defined in Buraschi, Kosowski, and Trojani (2014), *LIQ* is the liquidity risk factor as defined in Sadka (2010), and *UNC* is the macroeconomic uncertainty index as defined in Bali, Brown, and Caglayan (2014).

Panel A: *LBVIX* Summary Statistics

Period	Mean	StdDev	P1	P5	P25	P50	P75	P95	P99	Skew	Kurt
Full sample	0.0110	0.4940	–0.5354	–0.4766	–0.3451	–0.0851	0.1250	1.1736	1.6677	1.6581	5.5294
04/06–03/09	0.1119	0.5389	–0.5354	–0.5075	–0.1674	–0.0315	0.1977	1.3707	1.6625	1.3334	4.1705
04/09–12/12	–0.0697	0.4447	–0.5335	–0.4552	–0.3766	–0.1848	0.0313	0.8194	1.6677	2.0152	7.5323

Panel B: Pearson correlation among factors

	PTFSBD	PTFSFX	PTFSCOM	BD10RET	BAAMTSY	SNPMRF	SCMLC	LBVIX	RetVIX	CR	LIQ	UNC
PTFSBD	1											
PTFSFX	0.43	1										
PTFSCOM	0.32	0.54	1									
BD10RET	0.43	0.21	0.19	1								
BAAMTSY	–0.27	–0.40	–0.29	–0.34	1							
SNPMRF	–0.40	–0.36	–0.23	–0.22	0.38	1						
SCMLC	–0.26	–0.21	–0.15	–0.11	0.18	0.45	1					
LBVIX	0.29	0.32	0.20	0.20	–0.26	–0.58	–0.23	1				
RetVIX	0.32	0.34	0.18	0.14	–0.26	–0.71	–0.33	0.74	1			
CR	0.36	0.32	0.23	0.26	–0.36	–0.60	–0.30	0.74	0.60	1		
LIQ	0.06	–0.21	–0.16	0.05	0.39	0.24	0.09	–0.20	–0.24	–0.19	1	
UNC	–0.05	–0.08	–0.19	–0.02	0.31	0.08	0.14	–0.14	–0.13	–0.22	0.14	1

Table 2

Time-series results with the 8-factor model

This table reports factor exposures of the nine-factor model in Eq. (1) during April 2006 – December 2012 period:

$$r_{i,t} = \alpha_i + \beta_i^1 PTFSBD_t + \beta_i^2 PTFSFX_t + \beta_i^3 PTFSCOM_t + \beta_i^4 BD10RET_t(1) + \beta_i^5 BAAMTSY_t + \beta_i^6 SNPMRF_t + \beta_i^7 SCMLC_t + \beta_i^8 LBVIX_t + \varepsilon_{i,t},$$

where $r_{i,t}$ is the excess return on fund *i* in month *t*, *PTFSBD*, *PTFSFX*, and *PTFSCOM* are the bond, currency and trend following factors as defined in Fung and Hsieh (2004), *BD10RET* is the monthly change in the 10-year treasury constant maturity bond yields, *BAAMTSY* is the monthly change in the difference between Moody's Baa rated bond and 10-year treasury constant maturity bond yields, *SNPMRF* is the monthly S&P 500 excess return, *SCMLC* is the difference between returns on the Russell 2000 index and S&P 500 index, and *LBVIX* is the VOV factor defined as the monthly returns on a lookback straddle written on the VIX index. The 8 indexes are from Dow Jones Credit Suisse. HFI, CA, MN, ED, GM, LS, MF, and MS stand for Hedge Fund Index, Convertible Arbitrage, Equity Market Neutral, Event Driven, Global Macro, Long/Short Equity, Managed Futures, and Multi Strategy indexes, respectively. The final row reports the pooled panel regressions with heteroskedasticity-consistent standard errors after allowing for cross-correlations.

	PTFSBD	PTFSFX	PTFSCOM	BD10RET	BAAMTSY	SNPMRF	SCMLC	LBVIX	Alpha	RMSE	Adj.R^2
HFI	**–0.002**	**0.005**	**0.006**	**–0.098**	**0.237**	**0.216**	**–0.041**	**–0.006**	**0.001**	**0.0112**	**66.20%**
	[–0.18]	[0.67]	[0.55]	[–1.42]	[4.49]	[5.90]	[–0.71]	[–1.98]	[0.63]		
CA	**0.004**	**–0.014**	**–0.017**	**0.040**	**0.557**	**0.176**	**–0.145**	**–0.008**	**0.000**	**0.0160**	**67.23%**
	[0.27]	[–1.22]	[–1.16]	[0.40]	[7.37]	[3.37]	[–1.74]	[–1.72]	[0.04]		
MN	**–0.111**	**0.054**	**0.042**	**0.086**	**0.406**	**0.255**	**0.206**	**0.011**	**–0.009**	**0.0414**	**23.37%**
	[–3.06]	[1.83]	[1.14]	[0.34]	[2.08]	[1.89]	[0.96]	[0.98]	[–1.85]		
ED	**–0.010**	**0.014**	**–0.009**	**–0.267**	**0.219**	**0.203**	**0.018**	**–0.005**	**0.002**	**0.0106**	**73.32%**
	[–1.04]	[1.87]	[–0.93]	[–4.08]	[4.37]	[5.87]	[0.33]	[–1.80]	[1.54]		
GM	**0.020**	**–0.010**	**0.020**	**0.054**	**0.167**	**0.089**	**–0.153**	**–0.007**	**0.004**	**0.0160**	**16.62%**
	[1.41]	[–0.87]	[1.40]	[0.54]	[2.22]	[1.71]	[–1.83]	[–1.88]	[2.03]		
LS	**–0.002**	**0.007**	**–0.003**	**–0.173**	**0.133**	**0.338**	**–0.001**	**–0.010**	**0.001**	**0.0137**	**71.76%**
	[–0.17]	[0.73]	[–0.22]	[–2.04]	[2.05]	[7.57]	[–0.02]	[–2.46]	[0.31]		
MF	**0.060**	**0.003**	**0.066**	**–0.241**	**–0.082**	**0.013**	**–0.175**	**–0.024**	**0.004**	**0.0279**	**22.83%**
	[2.47]	[0.13]	[2.65]	[–1.40]	[–0.63]	[0.14]	[–1.20]	[–3.00]	[1.31]		
MS	**–0.010**	**0.003**	**–0.006**	**–0.078**	**0.318**	**0.172**	**–0.072**	**–0.005**	**0.001**	**0.0191**	**68.79%**
	[–1.06]	[0.35]	[–0.59]	[–1.15]	[6.18]	[4.82]	[–1.27]	[–1.96]	[0.64]		
Pooled	**–0.008**	**0.008**	**0.013**	**–0.095**	**0.235**	**0.188**	**–0.055**	**–0.006**	**0.002**	**0.0237**	**26.73%**
	[–1.04]	[1.43]	[1.76]	[–1.84]	[5.95]	[6.88]	[–1.25]	[–2.49]	[1.27]		

Table 3

Time-series results with the 12-factor model

This table reports factor exposures of the 15-factor model in Eq. (2) during April 2006 – June 2012 period:

$$r_{i,t} = \alpha_i + \beta_i^1 PTFSBD_t + \beta_i^2 PTFSFX_t + \beta_i^3 PTFSCOM_t + \beta_i^4 BD10RET_t(1) + \beta_i^5 BAAMTSY_t + \beta_i^6 SNPMRF_t + \beta_i^7 SCMLC_t + \beta_i^8 LBVIX_t + \beta_i^9 RetVIX_t + \beta_i^{10} LIQ_t + \beta_i^{11} CR_t + \beta_i^{12} UNC_t + \varepsilon_{i,t}\,,$$

where $r_{i,t}$ is the excess return on fund *i* in month *t*, *PTFSBD*, *PTFSFX*, and *PTFSCOM* are the bond, currency and trend following factors as defined in Fung and Hsieh (2004), *BD10RET* is the monthly change in the 10-year treasury constant maturity bond yields, *BAAMTSY* is the monthly change in the difference between Moody's Baa rated bond and 10-year treasury constant maturity bond yields, *SNPMRF* is the monthly S&P 500 excess return, *SCMLC* is the difference between returns on the Russell 2000 index and S&P 500 index, *LBVIX* is the VOV factor defined as the monthly returns on a lookback straddle written on the VIX index, *RetVIX* is the monthly return on the VIX index, *CR* is the correlation risk factor as defined in Buraschi, Kosowski, and Trojani (2014), *LIQ* is the liquidity risk factor as defined in Sadka (2010), and *UNC* is the macroeconomic uncertainty index as defined in Bali, Brown, and Caglayan (2014). The 8 indexes are from Dow Jones Credit Suisse. HFI, CA, MN, ED, GM, LS, MF, and MS stand for Hedge Fund Index, Convertible Arbitrage, Equity Market Neutral, Event Driven, Global Macro, Long/Short Equity, Managed Futures, and Multi Strategy indexes, respectively. The final row reports the pooled panel regressions with heteroskedasticity-consistent standard errors after allowing for cross-correlations.

	PTFSBD	PTFSFX	PTFSCOM	BD10RET	BAAMTSY	SNPMRF	SCMLC	LBVIX	RetVIX	LIQ	CR	UNC	Alpha	RMSE	Adj.R^2
HFI	**–0.001**	**0.006**	**0.005**	**–0.096**	**0.206**	**0.185**	**–0.055**	**–0.009**	**–0.002**	**0.179**	**–0.041**	**–0.000**	**0.001**	**0.0111**	**69.03%**
	[–0.06]	[0.70]	[0.50]	[–1.35]	[3.36]	[4.39]	[–0.91]	[–2.52]	[–0.16]	[1.06]	[–2.91]	[–0.25]	[0.66]		
CA	**0.005**	**–0.018**	**–0.014**	**0.035**	**0.527**	**0.137**	**–0.196**	**–0.011**	**–0.016**	**0.001**	**–0.024**	**0.001**	**–0.001**	**0.0158**	**70.55%**
	[0.37]	[–1.54]	[–0.91]	[0.35]	[6.03]	[2.29]	[–2.31]	[–2.16]	[–1.18]	[0.00]	[–1.18]	[1.62]	[–0.31]		
MN	**–0.124**	**0.056**	**0.043**	**0.183**	**0.474**	**0.336**	**0.258**	**0.016**	**0.085**	**0.362**	**–0.055**	**–0.003**	**–0.007**	**0.0415**	**28.53%**
	[–3.22]	[1.83]	[1.08]	[0.69]	[2.06]	[2.12]	[1.15]	[1.18]	[2.30]	[0.57]	[–1.03]	[–1.45]	[–1.19]		
ED	**–0.008**	**0.015**	**–0.009**	**–0.264**	**0.184**	**0.179**	**0.008**	**–0.008**	**–0.001**	**0.147**	**–0.038**	**–0.000**	**0.002**	**0.0106**	**74.76%**
	[–0.81]	[1.87]	[–0.89]	[–3.89]	[3.14]	[4.43]	[0.14]	[–2.36]	[–0.06]	[0.91]	[–2.82]	[–0.26]	[1.41]		
GM	**0.021**	**–0.009**	**0.019**	**0.049**	**0.124**	**0.031**	**–0.176**	**–0.012**	**–0.014**	**0.276**	**–0.046**	**–0.000**	**0.004**	**0.0161**	**20.19%**
	[1.40]	[–0.77]	[1.26]	[0.47]	[1.39]	[0.50]	[–2.02]	[–2.22]	[–1.00]	[1.12]	[–2.23]	[–0.26]	[1.93]		
LS	**0.001**	**0.008**	**–0.003**	**–0.183**	**0.101**	**0.286**	**–0.024**	**–0.014**	**–0.021**	**0.095**	**–0.030**	**0.000**	**0.000**	**0.0140**	**72.38%**
	[0.10]	[0.76]	[–0.21]	[–2.05]	[1.30]	[5.37]	[–0.31]	[–3.04]	[–1.68]	[0.45]	[–1.66]	[0.29]	[0.22]		
MF	**0.066**	**0.004**	**0.062**	**–0.242**	**–0.203**	**–0.059**	**–0.197**	**–0.032**	**0.002**	**0.380**	**–0.128**	**0.000**	**0.005**	**0.0263**	**32.23%**
	[2.68]	[0.18]	[2.47]	[–1.44]	[–1.39]	[–0.59]	[–1.39]	[–3.79]	[0.11]	[0.94]	[–3.77]	[0.08]	[1.29]		
MS	**–0.009**	**0.003**	**–0.006**	**–0.069**	**0.311**	**0.151**	**–0.085**	**–0.007**	**0.001**	**0.077**	**–0.030**	**–0.000**	**0.001**	**0.0110**	**70.16%**
	[–0.91]	[0.34]	[–0.59]	[–0.97]	[5.09]	[3.60]	[–1.43]	[–1.96]	[0.11]	[0.46]	[–2.13]	[–0.08]	[0.58]		
Pooled	**–0.009**	**0.009**	**0.011**	**–0.078**	**0.225**	**0.157**	**–0.060**	**–0.009**	**0.004**	**0.193**	**–0.044**	**–0.001**	**0.003**	**0.0240**	**29.01%**
	[–0.59]	[1.30]	[1.50]	[–1.51]	[2.92]	[4.69]	[–1.10]	[–2.76]	[0.36]	[1.28]	[–4.80]	[–1.32]	[2.26]		

Table 4

Sub-period analysis

This table reports the estimates of the 12-factor model for sub-periods April 2006 – March 2009 and April 2009 – June 2012. All variables are as defined in Table 3.

	PTFSBD	PTFSFX	PTFSCOM	BD10RET	BAAMTSY	SNPMRF	SCMLC	LBVIX	RetVIX	LIQ	CR	UNC	Alpha	RMSE	Adj.R^2
Panel A: 04/2006–03/2009															
HFI	**–0.016**	**0.000**	**0.025**	**–0.155**	**0.299**	**0.129**	**–0.114**	**–0.011**	**–0.008**	**0.410**	**–0.029**	**–0.000**	**–0.000**	**0.0133**	**61.61%**
	[–0.73]	[0.01]	[1.41]	[–1.25]	[2.97]	[1.81]	[–0.98]	[–2.08]	[–0.48]	[1.54]	[–0.75]	[–0.14]	[–0.16]		
CA	**–0.016**	**–0.021**	**0.007**	**–0.039**	**0.677**	**0.090**	**–0.382**	**–0.018**	**–0.036**	**0.151**	**0.022**	**0.001**	**–0.001**	**0.0185**	**69.78%**
	[–0.51]	[–1.13]	[0.27]	[–0.23]	[4.82]	[0.91]	[–2.34]	[–2.44]	[–1.62]	[0.40]	[0.41]	[0.84]	[–0.31]		
MN	**–0.244**	**0.102**	**0.037**	**–0.199**	**0.133**	**0.361**	**0.972**	**0.024**	**0.113**	**1.241**	**–0.276**	**–0.001**	**–0.018**	**0.0518**	**42.37%**
	[–2.83]	[1.94]	[0.52]	[–0.41]	[0.34]	[1.30]	[2.13]	[1.12]	[1.81]	[1.19]	[–1.79]	[–0.26]	[–1.79]		
ED	**–0.016**	**0.008**	**0.014**	**–0.244**	**0.277**	**0.123**	**–0.064**	**–0.010**	**–0.013**	**0.333**	**–0.001**	**–0.000**	**0.001**	**0.0119**	**61.82%**
	[–0.84]	[0.64]	[0.88]	[–2.21]	[3.08]	[1.94]	[–0.61]	[–2.14]	[–0.92]	[1.40]	[–0.03]	[–0.56]	[0.30]		
GM	**0.013**	**–0.017**	**0.036**	**0.077**	**0.311**	**–0.091**	**–0.346**	**–0.019**	**–0.018**	**0.528**	**–0.028**	**–0.001**	**0.003**	**0.0190**	**27.26%**
	[0.41]	[–0.87]	[1.40]	[0.43]	[2.16]	[–0.89]	[–2.07]	[–2.50]	[–0.78]	[1.38]	[–0.49]	[–0.60]	[0.90]		
LS	**0.002**	**–0.011**	**0.030**	**–0.166**	**0.230**	**0.236**	**–0.208**	**–0.016**	**–0.022**	**0.345**	**0.001**	**0.001**	**0.001**	**0.0171**	**57.78%**
	[0.06]	[–0.61]	[1.29]	[–1.04]	[1.77]	[2.57]	[–1.38]	[–2.23]	[–1.04]	[1.00]	[0.01]	[0.47]	[0.40]		
MF	**0.090**	**–0.010**	**0.062**	**–0.329**	**–0.143**	**–0.249**	**–0.104**	**–0.037**	**0.005**	**0.275**	**–0.188**	**–0.002**	**0.001**	**0.0260**	**36.97%**
	[2.07]	[–0.39]	[1.77]	[–1.36]	[–0.73]	[–1.79]	[–0.45]	[–3.53]	[0.17]	[0.53]	[–2.43]	[–0.96]	[0.18]		
MS	**–0.028**	**0.005**	**0.011**	**–0.187**	**0.420**	**0.100**	**–0.149**	**–0.011**	**–0.010**	**0.296**	**–0.011**	**0.000**	**–0.001**	**0.0124**	**69.72%**
	[–1.35]	[0.37]	[0.63]	[–1.63]	[4.47]	[1.51]	[–1.36]	[–2.12]	[–0.65]	[1.19]	[–0.30]	[0.24]	[–0.47]		
Panel B: 04/2009–06/2012															
HFI	**0.009**	**0.015**	**–0.007**	**–0.038**	**0.011**	**0.270**	**–0.051**	**–0.006**	**0.010**	**0.101**	**–0.041**	**0.001**	**–0.001**	**0.0072**	**81.34%**
	[0.88]	[1.76]	[–0.63]	[–0.46]	[0.13]	[5.47]	[–0.89]	[–1.42]	[0.84]	[0.41]	[–3.42]	[2.20]	[–0.30]		
CA	**0.006**	**–0.008**	**–0.003**	**0.041**	**0.264**	**0.159**	**–0.053**	**–0.004**	**0.013**	**–0.351**	**–0.026**	**0.003**	**–0.001**	**0.0090**	**77.48%**
	[0.47]	[–0.73]	[–0.21]	[0.39]	[2.41]	[2.54]	[–0.73]	[–0.70]	[0.88]	[–1.13]	[–1.68]	[4.40]	[–0.42]		
MN	**–0.026**	**0.013**	**0.007**	**0.082**	**0.276**	**0.325**	**–0.140**	**0.004**	**0.015**	**–0.240**	**0.005**	**–0.001**	**–0.001**	**0.0103**	**61.65%**
	[–1.74]	[1.01]	[0.43]	[0.70]	[2.21]	[4.55]	[–1.69]	[0.73]	[0.85]	[–0.67]	[0.27]	[–1.70]	[–0.30]		
ED	**–0.000**	**0.026**	**–0.031**	**–0.224**	**0.030**	**0.239**	**–0.005**	**–0.008**	**0.015**	**0.173**	**–0.044**	**0.001**	**–0.000**	**0.0086**	**84.14%**
	[–0.00]	[2.51]	[–2.28]	[–2.27]	[0.28]	[4.01]	[–0.07]	[–1.33]	[1.03]	[0.58]	[–3.03]	[1.75]	[–0.16]		
GM	**0.026**	**–0.005**	**0.026**	**0.050**	**–0.143**	**0.192**	**–0.126**	**0.002**	**0.006**	**0.134**	**–0.046**	**0.002**	**0.002**	**0.0104**	**30.60%**
	[1.78]	[–0.37]	[1.56]	[0.42]	[–1.13]	[2.66]	[–1.50]	[0.25]	[0.35]	[0.37]	[–2.59]	[1.92]	[0.74]		
LS	**–0.002**	**0.028**	**–0.028**	**–0.052**	**0.032**	**0.426**	**0.000**	**–0.009**	**–0.005**	**0.151**	**–0.036**	**0.000**	**–0.003**	**0.0093**	**87.22%**
	[–0.13]	[2.43]	[–1.89]	[–0.48]	[0.28]	[6.61]	[0.01]	[–1.55]	[–0.32]	[0.47]	[–2.31]	[0.46]	[–1.12]		
MF	**0.085**	**0.010**	**0.031**	**0.004**	**–0.477**	**0.335**	**–0.402**	**–0.021**	**0.007**	**1.488**	**–0.134**	**0.002**	**–0.005**	**0.0264**	**30.31%**
	[2.25]	[0.31]	[0.75]	[0.01]	[–1.49]	[1.83]	[–1.90]	[–1.32]	[0.16]	[1.64]	[–3.00]	[0.72]	[–0.71]		
MS	**–0.006**	**0.009**	**–0.010**	**–0.003**	**0.140**	**0.219**	**–0.047**	**–0.001**	**0.016**	**–0.172**	**–0.023**	**0.001**	**0.002**	**0.0068**	**77.47%**
	[–0.65]	[1.07]	[–0.89]	[–0.04]	[1.70]	[4.63]	[–0.86]	[–0.25]	[1.42]	[–0.73]	[–1.99]	[1.51]	[1.25]		

Table 5
Individual Hedge Fund Characteristics

This table presents individual fund characteristics throughout the sample period April 2006 – December 2012 for a total of 13,283 funds in the union database. *Return* is the average monthly return, *AUM* is the monthly assets under management (in million dollars), *Age* is number of months that a fund is in business since inception (in years), *Lockup* is the minimum number amount of time that the investor has to wait before she can withdraw her investment from the fund (in years), *Redemption* is the minimum amount of time an investor needs to notify the fund before she can redeem the invested amount from the fund (in years), *MinInv* is the minimum initial investment amount (in million dollars) that the fund requires its investors to invest in the fund, *MgmtFee* is a fixed percentage fee of assets under management, *IncFee* is a fixed percentage fee of the fund's net annual profits above a pre-specified hurdle rate, *Delta* is the expected dollar change in the manager's compensation for a 1% change in the fund's net asset value (in thousand dollars), and *Vega* is the expected dollar change in the manager's compensation for a 1% change in the volatility of fund's net asset value (in thousand dollars).

Fund Characteristic	Mean	StdDev	P25	Median	P75
Return (% per month)	0.58	10.73	–1.10	0.60	2.26
AUM ($M)	223.00	734.00	14.00	49.80	170.00
Age (years)	4.52	4.35	1.33	3.00	6.42
Lockup (years)	0.33	0.58	0.00	0.00	1.00
Redemption (years)	0.17	0.22	0.08	0.08	0.25
Min Inv. ($M)	1.24	3.04	0.15	0.50	1.00
Mgmt Fee (%)	1.49	0.62	1.00	1.50	2.00
Inc Fee (%)	18.29	5.77	20.00	20.00	20.00
Delta ($'000)	419.83	4741.31	7.63	45.60	209.96
Vega ($'000)	81.16	995.79	0.07	4.38	29.13

Table 6

Univariate portfolio sorts based on VOV betas

This table reports next-month value-weighted return, next-month 8-factor alpha, and average $\beta_{i,t}^{LBVIX}$ of five VOV beta sorted quintile portfolios. Funds' monthly VOV betas are estimated via time-series regressions over 36-month rolling windows:

$$r_{i,t} = \alpha_{i,t} + \beta_{i,t}^{LBVIX} LBVIX_t + \varepsilon_{i,t} \ ,$$

where $r_{i,t}$ is the excess return on fund *i* in month *t*, $LBVIX_t$ is proxy for VOV and is the monthly return on a lookback straddle written on the VIX index, and $\beta_{i,t}^{LBVIX}$ is the VOV beta for fund *i* in month *t*. Each month, from March 2009 to December 2012, hedge funds are sorted into quintile portfolios based on their $\beta_{i,t}^{LBVIX}$. Quintile 1 (5) contains funds with the lowest (highest) VOV betas.

	QUINTILE PORTFOLIOS					
	1 (LOW)	2	3	4	5 (HIGH)	5–1
Avg. Return	1.698	1.042	0.603	0.742	0.082	–1.616
	[2.36]	[2.48]	[2.32]	[4.92]	[0.59]	[–2.38]
8-Factor Alpha	1.643	0.795	0.395	0.631	–0.249	–1.892
	[2.17]	[2.06]	[1.45]	[2.80]	[–1.51]	[–2.36]
Average βLBVIX	–0.089	–0.044	–0.024	–0.008	0.015	

Table 7

Bivariate portfolio sorts based on VOL and VOV betas

This table reports next month's value-weighted return, and next-month 8-factor alphas of 25 portfolios sorted with respect to their VOL and VOV betas. Funds' monthly VOL betas are estimated via time-series regressions over 36-month rolling windows:

$$r_{i,t} = \alpha_{i,t} + \beta_{i,t}^{MKT} MKT_t + \beta_{i,t}^{VOL} VOL_t + \varepsilon_{i,t} \ ,$$

where $r_{i,t}$ is the excess return on fund *i* in month t, MKT_t is the monthly excess market return, and VOL_t is the monthly change in the VIX index. VOV betas are estimated following Eq. (3). Each month, from March 2009 to December 2012, hedge funds are sorted into 25 portfolios first based on their VOL and then VOV betas. Quintile 1 (5) contains funds with the lowest (highest) VOL and VOV betas.

	β^{LBVIX}					(5-1)	
β^{VOL}	1 (LOW)	2	3	4	5 (HIGH)	RAW	8-factor
1 (LOW)	**1.747**	**1.069**	**0.614**	**0.621**	**0.097**	**–1.650**	**–1.714**
	[2.38]	[2.65]	[2.03]	[2.24]	[0.32]	[–2.11]	[–1.81]
2	**1.684**	**1.013**	**0.643**	**0.906**	**0.209**	**–1.474**	**–1.789**
	[2.51]	[2.34]	[2.56]	[4.53]	[1.08]	[–2.07]	[–2.25]
3	**1.561**	**1.183**	**0.834**	**0.668**	**0.133**	**–1.428**	**–1.656**
	[2.12]	[2.58]	[2.83]	[4.11]	[0.80]	[–2.04]	[–2.02]
4	**1.934**	**1.280**	**0.613**	**0.438**	**–0.014**	**–1.948**	**–2.490**
	[2.40]	[2.50]	[1.93]	[1.68]	[–0.08]	[–2.45]	[–2.81]
5 (HIGH)	**1.818**	**1.017**	**0.692**	**–0.030**	**–0.119**	**–1.936**	**–2.066**
	[2.04]	[1.87]	[1.40]	[–0.07]	[–0.50]	[–2.26]	[–2.07]
5–1 (RAW)	**0.071**	**–0.052**	**0.077**	**–0.651**	**–0.215**		
	[0.21]	[–0.17]	[0.23]	[–1.07]	[–0.69]		
5–1 (8-factor)	**–0.061**	**–0.263**	**–0.428**	**–1.055**	**–0.413**		
	[–0.23]	[–0.62]	[–1.42]	[–2.11]	[–1.08]		

Table 8
Fama-MacBeth regressions

This table reports average intercept and time-series averages of the slope coefficients from the monthly cross-sectional regressions of one-month ahead hedge fund excess returns on VOV beta and a large set of fund characteristics for the period of March 2009 – December 2012:

$$r_{i,t+1} = \lambda_{0,t} + \lambda_{LBVIX,t}\beta_{i,t}^{LBVIX} + \lambda_{r,t}r_{i,t} + \lambda_{Size,t}Size_{i,t} + \lambda_{Age,t}Age_{i,t} + \lambda_{MgmtFee,t}MgmtFee_{i,t} + \lambda_{IncFee,t}IncFee_{i,t} + \lambda_{Redemption,t}Redemption_{i,t} + \lambda_{MinInv,t}MinInv_{i,t} + \lambda_{Lockup,t}Lockup_{i,t} + \lambda_{Delta,t}Delta_{i,t} + \lambda_{Vega,t}Vega_{i,t} + \lambda_{VOL,t}\beta_{i,t}^{VOL}\varepsilon_{i,t+1},$$

where $r_{i,t+1}$ is the excess return on fund *i* in month *t+1*, $\beta_{i,t}^{LBVIX}$ is the VOV beta of fund *i* in month *t*, $r_{i,t}$ is the one-month lagged return on fund *i* in month *t*, *Size* is the monthly assets under management (in billion dollars), *Age* is number of months that a fund is in business since inception, *MgmtFee* is a fixed percentage fee of assets under management, *IncFee* is a fixed percentage fee of the fund's net annual profits above a pre-specified hurdle rate, *Redemption* is the minimum number of days an investor needs to notify the fund before she can redeem the invested amount from the fund, *MinInv* is the minimum initial investment amount (in million dollars) that the fund requires its investors to invest in the fund, *Lockup* is the minimum number of days that the investor has to wait before she can withdraw her investment from the fund, *Delta* is the expected dollar change in the manager's compensation for a 1% change in the fund's net asset value, *Vega* is the expected dollar change in the manager's compensation for a 1% change in the volatility of fund's net asset value; and $\beta_{i,t}^{VOL}$ is the VOL beta of fund *i* in month *t* estimated using Eq. (4). The numbers in the parentheses are the Newey-West (1987) and Shanken (1992) corrected *t*-statistics.

	1	2	3	4	5	6
βLBVIX	−0.1770	−0.1182	−0.1174	−0.1184	−0.1968	−0.1238
	[−2.15]	[−1.73]	[−1.73]	[−1.75]	[−2.21]	[−1.74]
Ret_t		0.0136	0.0156	0.0146		0.0263
		[0.42]	[0.49]	[0.46]		[0.78]
Size		−0.1110	−0.0333	−0.1170		−0.0125
		[−1.88]	[−1.52]	[−2.12]		[−2.33]
Age		−0.0005	−0.0006	−0.0005		−0.0006
		[−0.98]	[−1.14]	[−0.95]		[−1.05]
MgmtFee			0.0228	0.0251		0.0204
			[0.34]	[0.37]		[0.30]
IncFee			0.0013	0.0014		0.0011
			[0.17]	[0.17]		[0.15]
Redemption		0.0006	0.0006	0.0006		0.0006
		[1.24]	[1.29]	[1.30]		[1.38]
MinInv		0.0028	0.0026	0.0025		0.0029
		[0.53]	[0.48]	[0.48]		[0.51]
Lockup		0.0005	0.0005	0.0005		0.0005
		[2.92]	[3.05]	[2.96]		[2.93]
Delta		0.1250		0.1300		0.1380
		[2.60]		[2.90]		[3.30]
Vega		−0.0846		−0.0866		−0.0705
		[−0.38]		[−0.41]		[−0.33]
βVOL					−0.0461	−0.0472
					[−0.15]	[−0.19]
Intercept	0.3769	0.3876	0.3363	0.3217	0.3856	0.3421
	[2.58]	[2.94]	[2.05]	[1.96]	[2.77]	[2.04]
Adj. R^2	12.38%	16.52%	16.80%	16.93%	14.46%	19.26%

Table 9

Summary statistics for statistical and parameterized proxies of VOV

Panel A reports summary statistics of two statistical proxies (*RVIX* and *SDVIX*) and one parameterized proxy (*SVOL*) of volatility of aggregate volatility during the sample period of January 1994 – December 2013. *RVIX* and *SDVIX* are defined as the monthly range of the VIX index and monthly standard deviation of the VIX index, respectively. *SVOL* is calculated first via estimating the parameters of Heston (1993) type stochastic volatility process in Eq. (9) using the methodology outlined in Aït-Sahalia and Kimmel (2007), and then interpolating the estimated model to the period covering January 1994 – December 2013 using Equation (10) . Panel B reports the correlations between the three non-traded VOV proxies and our investable proxy LBVIX during the common sample period of April 2006–December 2012. Panels C and D report the correlations between the three VOV proxies during the extended sample period January 1994–December 2013, and the period prior to the availability of VIX option data, i.e. January 1994–March 2006, respectively.

Panel A: Summary Statistics

VOV proxy	Mean	StdDev	Min	Max	Skew	Kurt
RVIX	0.29	0.12	0.10	0.82	1.39	5.55
SDVIX	1.82	1.39	0.38	10.69	2.78	13.73
SVOL	0.34	0.19	0.09	1.27	1.95	7.89

Panel B: Correlations (04/2006–12/2012)

	LBVIX	RVIX	SDVIX	SVOL
LBVIX	1			
RVIX	0.7641	1		
SDVIX	0.4923	0.7862	1	
SVOL	0.6602	0.6090	0.4955	1

Panel C: Correlations (01/1994–12/2013)

	RVIX	SDVIX	SVOL
RVIX	1		
SDVIX	0.8070	1	
SVOL	0.5965	0.5856	1

Panel D: Correlations (01/1994–03/2006)

	RVIX	SDVIX	SVOL
RVIX	1		
SDVIX	0.8099	1	
SVOL	0.6905	0.8123	1

Table 10

Time-series results with the 8-factor mode using SVOL as the VOV proxy

This table reports factor exposures of the eight-factor model in Eq. (1) during January 1994 – December 2013 period:

$$r_{i,t} = \alpha_i + \beta_i^1 PTFSBD_t + \beta_i^2 PTFSFX_t + \beta_i^3 PTFSCOM_t + \beta_i^4 BD10RET_t(1) + \beta_i^5 BAAMTSY_t + \beta_i^6 SNPMRF_t + \beta_i^7 SCMLC_t + \beta_i^8 SVOL_t + \varepsilon_{i,t}\ ,$$

where $r_{i,t}$ is the excess return on fund *i* in month *t*, *PTFSBD*, *PTFSFX*, and *PTFSCOM* are the bond, currency and trend following factors as defined in Fung and Hsieh (2004), *BD10RET* is the monthly change in the 10-year treasury constant maturity bond yields, *BAAMTSY* is the monthly change in the difference between Moody's Baa rated bond and 10-year treasury constant maturity bond yields, *SNPMRF* is the monthly S&P 500 excess return, and *SCMLC* is the difference between returns on the Russell 2000 index and S&P 500 index. *SVOL* is the parameterized VOV factor calculated first via estimating the parameters of Heston (1993) type stochastic volatility process in Equation (9) using the methodology outlined in Aït-Sahalia and Kimmel (2007), and then interpolating the estimated model parameters to the period covering January 1994 – December 2013 using Equation (10). The 8 indexes are from Dow Jones Credit Suisse. HFI, CA, MN, ED, GM, LS, MF, and MS stand for Hedge Fund Index, Convertible Arbitrage, Equity Market Neutral, Event Driven, Global Macro, Long/Short Equity, Managed Futures, and Multi Strategy indexes, respectively. The final row reports the pooled panel regressions with heteroskedasticity-consistent standard errors after allowing for cross-correlations.

	PTFSBD	PTFSFX	PTFSCOM	BD10RET	BAAMTSY	SNPMRF	SCMLC	SVOL	Alpha	Adj.R^2
HFI	–0.017	0.012	0.017	0.050	0.320	0.212	0.111	–0.021	0.007	49.56%
	[–2.31]	[2.10]	[2.15]	[0.87]	[5.30]	[8.48]	[3.60]	[–3.43]	[3.07]	
CA	–0.010	–0.006	–0.005	0.095	0.591	0.071	0.012	–0.013	0.003	45.67%
	[–1.42]	[–1.00]	[–0.69]	[1.75]	[10.20]	[2.97]	[0.39]	[–2.25]	[1.57]	
MN	–0.037	0.021	0.022	–0.033	0.330	0.181	0.060	0.026	–0.011	16.06%
	[–2.97]	[2.02]	[1.57]	[–0.33]	[3.12]	[4.16]	[1.11]	[2.38]	[–2.65]	
ED	–0.021	0.008	0.001	–0.073	0.272	0.183	0.092	–0.018	0.007	62.73%
	[–4.10]	[1.87]	[0.24]	[–1.76]	[6.20]	[10.10]	[4.13]	[–4.05]	[4.13]	
GM	–0.010	0.015	0.022	0.161	0.312	0.089	–0.022	–0.034	0.014	13.24%
	[–0.83]	[1.51]	[1.65]	[1.68]	[3.07]	[2.12]	[–0.43]	[–3.28]	[3.68]	
LS	–0.013	0.009	0.011	0.046	0.167	0.376	0.300	–0.012	0.004	60.81%
	[–1.56]	[1.32]	[1.13]	[0.69]	[2.38]	[12.95]	[8.35]	[–1.66]	[1.51]	
MF	0.038	0.039	0.046	0.096	0.088	–0.017	–0.005	–0.020	0.007	15.47%
	[2.62]	[3.28]	[2.79]	[0.83]	[0.71]	[–0.33]	[–0.09]	[–1.76]	[1.53]	
MS	–0.009	0.006	0.002	–0.011	0.383	0.080	0.034	–0.005	0.002	35.28%
	[–1.41]	[1.19]	[0.23]	[–0.24]	[7.74]	[3.89]	[1.32]	[–0.92]	[0.93]	
Pooled	–0.010	0.013	0.012	0.039	0.302	0.152	0.074	–0.012	0.004	19.97%
	[–2.79]	[4.61]	[3.16]	[1.41]	[10.06]	[12.11]	[4.76]	[–4.02]	[3.83]	

Table 11

Sub-period analysis

This table reports the estimates of the 8-factor model for sub-periods July 1998 – March 2000 and April 2006 – March 2009. All variables are as defined in Table 10.

	PTFSBD	PTFSFX	PTFSCOM	BD10RET	BAAMTSY	SNPMRF	SCMLC	SVOL	Alpha	Adj.R^2
Panel A: July 1998 – March 2000										
HFI	0.001	–0.063	0.006	0.591	1.706	0.310	0.254	–0.015	0.008	76.83%
	[0.04]	[–2.05]	[0.21]	[1.61]	[3.30]	[2.99]	[3.57]	[–0.60]	[0.65]	
CA	–0.010	–0.033	0.007	0.071	0.380	–0.001	–0.031	–0.065	0.030	43.53%
	[–0.36]	[–1.07]	[0.26]	[0.20]	[0.75]	[–0.01]	[–0.44]	[–2.71]	[2.57]	
MN	–0.009	0.030	–0.016	–0.200	–0.197	0.068	–0.006	–0.013	0.009	58.10%
	[–1.08]	[3.03]	[–1.87]	[–1.72]	[–1.20]	[2.06]	[–0.29]	[–1.65]	[2.32]	
ED	–0.072	0.033	0.001	–0.431	0.099	0.269	0.051	–0.048	0.021	91.86%
	[–4.90]	[2.01]	[0.06]	[–2.19]	[0.36]	[04.84]	[1.35]	[–3.68]	[3.30]	
GM	0.065	–0.145	0.013	1.175	2.735	0.237	0.205	–0.022	–0.003	52.22%
	[1.35]	[–2.68]	[0.27]	[1.84]	[3.03]	[1.31]	[1.65]	[–0.52]	[–0.13]	
LS	–0.027	–0.027	–0.006	0.678	1.759	0.644	0.509	–0.033	0.002	82.98%
	[–0.78]	[–0.70]	[–0.17]	[1.46]	[2.69]	[04.90]	[5.64]	[–1.97]	[0.13]	
MF	0.122	–0.032	0.036	0.668	0.107	0.029	0.115	0.000	–0.009	29.12%
	[2.69]	[–0.62]	[0.78]	[1.10]	[0.13]	[0.17]	[0.98]	[0.01]	[–0.47]	
MS	0.031	–0.051	–0.004	0.808	1.114	–0.058	–0.030	–0.032	0.017	39.62%
	[1.55]	[–2.25]	[–0.21]	[2.98]	[2.92]	[–0.76]	[–0.58]	[–1.77]	[1.88]	
Pooled	0.013	–0.036	0.005	0.420	0.963	0.187	0.133	–0.020	0.009	25.02%
	[0.76]	[–1.94]	[0.27]	[1.90]	[3.10]	[3.00]	[3.12]	[–1.88]	[1.30]	
Panel B: April 2006 – March 2009										
HFI	–0.002	0.005	0.007	–0.075	0.255	0.218	–0.043	–0.018	0.006	67.52%
	[–0.24]	[0.61]	[0.75]	[–1.08]	[4.87]	[6.51]	[–0.74]	[–2.58]	[2.47]	
CA	0.003	–0.015	–0.015	0.064	0.575	0.186	–0.148	–0.019	0.006	67.54%
	[0.23]	[–1.32]	[–1.02]	[0.64]	[7.57]	[3.83]	[–1.78]	[–1.92]	[1.59]	
MN	–0.110	0.055	0.039	0.054	0.381	0.237	0.210	0.027	–0.017	23.45%
	[–3.03]	[1.90]	[1.06]	[0.21]	[1.93]	[1.88]	[0.98]	[1.02]	[–1.82]	
ED	–0.010	0.014	–0.007	–0.239	0.238	0.199	0.018	–0.019	0.008	75.24%
	[–1.14]	[1.90]	[–0.74]	[–3.74]	[4.88]	[06.40]	[0.34]	[–3.01]	[3.35]	
GM	0.019	–0.010	0.023	0.094	0.195	0.079	–0.152	–0.027	0.012	22.63%
	[1.40]	[–0.94]	[1.66]	[0.97]	[2.65]	[1.69]	[–1.89]	[–2.82]	[3.46]	
LS	–0.003	0.006	–0.000	–0.138	0.158	0.346	–0.004	–0.026	0.008	73.04%
	[–0.24]	[0.63]	[–0.00]	[–1.65]	[2.47]	[08.46]	[–0.05]	[–3.12]	[2.74]	
MF	0.059	–0.002	0.069	–0.210	–0.052	0.084	–0.189	–0.036	0.015	17.59%
	[2.33]	[–0.09]	[2.69]	[–1.16]	[–0.38]	[0.95]	[–1.26]	[–1.97]	[2.26]	
MS	–0.010	0.002	–0.005	–0.064	0.329	0.179	–0.074	–0.011	0.004	68.85%
	[–1.10]	[0.27]	[–0.48]	[–0.94]	[6.33]	[5.39]	[–1.31]	[–1.61]	[1.66]	
Pooled	–0.026	0.006	0.023	–0.132	0.345	0.113	–0.009	–0.031	0.007	21.92%
	[–1.62]	[0.60]	[1.74]	[–1.38]	[4.45]	[2.42]	[–0.10]	[–3.26]	[2.18]	

Table 12
Univariate portfolio sorts with SVOL betas

This table reports next-month equally-weighted return, next-month 8-factor alpha, and average $\beta_{i,t}^{SVOL}$ of five *SVOL* beta sorted quintile portfolios. Funds' monthly *SVOL* betas are estimated via time-series regressions over 24-month rolling windows:

$$r_{i,t} = \alpha_{i,t} + \beta_{i,t}^{SVOL} SVOL_t + \varepsilon_{i,t} \,,$$

where $r_{i,t}$ is the excess return on fund *i* in month *t*, *SVOL* is the parameterized proxy for VOV calculated using the parameters estimated from Aït-Sahalia and Kimmel (2007) MLE methodology for a Heston (1993) type stochastic volatility process, and $\beta_{i,t}^{SVOL}$ is the *SVOL* beta for fund *i* in month *t*. Each month, from January 1994 to December 2013, hedge funds are sorted into quintile portfolios based on their $\beta_{i,t}^{SVOL}$. Quintile 1 (5) contains funds with the lowest (highest) *SVOL* betas.

	QUINTILE PORTFOLIOS					
	1 (LOW)	2	3	4	5 (HIGH)	5–1
Avg. Return	1.310	0.992	0.790	0.656	0.612	–0.698
	[3.46]	[4.67]	[5.74]	[7.33]	[5.10]	[–1.83]
8-Factor Alpha	1.300	0.980	0.774	0.653	0.601	–0.699
	[3.98]	[5.37]	[6.89]	[7.94]	[4.58]	[–2.09]
Average βSVOL	–18.010	–7.975	–3.801	–0.757	5.336	

Table 13
Fama-MacBeth regressions with SVOL betas

This table reports average intercept and time-series averages of the slope coefficients from the monthly cross-sectional regressions of one-month ahead hedge fund excess returns on *SVOL* beta and a large set of fund characteristics for the period of January 1994 – December 2013:

$$r_{i,t+1} = \lambda_{0,t} + \lambda_{LBVIX,t}\beta_{i,t}^{SVOL} + \lambda_{r,t}r_{i,t} + \lambda_{Size,t}Size_{i,t} + \lambda_{Age,t}Age_{i,t} + \lambda_{MgmtFee,t}MgmtFee_{i,t} + \lambda_{IncFee,t}IncFee_{i,t} + \lambda_{Redemption,t}Redemption_{i,t} + \lambda_{MinInv,t}MinInv_{i,t} + \lambda_{Lockup,t}Lockup_{i,t} + \lambda_{Delta,t}Delta_{i,t} + \lambda_{Vega,t}Vega_{i,t} + \lambda_{VOL,t}\beta_{i,t}^{VOL}\varepsilon_{i,t+1},$$

where $r_{i,t+1}$ is the excess return on fund *i* in month *t+1*, $\beta_{i,t}^{SVOL}$is the *SVOL* beta of fund *i* in month *t*, $r_{i,t}$ is the one-month lagged return on fund *i* in month *t*, *Size* is the monthly assets under management (in billion dollars), *Age* is number of months that a fund is in business since inception, *MgmtFee* is a fixed percentage fee of assets under management, *IncFee* is a fixed percentage fee of the fund's net annual profits above a pre-specified hurdle rate, *Redemption* is the minimum number of days an investor needs to notify the fund before she can redeem the invested amount from the fund, *MinInv* is the minimum initial investment amount (in million dollars) that the fund requires its investors to invest in the fund, *Lockup* is the minimum number of days that the investor has to wait before she can withdraw her investment from the fund, *Delta* is the expected dollar change in the manager's compensation for a 1% change in the fund's net asset value, *Vega* is the expected dollar change in the manager's compensation for a 1% change in the volatility of fund's net asset value; and $\beta_{i,t}^{VOL}$is the VOL beta of fund *i* in month *t* estimated using Eq. (4). The numbers in the parentheses are the Newey-West (1987) and Shanken (1992) corrected *t*-statistics.

	1	2	3	4	5	6
βSVOL	–0.0352	–0.0387	–0.0379	–0.0384	–0.0356	–0.0392
	[–2.10]	[–2.88]	[–2.85]	[–2.89]	[–1.96]	[–2.72]
Ret_t		0.0867	0.0863	0.0857		0.0847
		[4.66]	[4.73]	[4.70]		[4.58]
Size		0.1080	0.0078	0.0145		0.0222
		[0.25]	[0.31]	[0.03]		[0.04]
Age		–0.0008	–0.0008	–0.0007		–0.0008
		[–1.43]	[–1.35]	[–1.23]		[–1.42]
MgmtFee			0.1027	0.1050		0.0993
			[1.99]	[2.02]		[1.98]
IncFee			0.0164	0.0168		0.0162
			[4.02]	[3.93]		[4.12]
Redemption			0.0001	0.0001		0.0001
		[0.32]	[0.53]	[0.53]		[0.62]
MinInv		0.0080	0.0084	0.0088		0.0088
		[1.79]	[2.02]	[1.99]		[2.19]
Lockup		0.0003	0.0003	0.0003		0.0003
		[3.34]	[3.47]	[3.38]		[3.59]
Delta		0.1070		0.0046		0.0312
		[0.24]		[0.01]		[0.06]
Vega		0.0145		0.3070		0.2530
		[0.02]		[0.48]		[0.36]
βVOL					–0.1189	–0.0765
					[–0.46]	[–0.36]
Intercept	0.4478	0.4142	0.1933	0.1497	0.4685	0.1360
	[4.53]	[4.64]	[1.24]	[1.30]	[5.32]	[1.09]
Adj. R^2	8.90%	14.80%	15.57%	15.77%	10.98%	17.23%

Appendix A

This section presents the results of variable selection tests. Table A1 reports the results from the forward recursive variable selection method with the objective of identifying variables that achieve the highest improvement in adjusted R^2. Tables A2 and A3 report the findings using least angle regression and shrinkage (LARS) method of Efron et al. (2004) based on least absolute shrinkage and selection operator (LASSO) method of Tibshirani (1996), and model selection tests using Bayesian Information Criteria (BIC) following Raftery (1995) and Raftery, Madigan, and Hoeting (1997).

LASSO method chooses a variable by minimizing the residual sum of squares subject to the sum of the absolute value of the coefficients being less than a constant, and drops a variable if the coefficient is equal to zero. We also report Mallow's C_p statistic that assesses the fit of the model, and R-squared's for the selected models based on LASSO.

Bayesian Information Criteria (BIC) method is based on estimating the probability that a variable is part of a model under model uncertainty. We also report the PRE statistic which shows the proportional reduction in errors and root mean squared errors (RMSE) for the selected models based on BIC.

Table A1

Variable selection test

This table reports the results of the variable selection test as in Lindsay and Sheather (2010), where 1 indicates if a factor is selected in time-series regressions of excess fund index returns on the 12 factors based on its ability to improve the adjusted R^2 of the model. Panel A reports the results for the full sample period (April 2006 –June 2012). Panels B and C report the results for the two sub-periods: April 2006 – March 2009 and April 2009 – June 2012, respectively. We report the root mean squared errors (RMSE) and adjusted R-square values as model fit measures.

Panel A : 04/2006–06/2012

	PTFSBD	PTFSFX	PTFSCOM	BD10RET	BAAMTSY	SNPMRF	SCMLC	LBVIX	RetVIX	LIQ	CR	UNC	Total	RMSE	Adj.R^2.
HFI					1	1		1			1		4	0.0107	70.75%
CA		1			1	1	1	1				1	6	0.0154	71.81%
MN	1				1	1			1				4	0.0411	29.78%
ED				1	1	1		1			1		5	0.0103	76.14%
GM	1				1			1			1		4	0.0158	23.51%
LS				1	1	1		1					4	0.0135	74.35%
MF	1		1				1	1			1		5	0.0256	35.92%
MS					1	1		1			1		4	0.0106	72.15%
% Selected	37.50%	12.50%	12.50%	25.00%	87.50%	75.00%	25.00%	87.50%	12.50%	0.00%	62.50%	12.50%			

Panel B : 04/2006–03/2009

	PTFSBD	PTFSFX	PTFSCOM	BD10RET	BAAMTSY	SNPMRF	SCMLC	LBVIX	RetVIX	LIQ	CR	UNC	Total	RMSE	Adj.R^2.
HFI					1	1		1			1		4	0.0124	66.21%
CA					1		1	1	1				4	0.0167	75.26%
MN	1	1					1						3	0.0487	49.06%
ED				1	1	1		1					4	0.0111	66.43%
GM					1		1	1		1			4	0.0176	37.23%
LS					1	1		1					3	0.0160	62.99%
MF			1			1		1			1		4	0.0241	45.89%
MS	1			1	1	1		1					5	0.0116	73.47%
% Selected	25.00%	12.50%	12.50%	25.00%	75.00%	62.50%	37.50%	87.50%	12.50%	12.50%	25.00%	0.00%			

Panel C : 04/2009–06/2012

	PTFSBD	PTFSFX	PTFSCOM	BD10RET	BAAMTSY	SNPMRF	SCMLC	LBVIX	RetVIX	LIQ	CR	UNC	Total	RMSE	Adj.R^2.
HFI		1				1			1		1	1	5	0.0068	83.32%
CA					1	1			1			1	4	0.0085	80.25%
MN						1	1						2	0.0097	65.99%
ED				1		1					1	1	5	0.0082	85.77%
GM	1		1			1					1		4	0.0097	39.90%
LS					1	1					1		3	0.0086	89.25%
MF	1					1	1				1		4	0.0256	34.58%
MS					1	1			1		1	1	5	0.0064	80.03%
% Selected	25.00%	12.50%	12.50%	12.50%	37.50%	100.00%	25.00%	0.00%	37.50%	0.00%	75.00%	50.00%			

Table A2

Variable selection using LARS based on LASSO

This table reports the results of the variable selection test as in Efron et al. (2004) based on LASSO method of Tibshirani (1996). **1** indicates if a factor is selected in time-series regressions of excess fund index returns on the 12 factors based on LASSO, which chooses a variable by minimizing the residual sum of squares subject to the sum of the absolute value of the coefficients being less than a constant, and drops a variable if the coefficient is equal to zero. The last two columns in the table reports Mallow's C_p statistic and root mean squared errors (RMSE) and R-squared's for the selected modes. Panel A reports the results for the full sample period (April 2006 – June 2012). Panels B and C report the results for the two sub-periods: April 2006 – March 2009 and April 2009 –June 2012, respectively.

Panel A : 04/2006-06/2012															
	PTFSBD	PTFSFX	PTFSCOM	BD10RET	BAAMTSY	SNPMRF	SCMLC	LBVIX	RetVIX	LIQ	CR	UNC	Total	C_p	R^2
HFI				1	1	1		1		1	1		6	4.7434	72.49%
CA		1	1		1	1	1	1	1		1	1	9	8.6616	74.67%
MN	1	1	1		1	1	1		1		1	1	9	11.1392	40.12%
ED				1	1	1		1			1		5	5.9994	76.47%
GM	1		1		1	1	1	1	1	1	1		9	10.1460	29.74%
LS				1	1	1		1	1		1		6	3.6983	75.86%
MF	1		1				1	1			1		5	10.0420	33.11%
MS	1			1	1	1		1			1		6	6.5452	72.76%
% Selected	50.00%	25.00%	50.00%	50.00%	87.50%	87.50%	50.00%	87.50%	50.00%	25.00%	100.00%	25.00%			
Panel B : 04/2006-03/2009															
	PTFSBD	PTFSFX	PTFSCOM	BD10RET	BAAMTSY	SNPMRF	SCMLC	LBVIX	RetVIX	LIQ	CR	UNC	Total	C_p	R^2
HFI				1	1	1		1		1			5	8.6515	64.19%
CA		1			1	1	1	1	1				6	2.6063	76.73%
MN	1	1				1	1		1		1	1	7	10.0961	50.45%
ED				1	1	1		1		1			5	7.1793	65.98%
GM					1		1	1		1			4	5.3680	34.81%
LS				1	1	1		1	1	1			6	5.9117	66.33%
MF	1		1	1	1	1	1	1			1	1	9	9.5558	57.58%
MS	1			1	1	1		1			1		6	6.7671	75.12%
% Selected	37.50%	25.00%	12.50%	62.50%	87.50%	87.50%	50.00%	87.50%	37.50%	50.00%	37.50%	25.00%			
Panel C : 04/2009-06/2012															
	PTFSBD	PTFSFX	PTFSCOM	BD10RET	BAAMTSY	SNPMRF	SCMLC	LBVIX	RetVIX	LIQ	CR	UNC	Total	C_p	R^2
HFI		1			1	1		1	1		1	1	7	7.8498	84.85%
CA					1	1					1	1	4	5.5764	80.70%
MN					1	1	1						3	4.8052	63.87%
ED		1	1	1	1	1			1	1	1	1	9	9.0194	89.14%
GM	1		1	1	1	1	1				1	1	8	6.5210	49.73%
LS		1	1	1	1	1					1	1	7	6.5386	90.74%
MF	1		1			1	1				1		5	9.8280	36.13%
MS				1	1	1					1	1	5	8.5827	80.09%
% Selected	25.00%	37.50%	50.00%	50.00%	87.50%	100.00%	37.50%	12.50%	25.00%	12.50%	87.50%	75.00%			

Table A3

Model selection using Bayesian Information Criteria

This table reports the results of the model selection test under model uncertainty as in Raftery, Madigan, and Hoeting (1997). **1** indicates if a factor is selected in time-series regressions of excess fund index returns on the 12 factors based on Bayesian Information Criteria (BIC) estimating the probability that a variable is part of a model under model uncertainty. The last two columns in the table reports PRE statistic which shows the proportional reduction in errors and root mean squared errors (RMSE). Panel A reports the results for the full sample period (April 2006 – June 2012). Panels B and C report the results for the two sub-periods: April 2006 – March 2009 and April 2009 – June 2012, respectively.

	PTFSBD	PTFSFX	PTFSCOM	BD10RET	BAAMTSY	SNPMRF	SCMLC	LBVIX	RetVIX	LIQ	CR	UNC	Total	PRE	RMSE
Panel A : 04/2006-06/2012															
HFI					1	1		1			1		4	0.720	0.0110
CA		1			1	1	1						4	0.729	0.0156
MN	1	1			1								3	0.271	0.0413
ED					1	1		1					3	0.548	0.0105
GM					1			1					2	0.239	0.0160
LS				1		1		1					3	0.730	0.0137
MF	1		1					1			1		4	0.403	0.0261
MS					1	1		1					3	0.734	0.0108
% Selected	25.00%	25.00%	12.50%	12.50%	75.00%	62.50%	12.50%	75.00%	0.00%	0.00%	25.00%	0.00%			
Panel B : 04/2006-03/2009															
	PTFSBD	PTFSFX	PTFSCOM	BD10RET	BAAMTSY	SNPMRF	SCMLC	LBVIX	RetVIX	LIQ	CR	UNC	Total	PRE	RMSE
HFI				1	1	1		1			1		5	0.696	0.0129
CA					1		1	1	1				4	0.793	0.0175
MN	1	1					1				1		4	0.527	0.0518
ED				1	1	1							3	0.415	0.0109
GM					1		1	1		1			4	0.394	0.0175
LS					1	1		1					3	0.659	0.0167
MF	1					1		1			1	1	5	0.567	0.0250
MS					1	1		1					3	0.707	0.0120
% Selected	25.00%	12.50%	0.00%	25.00%	75.00%	62.50%	37.50%	75.00%	12.50%	12.50%	37.50%	12.50%			
Panel C : 04/2009-06/2012															
	PTFSBD	PTFSFX	PTFSCOM	BD10RET	BAAMTSY	SNPMRF	SCMLC	LBVIX	RetVIX	LIQ	CR	UNC	Total	PRE	RMSE
HFI		1				1		1			1	1	5	0.851	0.0070
CA					1	1			1			1	4	0.802	0.0087
MN					1	1	1				1		4	0.659	0.0100
ED				1		1							2	0.814	0.0084
GM	1		1			1					1		4	0.426	0.0101
LS						1					1		2	0.909	0.0089
MF	1					1	1				1		4	0.417	0.0261
MS					1	1					1	1	4	0.826	0.0066
% Selected	25.00%	12.50%	12.50%	12.50%	37.50%	100.00%	25.00%	12.50%	12.50%	0.00%	75.00%	37.50%			

Appendix B

This appendix presents the results of the 14-factor model that further controls for the aggregate volatility and jump risk factors of Cremers, Halling, and Weinbaum (2015), which are documented to be priced risk factors in the cross section of stock returns. The model to be tested is:

$$r_{i,t} = \alpha_i + \beta_i^1 PTFSBD_t + \beta_i^2 PTFSFX_t + \beta_i^3 PTFSCOM_t + \beta_i^4 BD10RET_t \qquad (14)$$

$$+\beta_i^5 BAAMTSY_t + \beta_i^6 SNPMRF_t + \beta_i^7 SCMLC_t + \beta_i^8 LBVIX_t$$

$$+ \beta_i^9 RetVIX_t + \beta_i^{10} LIQ_t + \beta_i^{11} CR_t + \beta_i^{12} UNC_t + \beta_i^{13} JUMP_t + \beta_i^{14} VOL_t + \varepsilon_{i,t} ,$$

where $r_{i,t}$ and the eight factors are as explained in Eq. (1), *RetVIX* is the orthogonalized version of monthly return on the VIX index, *LIQ* is the permanent-variable price impact component of Sadka (2006) liquidity measure, *CR* is the orthogonalized version of correlation risk factor as defined in Buraschi, Kosowski, and Trojani (2014), *UNC* is the economic uncertainty index capturing macroeconomic risk exposure of hedge funds as defined in Bali, Brown, and Caglayan (2014), and *JUMP* and *VOL* are the orthogonalized versions of aggregate jump and volatility risk factors as defined in Cremers, Halling, and Weinbaum (2015).[40]

[40] Due to the availability of aggregate volatility and jump risk factors up to March 2012, we conduct our empirical analyses of the 14-factor model over the period from April 2006 to March 2012.

Table B1
Correlations among factors

The table reports correlations between the 14 factors used in the analysis over the April 2006 – March 2012 period *PTFSBD*, *PTFSFX*, and *PTFSCOM* are the bond, currency and trend following factors as defined in Fung and Hsieh (2004), *BD10RET* is the monthly change in the 10-year treasury constant maturity bond yields, *BAAMTSY* is the monthly change in the difference between Moody's Baa rated bond and 10-year treasury constant maturity bond yields, *SNPMRF* is the monthly S&P 500 excess return, *SCMLC* is the difference between returns on the Russell 2000 index and S&P 500 index, *RetVIX* is the monthly return on the VIX index, *CR* is the correlation risk factor as defined in Buraschi, Kosowski, and Trojani (2014), *LIQ* is the liquidity risk factor as defined in Sadka (2010), *UNC* is the macroeconomic uncertainty index as defined in Bali, Brown, and Caglayan (2014), and *JUMP* and *VOL* are aggregate jump and volatility risk factors of Cremers, Halling, and Weinbaum (2015).

	PTFSBD	PTFSFX	PTFSCOM	BD10RET	BAAMTSY	SNPMRF	SCMLC	LBVIX	RetVIX	CR	LIQ	UNC	JUMP	VOL
PTFSBD	1													
PTFSFX	0.43	1												
PTFSCOM	0.32	0.54	1											
BD10RET	0.43	0.21	0.19	1										
BAAMTSY	–0.27	–0.40	–0.29	–0.34	1									
SNPMRF	–0.40	–0.36	–0.23	–0.22	0.38	1								
SCMLC	–0.26	–0.21	–0.15	–0.11	0.18	0.45	1							
LBVIX	0.29	0.32	0.20	0.20	–0.26	–0.58	–0.23	1						
RetVIX	0.32	0.34	0.18	0.14	–0.26	–0.71	–0.33	0.74	1					
CR	0.36	0.32	0.23	0.26	–0.36	–0.60	–0.30	0.74	0.60	1				
LIQ	0.06	–0.21	–0.16	0.05	0.39	0.24	0.09	–0.20	–0.24	–0.19	1			
UNC	–0.05	–0.08	–0.19	–0.02	0.31	0.08	0.14	–0.14	–0.13	–0.22	0.14	1		
JUMP	0.18	0.14	0.18	0.00	–0.26	-0.39	–0.14	0.58	0.71	0.56	–0.42	–0.11	1	
VOL	0.17	0.29	0.21	0.07	–0.41	-0.34	–0.24	0.59	0.67	0.57	–0.21	–0.16	0.57	1

Table B2

Time-series results with the 14-factor model

This table reports factor exposures of the 14-factor model in Eq. (14) during April 2006 – March 2012 period:

$$r_{i,t} = \alpha_i + \beta_i^1 PTFSBD_t + \beta_i^2 PTFSFX_t + \beta_i^3 PTFSCOM_t + \beta_i^4 BD10RET_t(1) + \beta_i^5 BAAMTSY_t + \beta_i^6 SNPMRF_t + \beta_i^7 SCMLC_t + \beta_i^8 LBVIX_t + \beta_i^9 RetVIX_t + \beta_i^{10} LIQ_t + \beta_i^{11} CR_t + \beta_i^{12} UNC_t + \beta_i^{13} JUMP_t + \beta_i^{14} VOL_t + \varepsilon_{i,t},$$

where $r_{i,t}$ is the excess return on fund *i* in month *t*, *PTFSBD*, *PTFSFX*, and *PTFSCOM* are the bond, currency and trend following factors as defined in Fung and Hsieh (2004), *BD10RET* is the monthly change in the 10-year treasury constant maturity bond yields, *BAAMTSY* is the monthly change in the difference between Moody's Baa rated bond and 10-year treasury constant maturity bond yields, *SNPMRF* is the monthly S&P 500 excess return, *SCMLC* is the difference between returns on the Russell 2000 index and S&P 500 index, *LBVIX* is the VOV factor defined as the monthly returns on a lookback straddle written on the VIX index, *RetVIX* is the monthly return on the VIX index, *CR* is the correlation risk factor as defined in Buraschi, Kosowski, and Trojani (2014), *LIQ* is the liquidity risk factor as defined in Sadka (2010), *UNC* is the macroeconomic uncertainty index as defined in Bali, Brown, and Caglayan (2014), and *JUMP* and *VOL* are the aggregate jump and volatility risk factors as defined in Cremers, Halling, and Weinbaum (2015). The 8 indexes are from Dow Jones Credit Suisse. HFI, CA, MN, ED, GM, LS, MF, and MS stand for Hedge Fund Index, Convertible Arbitrage, Equity Market Neutral, Event Driven, Global Macro, Long/Short Equity, Managed Futures, and Multi Strategy indexes, respectively. The final row reports the pooled panel regressions with heteroskedasticity-consistent standard errors after allowing for cross-correlations.

	PTFSBD	PTFSFX	PTFSCOM	BD10RET	BAAMTSY	SNPMRF	SCMLC	LBVIX	RetVIX	LIQ	CR	UNC	JUMP	VOL	Alpha	Adj.R^2
HFI	0.002	0.001	0.012	–0.136	0.182	0.222	–0.046	–0.007	0.013	0.072	–0.029	0.000	–0.029	–0.013	0.001	70.10%
	[0.15]	[0.06]	[1.07]	[–1.84]	[2.68]	[4.46]	[–0.77]	[–1.79]	[0.93]	[0.39]	[–1.72]	[0.09]	[–1.80]	[–0.45]	[0.67]	
CA	0.003	–0.030	–0.005	–0.029	0.478	0.214	–0.192	–0.006	0.014	–0.245	0.010	0.001	–0.061	–0.022	–0.001	73.74%
	[0.22]	[–2.48]	[–0.34]	[–0.28]	[5.14]	[3.13]	[–2.30]	[–1.21]	[0.74]	[–0.97]	[0.44]	[2.21]	[–2.75]	[–0.54]	[–0.56]	
MN	–0.122	0.056	0.052	0.065	0.279	0.512	0.220	0.025	0.145	0.381	–0.028	–0.002	–0.032	–0.202	–0.008	29.99%
	[–2.95]	[1.69]	[1.26]	[0.23]	[1.09]	[2.72]	[0.96]	[1.74]	[2.74]	[0.55]	[–0.45]	[–1.01]	[–0.53]	[–1.79]	[–1.33]	
ED	–0.010	0.013	–0.006	–0.285	0.171	0.189	0.007	–0.007	0.001	0.137	–0.033	–0.000	–0.005	–0.006	0.002	74.28%
	[–0.92]	[1.50]	[–0.53]	[–3.92]	[2.56]	[3.85]	[0.11]	[–1.96]	[0.07]	[0.75]	[–1.99]	[–0.08]	[–0.34]	[–0.21]	[1.21]	
GM	0.027	–0.017	0.027	0.020	0.123	0.060	–0.154	–0.010	0.001	0.100	–0.033	–0.000	–0.040	0.011	0.005	22.71%
	[1.71]	[–1.36]	[1.69]	[0.19]	[1.25]	[0.83]	[–1.75]	[–1.79]	[0.05]	[0.37]	[–1.35]	[–0.18]	[–1.70]	[0.26]	[2.18]	
LS	0.009	0.005	0.001	–0.193	0.123	0.284	0.001	–0.014	–0.017	–0.005	–0.032	0.000	–0.020	0.026	0.001	72.12%
	[0.67]	[0.47]	[0.07]	[–2.06]	[1.43]	[4.48]	[0.01]	[–2.83]	[–0.98]	[–0.02]	[–1.52]	[0.18]	[–0.99]	[0.68]	[0.56]	
MF	0.078	–0.002	0.072	–0.278	–0.182	–0.051	–0.159	–0.032	0.010	0.217	–0.127	0.000	–0.037	0.032	0.006	32.89%
	[2.97]	[–0.12]	[2.75]	[–1.58]	[–1.12]	[–0.43]	[–1.09]	[–3.46]	[0.31]	[0.49]	[–3.17]	[0.04]	[–0.96]	[0.44]	[1.55]	
MS	–0.010	–0.001	–0.001	–0.119	0.259	0.206	–0.089	–0.004	0.020	0.005	–0.015	0.000	–0.026	–0.042	0.000	71.57%
	[–0.96]	[–0.12]	[–0.06]	[–1.62]	[3.86]	[4.19]	[–1.49]	[–1.98]	[1.47]	[0.03]	[–0.88]	[0.49]	[–1.60]	[–1.43]	[0.26]	
Pooled	–0.005	0.004	0.019	–0.123	0.189	0.205	–0.053	–0.006	0.023	0.082	–0.030	–0.000	–0.032	–0.026	0.003	30.05%
	[–0.64]	[0.59]	[2.20]	[–2.16]	[3.62]	[5.33]	[–1.13]	[–2.13]	[2.15]	[0.58]	[–2.35]	[–1.04]	[–2.56]	[–1.11]	[2.18]	

Table B3

Sub-period analysis

This table reports the estimates of the 14-factor model for sub-periods April 2006 – March 2009 and April 2009 – March 2012. All variables are as defined in Table B2.

	PTFSBD	PTFSFX	PTFSCOM	BD10RET	BAAMTSY	SNPMRF	SCMLC	LBVIX	RetVIX	LIQ	CR	UNC	JUMP	VOL	Alpha	Adj.R^2
Panel A: 04/2006-03/2009																
HFI	–0.006	–0.017	0.042	–0.108	0.439	0.082	–0.011	–0.011	–0.004	0.246	–0.051	0.000	–0.058	0.143	–0.001	–0.006
	[–0.33]	[–1.33]	[2.61]	[–1.01]	[4.31]	[1.07]	[–0.10]	[–1.76]	[–0.16]	[1.03]	[–1.20]	[0.06]	[–2.18]	[2.51]	[–0.28]	[–0.33]
CA	–0.004	–0.041	0.024	0.000	0.799	0.075	–0.260	–0.015	–0.018	–0.065	0.019	0.001	–0.077	0.123	–0.001	–0.004
	[–0.13]	[–2.09]	[0.96]	[0.00]	[5.14]	[0.65]	[–1.60]	[–1.78]	[–0.51]	[–0.18]	[0.29]	[1.16]	[–1.88]	[1.41]	[–0.21]	[–0.13]
MN	–0.229	0.088	0.029	–0.283	–0.083	0.646	1.076	0.049	0.231	0.892	–0.114	0.001	–0.127	–0.234	–0.013	–0.229
	[–2.61]	[1.50]	[0.39]	[–0.58]	[–0.18]	[1.84]	[2.21]	[1.76]	[2.20]	[0.81]	[–0.59]	[0.21]	[–1.04]	[–0.90]	[–1.21]	[–2.61]
ED	–0.009	–0.005	0.028	–0.204	0.396	0.075	0.013	–0.007	–0.015	0.219	–0.025	–0.000	–0.040	0.122	0.000	–0.009
	[–0.52]	[–0.42]	[1.81]	[–2.01]	[4.12]	[1.04]	[0.12]	[–1.64]	[–0.68]	[0.97]	[–0.62]	[–0.51]	[–1.60]	[2.26]	[0.13]	[–0.52]
GM	0.023	–0.036	0.056	0.137	0.488	–0.164	–0.233	–0.020	–0.021	0.360	–0.063	–0.001	–0.060	0.182	0.003	0.023
	[0.78]	[–1.81]	[2.24]	[0.82]	[3.10]	[–1.38]	[–1.42]	[–2.17]	[–0.59]	[0.97]	[–0.96]	[–0.55]	[–1.44]	[2.06]	[0.74]	[0.78]
LS	0.013	–0.031	0.053	–0.093	0.444	0.137	–0.085	–0.018	–0.031	0.174	–0.049	0.001	–0.060	0.220	0.000	0.013
	[0.53]	[–1.95]	[2.62]	[–0.69]	[3.47]	[1.42]	[–0.64]	[–2.37]	[–1.10]	[0.58]	[–0.92]	[0.54]	[–1.80]	[3.07]	[0.12]	[0.53]
MF	0.094	–0.020	0.075	–0.287	–0.021	–0.317	–0.047	–0.040	–0.007	0.208	–0.223	–0.002	–0.023	0.126	0.000	0.094
	[2.09]	[–0.67]	[1.96]	[–1.14]	[–0.09]	[–1.76]	[–0.19]	[–2.81]	[–0.13]	[0.37]	[–2.23]	[–0.94]	[–0.37]	[0.94]	[0.02]	[2.09]
MS	–0.021	–0.007	0.022	–0.158	0.509	0.073	–0.079	–0.010	–0.005	0.183	–0.023	0.000	–0.040	0.092	–0.001	–0.021
	[–1.06]	[–0.51]	[1.28]	[–1.41]	[4.80]	[0.92]	[–0.71]	[–1.57]	[–0.23]	[0.73]	[–0.52]	[0.40]	[–1.44]	[1.54]	[–0.50]	[–1.06]
Panel B: 04/2009-03/2012																
HFI	0.016	0.016	0.004	0.009	–0.016	0.265	–0.006	–0.007	0.006	0.340	–0.060	0.002	0.024	–0.044	–0.002	83.95%
	[1.61]	[1.63]	[0.28]	[0.10]	[–0.19]	[4.31]	[–0.11]	[–1.81]	[0.37]	[1.33]	[–3.94]	[2.78]	[1.22]	[–1.17]	[–0.81]	
CA	0.005	–0.006	–0.007	0.075	0.272	0.151	–0.051	–0.004	0.011	–0.314	–0.033	0.004	0.012	–0.004	–0.002	73.72%
	[0.34]	[–0.43]	[–0.34]	[0.59]	[2.17]	[1.66]	[–0.60]	[–0.59]	[0.47]	[–0.83]	[–1.46]	[3.98]	[0.41]	[–0.07]	[–0.58]	
MN	–0.021	0.025	–0.002	0.200	0.323	0.224	–0.066	0.003	–0.011	–0.119	–0.028	–0.001	0.062	0.035	0.000	61.33%
	[–1.37]	[1.71]	[–0.09]	[1.55]	[2.52]	[2.41]	[–0.76]	[0.46]	[–0.48]	[–0.31]	[–1.21]	[–1.28]	[2.04]	[0.62]	[0.02]	
ED	0.001	0.024	–0.022	–0.156	0.007	0.240	0.019	–0.011	0.007	0.476	–0.065	0.002	0.037	–0.059	–0.003	85.85%
	[0.11]	[2.02]	[–1.33]	[–1.46]	[0.07]	[3.13]	[0.27]	[–2.12]	[0.37]	[1.49]	[–3.39]	[2.33]	[1.46]	[–1.26]	[–1.18]	
GM	0.036	–0.001	0.033	0.089	–0.144	0.147	–0.057	–0.001	–0.005	0.266	–0.061	0.002	0.027	0.002	0.004	33.67%
	[2.32]	[–0.04]	[1.65]	[0.69]	[–1.13]	[1.58]	[–0.66]	[–0.13]	[–0.22]	[0.69]	[–2.64]	[1.92]	[0.88]	[0.03]	[1.16]	
LS	0.012	0.033	–0.017	0.029	0.004	0.398	0.081	–0.011	–0.011	0.434	–0.069	0.001	0.035	–0.042	–0.003	90.99%
	[1.06]	[3.02]	[–1.11]	[0.30]	[0.04]	[5.64]	[1.22]	[–2.44]	[–0.64]	[1.48]	[–3.94]	[1.26]	[1.53]	[–0.98]	[–1.49]	
MF	0.103	0.002	0.064	–0.135	–0.594	0.412	–0.374	–0.024	0.030	1.593	–0.126	0.002	–0.056	–0.064	–0.004	26.55%
	[2.46]	[0.04]	[1.16]	[–0.38]	[–1.70]	[1.63]	[–1.58]	[–1.43]	[0.46]	[1.51]	[–1.99]	[0.66]	[–0.68]	[–0.41]	[–0.52]	
MS	–0.001	0.007	0.002	0.061	0.107	0.236	–0.016	–0.001	0.015	0.136	–0.043	0.001	0.028	–0.071	–0.000	82.62%
	[–0.14]	[0.76]	[0.18]	[0.79]	[1.39]	[4.22]	[–0.31]	[–0.40]	[1.08]	[0.59]	[–3.07]	[2.38]	[1.53]	[–2.09]	[–0.13]	

Table B4

Variable selection test

This table reports the results of the variable selection test as in Lindsay and Sheather (2010), where 1 indicates if a factor is selected in time-series regressions of excess fund index returns on the 14 factors based on its ability to improve the adjusted R^2 of the model. Panel A reports the results for the full sample period (April 2006 – March 2012). Panels B and C report the results for the two sub-periods: April 2006 – March 2009 and April 2009 – March 2012, respectively.

	PTFSBD	PTFSFX	PTFSCOM	BD10RET	BAAMTSY	SNPMRF	SCMLC	LBVIX	RetVIX	LIQ	CR	UNC	JUMP	VOL	Total
Panel A: 04/2006–03/2012															
HFI				1	1	1		1			1		1		6
CA		1			1	1	1	1				1	1		7
MN	1	1			1	1									4
ED				1	1	1		1			1				5
GM	1				1			1					1		4
LS				1		1		1					1		4
MF	1		1				1	1			1				5
MS				1	1	1			1				1	1	6
% Selected	37.50%	25.00%	12.50%	50.00%	75.00%	75.00%	25.00%	75.00%	12.50%	0.00%	37.50%	12.50%	62.50%	12.50%	
Panel B: 04/2006–03/2009															
	PTFSBD	PTFSFX	PTFSCOM	BD10RET	BAAMTSY	SNPMRF	SCMLC	LBVIX	RetVIX	LIQ	CR	UNC	JUMP	VOL	Total
HFI					1	1		1					1		4
CA		1			1			1					1	1	5
MN	1	1					1								3
ED			1	1	1	1							1	1	6
GM					1			1					1		3
LS					1	1		1					1	1	5
MF			1			1		1							3
MS				1	1	1		1					1	1	6
% Selected	12.50%	25.00%	25.00%	25.00%	75.00%	62.50%	12.50%	75.00%	0.00%	0.00%	0.00%	0.00%	75.00%	50.00%	
Panel C: 04/2009–12/2012															
	PTFSBD	PTFSFX	PTFSCOM	BD10RET	BAAMTSY	SNPMRF	SCMLC	LBVIX	RetVIX	LIQ	CR	UNC	JUMP	VOL	Total
HFI	1	1				1		1			1	1	1		7
CA					1	1			1			1			4
MN						1	1								2
ED				1		1		1	1		1	1		1	7
GM	1		1			1					1				4
LS		1	1		1	1		1			1				6
MF			1								1				2
MS					1	1					1	1	1	1	6
% Selected	25.00%	25.00%	37.50%	12.50%	37.50%	87.50%	12.50%	37.50%	25.00%	0.00%	75.00%	50.00%	25.00%	25.00%	

Table B5

Variable selection using LARS based on LASSO

This table reports the results of the variable selection test as in Efron et al. (2004) based on LASSO method of Tibshirani (1996). **1** indicates if a factor is selected in time-series regressions of excess fund index returns on the 14 factors based on LASSO, which chooses a variable by minimizing the residual sum of squares subject to the sum of the absolute value of the coefficients being less than a constant, and drops a variable if the coefficient is equal to zero. Panel A reports the results for the full sample period (April 2006 – March 2012). Panels B and C report the results for the two sub-periods: April 2006 – March 2009 and April 2009 – March 2012, respectively.

Panel A: 04/2006–03/2012

	PTFSBD	PTFSFX	PTFSCOM	BD10RET	BAAMTSY	SNPMRF	SCMLC	LBVIX	RetVIX	LIQ	CR	UNC	JUMP	VOL	Total
HFI				1	1	1		1			1		1		6
CA		1			1	1	1	1				1	1		7
MN	1	1			1	1									4
ED				1	1	1		1			1				5
GM	1				1			1					1		4
LS				1		1		1					1		4
MF	1		1				1	1			1				5
MS				1	1	1			1				1	1	6
% Selected	37.50%	25.00%	12.50%	50.00%	75.00%	75.00%	25.00%	75.00%	12.50%	0.00%	37.50%	12.50%	62.50%	12.50%	

Panel B: 04/2006–03/2009

	PTFSBD	PTFSFX	PTFSCOM	BD10RET	BAAMTSY	SNPMRF	SCMLC	LBVIX	RetVIX	LIQ	CR	UNC	JUMP	VOL	Total
HFI					1	1		1					1		4
CA		1			1			1					1	1	5
MN	1	1					1								3
ED			1	1	1	1							1	1	6
GM					1			1					1		3
LS					1	1		1					1	1	5
MF			1			1		1							3
MS				1	1	1		1					1	1	6
% Selected	12.50%	25.00%	25.00%	25.00%	75.00%	62.50%	12.50%	75.00%	0.00%	0.00%	0.00%	0.00%	75.00%	50.00%	

Panel C: 04/2009–12/2012

	PTFSBD	PTFSFX	PTFSCOM	BD10RET	BAAMTSY	SNPMRF	SCMLC	LBVIX	RetVIX	LIQ	CR	UNC	JUMP	VOL	Total
HFI	1	1				1		1			1	1	1		7
CA					1	1			1			1			4
MN						1	1								2
ED				1		1		1	1		1	1		1	7
GM	1		1			1					1				4
LS		1	1		1	1		1			1				6
MF			1								1				2
MS					1	1					1	1	1	1	6
% Selected	25.00%	25.00%	37.50%	12.50%	37.50%	87.50%	12.50%	37.50%	25.00%	0.00%	75.00%	50.00%	25.00%	25.00%	

Table B6

Model selection using Bayesian Information Criteria

This table reports the results of the model selection test under model uncertainty as in Raftery, Madiagan, and Hoeting (1997). **1** indicates if a factor is selected in time-series regressions of excess fund index returns on the 14 factors based on Bayesian Information Criteria (BIC) estimating the probability that a variable is part of a model under model uncertainty. Panel A reports the results for the full sample period (April 2006 – March 2012). Panels B and C report the results for the two sub-periods: April 2006 – March 2009 and April 2009 – March 2012, respectively.

Panel A: 04/2006–03/2012															
	PTFSBD	PTFSFX	PTFSCOM	BD10RET	BAAMTSY	SNPMRF	SCMLC	LBVIX	RetVIX	LIQ	CR	UNC	JUMP	VOL	Total
HFI				1	1	1		1			1		1		6
CA		1			1	1	1	1				1	1		7
MN	1	1			1	1									4
ED				1	1	1		1			1				5
GM	1				1			1					1		4
LS				1		1		1					1		4
MF	1		1				1	1			1				5
MS				1	1	1			1				1	1	6
% Selected	37.50%	25.00%	12.50%	50.00%	75.00%	75.00%	25.00%	75.00%	12.50%	0.00%	37.50%	12.50%	62.50%	12.50%	
Panel B: 04/2006–03/2009															
	PTFSBD	PTFSFX	PTFSCOM	BD10RET	BAAMTSY	SNPMRF	SCMLC	LBVIX	RetVIX	LIQ	CR	UNC	JUMP	VOL	Total
HFI					1	1		1					1		4
CA		1			1			1					1	1	5
MN	1	1					1								3
ED			1	1	1	1							1	1	6
GM					1			1					1		3
LS					1	1		1					1	1	5
MF			1			1		1							3
MS				1	1	1		1					1	1	6
% Selected	12.50%	25.00%	25.00%	25.00%	75.00%	62.50%	12.50%	75.00%	0.00%	0.00%	0.00%	0.00%	75.00%	50.00%	
Panel C: 04/2009–12/2012															
	PTFSBD	PTFSFX	PTFSCOM	BD10RET	BAAMTSY	SNPMRF	SCMLC	LBVIX	RetVIX	LIQ	CR	UNC	JUMP	VOL	Total
HFI	1	1				1		1			1	1	1		7
CA					1	1			1			1			4
MN						1	1								2
ED				1		1		1	1		1	1		1	7
GM	1		1			1					1				4
LS		1	1		1	1		1			1				6
MF			1								1				2
MS					1	1					1	1	1	1	6
% Selected	25.00%	25.00%	37.50%	12.50%	37.50%	87.50%	12.50%	37.50%	25.00%	0.00%	75.00%	50.00%	25.00%	25.00%	

Appendix C

This section presents the results of time-series and cross-sectional tests using statistical proxies of VOV. The two statistical VOV proxies we use are the monthly range of the VIX index, and the monthly standard deviation of the VIX index, which are defined in Eq. (6) and Eq. (7) in the main text, respectively.

Table C1

Time-series results with the 8-factor model using RVIX and SDVIX as VOV proxies

This table reports VOV factor exposures of the eight-factor model in Eq. (1) during January 1994 – December 2013 period using either *RVIX* or *SDVIX* as VOV factor. The 8 indexes are from Dow Jones Credit Suisse. HFI, CA, MN, ED, GM, LS, MF, and MS stand for Hedge Fund Index, Convertible Arbitrage, Equity Market Neutral, Event Driven, Global Macro, Long/Short Equity, Managed Futures, and Multi Strategy indexes, respectively. The final row reports the pooled panel regressions with heteroskedasticity-consistent standard errors after allowing for cross-correlations.

	01/1994–12/2013		01/1994–06/1998		07/1998–03/2000		04/2000–03/2006		04/2006–03/2009		04/2009–12/2013	
	RVIX	**SDVIX**	**RVIX**	**SDVIX**	**RVIX**	**SDVIX**	**RVIX**	**SDVIX**	**RVIX**	**SDVIX**	**RVIX**	**SDVIX**
HFI	–0.030	–0.002	–0.034	–0.003	–0.022	–0.007	–0.006	–0.000	–0.022	–0.002	–0.020	–0.003
	[–3.39]	[–2.73]	[–1.22]	[–1.01]	[–1.73]	[–1.60]	[–0.49]	[–0.02]	[–2.39]	[–1.76]	[–2.33]	[–2.64]
CA	–0.026	–0.001	–0.036	–0.003	–0.047	–0.016	0.000	0.002	–0.023	–0.000	–0.019	–0.000
	[–3.05]	[–1.73]	[–2.70]	[–1.82]	[–4.35]	[–3.97]	[0.01]	[1.55]	[–1.70]	[–0.36]	[–1.49]	[–0.02]
MN	–0.011	–0.005	0.009	0.000	–0.004	–0.001	–0.005	–0.000	–0.011	–0.008	–0.007	–0.001
	[–0.69]	[–3.18]	[0.77]	[0.22]	[–0.86]	[–0.72]	[–0.63]	[–0.34]	[–0.31]	[–2.30]	[–0.66]	[–0.47]
ED	–0.020	–0.002	0.000	0.000	–0.028	–0.009	–0.011	–0.001	–0.015	–0.001	–0.021	–0.004
	[–3.05]	[–2.68]	[0.01]	[0.14]	[–3.88]	[–3.01]	[–0.95]	[–0.85]	[–1.69]	[–1.35]	[–1.96]	[–3.31]
GM	–0.036	–0.003	–0.041	–0.004	–0.039	–0.014	0.032	0.004	–0.021	–0.001	–0.004	–0.000
	[–2.43]	[–1.80]	[–0.85]	[–0.63]	[–1.80]	[–1.77]	[1.66]	[2.29]	[–1.57]	[–1.09]	[–0.30]	[–0.18]
LS	–0.020	–0.000	–0.010	0.001	0.013	0.005	–0.024	–0.002	–0.020	0.000	–0.020	–0.003
	[–2.03]	[–0.45]	[–0.59]	[0.34]	[0.69]	[0.80]	[–1.23]	[–0.99]	[–1.75]	[0.29]	[–2.08]	[–2.48]
MF	–0.034	–0.001	0.024	–0.002	0.034	0.012	0.030	0.004	–0.082	–0.003	–0.074	–0.009
	[–1.87]	[–0.83]	[0.56]	[–0.33]	[1.61]	[1.56]	[0.63]	[0.94]	[–3.29]	[–1.21]	[–2.45]	[–2.75]
MS	–0.005	–0.001	0.052	0.005	–0.020	–0.007	–0.015	–0.001	–0.017	–0.001	–0.013	–0.002
	[–0.67]	[–1.78]	[2.51]	[1.97]	[–1.95]	[–2.03]	[–1.25]	[–0.55]	[–1.91]	[–1.74]	[–1.69]	[–1.78]
Pooled	–0.023	–0.002	–0.005	–0.001	–0.022	–0.005	0.001	0.001	–0.037	–0.001	–0.023	–0.003
	[–5.01]	[–4.50]	[–0.42]	[–0.51]	[–1.71]	[–1.69]	[0.09]	[1.22]	[–2.37]	[–0.73]	[–3.68]	[–3.77]

Table C2

Univariate portfolio sorts with *RVIX* and *SDVIX* betas

This table reports next-month equally-weighted return, next-month 8-factor alpha, and average VOV exposures of five portfolios sorted with respect to either *RVIX* or *SDVIX* exposures. Funds' monthly VOV betas are estimated via time-series regressions over 24-month rolling windows:

$$r_{i,t} = \alpha_{i,t} + \beta_{i,t}^{VOV} VOV_t + \varepsilon_{i,t} \,,$$

where $r_{i,t}$ is the excess return on fund *i* in month *t*, *VOV* is defined as either monthly range of the VIX index (*RVIX*), or monthly standard deviation of the VIX index (*SDVIX*), and $\beta_{i,t}^{VOV}$ is the VOV beta for fund *i* in month *t*. Each month, from January 1994 to December 2013, hedge funds are sorted into quintile portfolios based on their $\beta_{i,t}^{VOV}$. Quintile 1 (5) contains funds with the lowest (highest) VOV betas.

	Panel A: Quintile Portfolios Sorted with respect to RVIX Betas					
	1 (LOW)	2	3	4	5 (HIGH)	5–1
Avg. Return	1.334	1.010	0.876	0.845	0.750	–0.584
	[4.36]	[5.46]	[5.30]	[7.06]	[8.03]	[–2.28]
8-Factor Alpha	1.139	0.919	0.786	0.737	0.701	–0.439
	[3.96]	[5.39]	[5.53]	[7.17]	[8.77]	[–1.81]
Average βRVIX	–22.683	–9.713	–4.317	0.021	9.560	
	Panel A: Quintile Portfolios Sorted with respect to SDVIX Betas					
	1 (LOW)	2	3	4	5 (HIGH)	5–1
Avg. Return	1.241	1.022	0.905	0.792	0.722	–0.519
	[3.59]	[5.30]	[6.14]	[6.38]	[9.00]	[–1.75]
8-Factor Alpha	1.058	0.918	0.832	0.708	0.653	–0.405
	[3.53]	[5.41]	[5.01]	[6.58]	[8.73]	[–1.55]
Average βSDVIX	–2.752	–1.213	–0.588	–0.067	1.067	

Table C3

Fama-MacBeth regressions with $RVIX$ and $SDVIX$ betas

This table reports average intercept and time-series averages of the slope coefficients from the monthly cross-sectional regressions of one-month ahead hedge fund excess returns on $SVOL$ beta and a large set of fund characteristics for the period of January 1994 – December 2013:

$$r_{i,t+1} = \lambda_{0,t} + \lambda_{VOV,t}\beta_{i,t}^{VOV} + \lambda_{r,t}r_{i,t} + \lambda_{Size,t}Size_{i,t} + \lambda_{Age,t}Age_{i,t} + \lambda_{MgmtFee,t}MgmtFee_{i,t} + \lambda_{IncFee,t}IncFee_{i,t} + \lambda_{Redemption,t}Redemption_{i,t} + \lambda_{MinInv,t}MinInv_{i,t} + \lambda_{Lockup,t}Lockup_{i,t} + \lambda_{Delta,t}Delta_{i,t} + \lambda_{Vega,t}Vega_{i,t} + \lambda_{VOL,t}\beta_{i,t}^{VOL}\varepsilon_{i,t+1}\,,$$

where $r_{i,t+1}$ is the excess return on fund *i* in month *t+1*, $\beta_{i,t}^{VOV}$ is the VOV (*RVIX* or *SDVIX*) beta of fund *i* in month *t*, $r_{i,t}$ is the one-month lagged return on fund *i* in month *t*, *Size* is the monthly assets under management (in billion dollars), *Age* is number of months that a fund is in business since inception, *MgmtFee* is a fixed percentage fee of assets under management, *IncFee* is a fixed percentage fee of the fund's net annual profits above a pre-specified hurdle rate, *Redemption* is the minimum number of days an investor needs to notify the fund before she can redeem the invested amount from the fund, *MinInv* is the minimum initial investment amount (in million dollars) that the fund requires its investors to invest in the fund, *Lockup* is the minimum number of days that the investor has to wait before she can withdraw her investment from the fund, *Delta* is the expected dollar change in the manager's compensation for a 1% change in the fund's net asset value, *Vega* is the expected dollar change in the manager's compensation for a 1% change in the volatility of fund's net asset value; and $\beta_{i,t}^{VOL}$ is the VOL beta of fund *i* in month *t* estimated using Eq. (4). The numbers in the parentheses are the Newey-West (1987) and Shanken (1992) corrected *t*-statistics.

	Using *RVIX* Betas	Using *SDVIX* Betas
βVOV	–0.0179	–0.1773
	[–2.44]	[–2.54]
Ret_t	0.0942	0.0844
	[5.64]	[4.89]
Size	0.6330	0.7140
	[1.12]	[1.21]
Age	–0.0013	–0.0022
	[–1.48]	[–2.59]
MgmtFee	0.0624	0.0668
	[1.45]	[1.50]
IncFee	0.0164	0.0157
	[4.58]	[3.95]
Redemption	0.0000	0.0001
	[0.08]	[0.46]
MinInv	0.0041	0.0046
	[1.06]	[1.20]
Lockup	0.0003	0.0003
	[2.79]	[2.37]
Delta	0.5600	0.6560
	[1.02]	[1.13]
Vega	0.0764	0.1790
	[0.09]	[0.20]
βVOL	–0.0728	–0.1421
	[–0.49]	[–0.99]
Intercept	0.2203	0.2860
	[1.76]	[2.15]
Adj. R^2	17.53%	17.80%