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Abstract

This paper investigates empirically whether uncertainty about volatility of the market portfolio can explain the performance of hedge funds both in the cross-section and over time. We measure uncertainty about volatility of the market portfolio via volatility of aggregate volatility (VOV) and construct an investable version of this measure by computing monthly returns on lookback straddles on the VIX index. We find that VOV exposure is a significant determinant of hedge fund returns at the overall index level, at different strategy levels, and at an individual fund level. After controlling for a large set of fund characteristics, we document a robust and significant negative risk premium for VOV exposure in the cross-section of hedge fund returns. We further show that strategies with less negative VOV betas outperform their counterparts during the financial crisis period when uncertainty was at its highest. On the contrary, strategies with more negative VOV betas generate superior returns when uncertainty in the market is less. Finally, we demonstrate that VOV exposure-return relationship of hedge funds is distinct from that of mutual funds and is consistent with the dynamic trading of hedge funds and risk-taking incentives arising from performance-based compensation of hedge funds.

JEL Classification: G10; G11; C13

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Volatility of Aggregate Volatility and Hedge Fund Returns

Following the early works of Knight (1921) and Ellsberg (1961), there is now considerable evidence showing that uncertainty, in addition to risk, should influence investors' decision making.[1] Studies that link uncertainty to second-order risk aversion posit that agents care not only about the variance of a risky asset's payoff but also about the ambiguity of events over which the variance occurs.[2] Furthermore, when agents are unsure of the correct probability law governing the market return they demand a higher premium to hold the market portfolio.[3] In the light of the above, uncertainty about volatility of the market portfolio can 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.[4]

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] See Epstein and Schneider (2010), and Guidolin and Rinaldi (2013) for a detailed review of literature.

[2] See Segal (1987, 1990), Klibanoff, Marinacci, and Mukerji (2005), Nau (2006), Ergin and Gul (2009), Seo (2009), and Neilson (2010) for studies which establish the link between second-order risk and uncertainty aversion.

[3] See Hansen and Sargent (1995), Hansen, Sargent, and Tallarini (1999), Chen and Epstein (2002), Anderson, Hansen, and Sargent (2003), Uppal and Wang (2003), Kogan and Wang (2003), Maenhout (2004, 2006), Liu, Pan, and Wang (2005), Cao, Wang, and Zhang (2005), Hansen et al. (2006), and Anderson, Ghysels, and Juergens (2009) for studies that theoretically motivate why and how uncertainty affects investors' optimal decision making and asset prices.

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

(2014) who document that volatility of volatility of *individual stocks* is an important factor in the cross-section of stock returns. Arguably, hedge funds invest in a portfolio of stocks, as a result individual stock specific risk gets diversified away and what remains is primarily 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*).[5] 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.[6] 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.[7] 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).[8]

[5] We also tried 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 the risk exposures of hedge funds and to even replicate the funds' returns.

[6] VVIX index, which is the implied volatility of VIX index, 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.

[7] See Fung and Hsieh (1997, 2001, 2004), Mitchell and Pulvino (2001), Agarwal and Naik (2004), Hasanhodzic and Lo (2007), and Fung et al. (2008) for option-like characteristics of hedge fund returns. Fung and Hsieh (2001, 2004) use returns on lookback straddles on bonds, currencies, and commodities as systematic factors to explain hedge fund returns.

[8] In most models of uncertainty, the effect of uncertainty aversion is shown to be stronger when the perceived level of uncertainty is high (Dimmock, Kouwenberg, and Wakker, 2013).

To the best of our knowledge, this is the first study to examine whether uncertainty about market volatility is priced in the cross-section of hedge fund returns. Previous work has examined uncertainty in other contexts. For example Zhang (2006) examines uncertainty about the quality of information, and finds that information uncertainty enhances price continuation anomalies. Cremers and Yan (2009), 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. In addition, there exists literature in option pricing with stochastic volatility models and the literature on the relationship between uncertainty and second-order beliefs. The volatility of aggregate volatility measure that we use in this paper is closer to these two strands of literature, because it is calculated from option prices and it essentially measures variation in the expectations about the equity market volatility, whereas dispersion statistics in the above mentioned literature are calculated from analysts' forecasts and capture variation in aggregate earnings forecasts. Our study is also related to recent studies by Bali, Brown, and Caglayan (2014) and Buraschi, Kosowski, and Trojani (2014) who show that hedge fund returns are related to macroeconomic uncertainty and correlation risk, respectively. However, we examine the effect of uncertainty about future movements of market volatility on hedge fund performance. Hence the uncertainty mechanism we examine is distinct from macroeconomic risk of Bali, Brown, and Caglayan (2014) and correlation risk of Buraschi, Kosowski, and Trojani (2014).

Using monthly *LBVIX* returns as an investable measure of volatility of aggregate volatility (hereafter VOV), our findings can be summarized as follows. During the sample period of April 2006 to December 2012, hedge 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 eight Dow Jones Credit Suisse hedge fund indices as our test indices, we find that the aggregate hedge fund index as well as the strategy-specific indices (convertible arbitrage, event driven, global macro, long/short equity, managed futures, and multi strategy) all exhibit significant and negative VOV betas.[9] The relationship is robust to inclusion of liquidity factor of Sadka (2010), correlation factor of Buraschi, Kosowski, and Trojani (2014), macroeconomic uncertainty factor of Bali, Brown, and Caglayan (2014), and aggregate volatility and jump risk factors of Cremers et al. (2014). Stepwise regressions and variable selection tests all point to the significance and high explanatory power of VOV in explaining hedge fund index returns. The findings are robust to the use of alternative databases of hedge fund indices from the Center for International Securities and Derivatives Markets (CISDM), Eurekahedge, and Hedge Fund Research (HFR).

Having documented a significant hedge fund exposure to VOV at the index level, we next investigate whether VOV is a systematic risk factor for the hedge fund industry as a whole, and if so, what are the pricing implications of this factor in the cross-section of hedge fund returns. Do funds with different VOV exposures generate significantly different performance? Is there a relationship between certain fund characteristics and their exposures to VOV? To answer these questions, we use a comprehensive database created by the union of four hedge fund databases, Eurekahedge, HFR, Lipper TASS, and Morningstar, which cover a large portion of the hedge fund universe.

We start with examining the relationship between hedge fund 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

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

individual 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 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 are documented to be important determinants of hedge fund returns, using 24-month window rolling windows for estimating 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 is not simply capturing market volatility risk premium, we conduct bivariate portfolio sorts based on funds' volatility (VOL) betas and VOV betas. Bivariate portfolio sorts confirm our previous 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 further investigate whether different fund strategies exhibit different VOV exposure-return relationship. By allocating individual hedge funds into ten different strategies, we document that the negative VOV exposure-return relationship uncovered both at univariate and multivariate cross-sectional tests is not homogeneous across different

[10] See Ang et al. (2006), Bali and Engle (2010), and Cremers, Halling, and Weinbaum (2014) for studies that document a negative market volatility risk premium in the cross section of stock returns.

strategies. In general, strategies with lower VOV beta spreads, less negative VOV betas in the lowest quintile and more positive VOV betas in the highest quintile (such as managed futures, global macro, and equity market neutral) outperform other funds during the first sub-period corresponding to the financial crisis when uncertainty about market risk was relatively high. On the contrary, strategies with higher VOV beta spreads, and more negative VOV betas in the lowest quintile (such as emerging markets, convertible arbitrage, and long/short equity) outperform their counterparts during the second sub-period when the level of uncertainty about overall market conditions was relatively low.

We also analyze the fund characteristics that can explain the cross-sectional variation in the VOV betas to understand the differences in the risk-taking behavior of hedge fund managers. Since funds with more negative VOV betas earn higher returns during normal times but lose more during periods of increased uncertainty, more negative VOV exposures are associated with greater risk taking. In contrast, funds with more positive VOV betas earn lower returns during normal times but outperform funds with more negative VOV betas during the crisis period. Therefore, more positive VOV betas are associated with hedging uncertainty. Separating the funds into positive and negative VOV betas, we find that funds with longer lockup period, greater leverage, longer time in existence, larger assets under management, higher delta, and lower moneyness are associated with increased risk taking, i.e. more negative VOV betas. These results suggest that the differences in the VOV exposures are related to the fund characteristics that are readily observable to the investors.

Finally, we test the robustness of the distinct impact of VOV exposure on hedge fund performance by comparing and contrasting the cross-sectional explanatory power of VOV exposures of hedge funds with that of mutual funds. We find a negative VOV exposure in the overall U.S. equity mutual fund industry. However, in contrast with hedge funds, VOV exposure of mutual funds is not able to explain cross-sectional variation in mutual fund performance. This finding suggests that the distinct dynamic trading behavior and risk-taking incentives arising from the performance-based compensation in the hedge fund industry is associated with a large cross-sectional variation in VOV exposure and hedge fund performance.

The remainder of the paper is organized as follows. Section 1 sets up the theoretical motivation that links VOV to the literature on uncertainty. Section 2 presents data and details the construction of LBVIX, which is our investable proxy for aggregate uncertainty measured by the VOV. Sections 3 and 4 conduct time-series and cross-sectional analysis of hedge fund performance, respectively, to examine the relation between VOV exposure and fund performance. Section 5 investigates the unique hedge fund styles and characteristics that are associated with VOV exposures, and the depth of the VIX options market that can help funds to hedge VOV risk. Section 6 offers concluding remarks.

1. Literature Review and Theoretical Motivation

Under subjective expected utility framework (SEU), if preferences satisfy certain axioms, there are numerical probabilities and utilities that represent decisions under uncertainty. This assumption that investors can assign probabilities to uncertain states of the world has first been challenged by Knight (1921) who distinguishes clearly between risk (which corresponds to situations where investors can objectively (or subjectively) attach probabilities to all states of the world) and uncertainty (which correspond to situations in which some states do not have an obvious probability assignment). *Knightian uncertainty* gained much attention in economics following the famous experiment by Ellsberg (1961) who showed that individuals are averse to playing gambles with uncertain outcomes and rather choose gambles to which they can attach probabilities (also known as the *Ellsberg paradox*).

Building on the works of Knight (1921) and Ellsberg (1961), there is now a well-developed literature which relates uncertainty aversion to second-order risk aversion, which posits that if agents are second-order risk averse, they will care not only about the variance of a risky asset's payoff but also on the ambiguity of events over which the variance occurs.[11] For example, Klibanoff et al. (2005) consider a dynamic setting by incorporating agents' attitude to uncertainty in portfolio choice problem, which makes the model more relevant for finance-related applications.[12] In their model, investors have second-order utility functions of the form:

$$V(f) = \int_{\Delta} \phi\left(\int_{S} u(f) d\pi\right) d\mu = E_{\mu}\left[\phi E_{\pi}[u(f)]\right] \tag{1}$$

where u is a standard Von Neumann-Morgenstern utility function which determines risk attitudes toward known outcomes defined over state space S, ϕ determines uncertainty attitude in the sense that a concave ϕ implies uncertainty aversion, and μ determines the subjective belief, including any uncertainty perceived therein by the decision maker. The inner integral reflects the expected utility in case of known probabilities for outcomes, and the outer integral captures subjective uncertainty about probabilities of outcomes in each state, hence about the expected utility. In the case of mean-variance utility function for $u(f)$, it can be shown that uncertainty about π implies uncertainty about mean and variance of outcomes, i.e., $E_S(f)$ and $\sigma_S(f)$.[13]

Uncertainty about probabilities that determines the risk and return dynamics of the market portfolio can have important implications in investment decision making and portfolio

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[11] See Anderson, Hansen, and Sargent (2003), Maccheroni, Marinacci, and Rustichini (2006), Barillas, Hansen, and Sargent (2009), Kleshchelski and Vincent (2009) and Strzalecki (2011) for variations of robust control approach of model uncertainty and Gilboa and Scmeidler (1989), Epstein and Schneider (2007, 2008), Hansen (2007), Chen, Ju, and Miao (2009), and Ju and Miao (2012) for recursive multiple prior models which incorporate learning into models under uncertainty.

[12] Several other studies examine the impact of uncertainty aversion on finance-related questions. For example, Dow and Werlang (1992), Easley and O'Hara (2009), Cao, Wang, and Zhang (2005), and Bossaerts et al. (2010) develop models where uncertainty aversion helps explain investors' limited stock market participation (or non-participation). Uppal and Wang (2003), Boyle et al. (2012), and Benigno and Nistico (2012) offer uncertainty aversion as a potential explanation to familiarity bias, and provide theoretical framework to explain why investors prefer holding assets that are familiar to them when faced with uncertainty. Easley and O'Hara (2010) show that uncertainty can cause market freezes and illiquidity where agents do not trade in certain price intervals. Epstein and Schneider (2007) and Garlappi, Uppal, and Wang (2007) incorporate uncertainty to dynamic portfolio choice models with learning.

[13] The reader is referred to Appendix A for a detailed numerical example that establishes the link between uncertainty and volatility of volatility.

choice. Under homogeneous expectations, i.e. when investors all agree about mean and variance of individual stock returns, and hence the market portfolio, Markowitz mean-variance framework entails investors to hold a combination of the risk-free asset and the market portfolio in their optimal portfolios. However, when investors are uncertain about probabilities that generate possible mean-variance pairs of market returns over the state space S, the probability measure that captures this uncertainty, μ, is defined not only by consensus beliefs about expected market returns $E_\Delta(E_S(R_m)$, and market volatility $E_\Delta(\sigma_S(R_m))$, but also dispersion in beliefs about expected market returns $\sigma_\Delta(E_S(R_m))$, and dispersion in beliefs about market volatility, $\sigma_\Delta(\sigma_S(R_m))$. Hence, when investors are uncertain about probabilities that generate expected market returns, the last term, which represents volatility of aggregate volatility, becomes crucial in decision making and portfolio allocation.

Asset pricing implications of uncertainty have been examined in various studies.[14] For example, Kogan and Wang (2003) consider a standard one-period representative agent economy, characterized by N risky assets and a riskless asset and extend the well-known result of asset pricing to the case in which investors do not have a perfect knowledge of distribution of return process $\boldsymbol{R} \equiv [R_1, R_2, \cdots, R_N]'$, where $\boldsymbol{R}$ follows a joint multivariate normal distribution with known variance-covariance matrix and an unknown vector of mean return, $\boldsymbol{\mu}$. In their model, agents are presented with incomplete sources of information about the mean return process, but they can still estimate reference probabilistic models (hence reference mean returns) for the joint distribution of asset returns. In the absence of arbitrage opportunities, Kogan and Wang (2003) show that:

$$\boldsymbol{\mu} - r\mathbf{1} = \lambda\boldsymbol{\beta} + \lambda_u\boldsymbol{\beta_u} \tag{2}$$

[14] See Epstein and Wang (1994, 1995), Chen and Epstein (2002), Trojani and Vanini (2002), Sbuelz and Trojani (2008), Gagliardini, Porchia, and Trojani (2008), Epstein and Schneider (2008), Barillas, Hansen, and Sargent (2009), and Illeditsch (2012) for implications of uncertainty on asset pricing.

where the first term is the standard, static CAPM component with λ being the market risk premium, and $\boldsymbol{\beta}$ is the vector of betas measured with respect to returns on the market portfolio (market beta); and the second term captures uncertainty in asset prices via the risk premium on ambiguity λ_u, and $\boldsymbol{\beta_u}$, which can be interpreted as a vector of betas that measure the exposure of an asset's return to uncertainty contained in the return on the market portfolio (uncertainty beta). In their setting, uncertainty is only partially diversifiable in the sense that, in equilibrium, for any asset, only its individual contribution to total market ambiguity will be compensated. Since investors bear both market risk and *Knightian uncertainty*, two assets with the same beta with respect to the market risk may still have considerably different expected returns due to their different uncertainty betas.

Finally, our study is also related to the well-established strand of literature in option pricing with stochastic volatility. It is now common in option pricing models to assume stochastic volatility for the dynamics of the underlying asset. 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. Our VOV measure in that sense is similar to the stochastic volatility parameter (κ) that captures volatility in aggregate volatility dynamics as a separate source of risk. 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. Drechsler and Yaron (2011) draw a link between uncertainty and investors' demand for compensation against stochastic volatility. Using volatility of volatility implied by a cross-section of the VIX options (VVIX), Park (2013) shows that the model-free risk-neutral VVIX index has forecasting power for future tail risk in hedge fund 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. Buraschi, Trojani, and Vedolin (2014) further examine the link between market-wide uncertainty, difference of opinions, and co-movement of stock returns and show that this link plays an important role in explaining the dynamics of equilibrium volatility and correlation risk premia.

2. Data and Variable Construction

In this section, we first describe the hedge fund data used in our index and individual fund level analyses. Next, we present risk factors that have been documented as important in the literature in explaining hedge fund performance. Finally, we explain the construction of our VOV measure, *LBVIX*.

2.1. Hedge fund database

Index level hedge fund data for our baseline analyses is from Dow Jones Credit Suisse. We further use CISDM, Eurekahedge, and HFR indices 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 resolve potential discrepancies among different databases as well as 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 USD we have 13,283 funds in our sample, which form the basis of our analyses at the individual hedge fund level.

2.2. Hedge fund risk factors

The factors that we use in our analysis follow the standard 7-factor model used in Fung and Hsieh (2004). We further add an emerging market factor as an eighth factor. These eight factors have been shown to have considerable explanatory power for hedge fund returns in the literature. Specifically, the eight 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.[15]

Throughout our analysis, we further 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).[16] Furthermore, VOV can also be related to jump and volatility risks at the aggregate level, which have been documented to be important factors in explaining the cross-section of stock returns by Cremers et al. (2014). We further test the robustness of VOV against aggregate jump (*JUMP)* and aggregate volatility (*VOL)* risk factors of Cremers et al. (2014) and the results are reported in Appendix C.[17]

[15] 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 and emerging market risk factors are from *Datastream*. Bond-oriented risk factors are from the Board of Governors of the Federal Reserve System.

[16] We would like to thank to Ronnie Sadka, Robert Kosowski, and Turan Bali for kindly providing the risk factors used in their studies.

[17] We would like to thank to Martijn Cremers for kindly providing the factors used in their study.

2.3. Construction of VOV factor

Our main proxy to capture the uncertainty risk in hedge fund returns is VOV. Our hypothesis is that if hedge 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 construct hedge 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 (also known as the fear index), 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.[18] Using a cross-section of VIX call and put options, we create our proxy for 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.

[18] Obviously, the tradeoff here is between the relatively short time-series available to estimate VOV exposures and the ability to replicate an investable strategy to be able to capture funds' VOV exposure. We also try statistical versions of VOV using monthly standard deviation of VIX, and monthly range of VIX which is defined as the difference between the maximum and minimum levels that VIX takes in a given month. Our results which extend to January 1994 are qualitatively similar with these alternative statistical measures and the details can be found in the Appendix B. However, we believe that creating an investable proxy to track funds' VOV exposure is more relevant. Furthermore, as our sample period covers one of the most turbulent times of financial markets' history, the length of time series that we use should be representative enough to capture both an episode of extreme uncertainty about expected returns, and a calmer period with less uncertainty.

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 same maturity written on the VIX index.[19] We define one of the straddles as "up straddle", and the other straddle is called 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 applied to the up straddle. Suppose on the next trading day, denoted by t = 1, VIX rises above the up straddle's strike price, i.e. $K_{up}(0)$. In this case, we roll the up straddle to the next higher strike price, selling the put and call at the existing strike price of $K_{up}(0)$ and buying a new straddle at the next higher strike price, $K_{up}(1) > K_{up}(0)$. If on the other hand, VIX does not rise above $K_{up}(0)$ on the next trading day, then the investor holds on to her existing position, i.e. $K_{up}(1) = K_{up}(0)$. By following this strategy during the calendar month, $K_{up}(j)$ tracks the highest value of VIX attained in a given month.

Next, we describe the trading strategy applied to the down straddle. Suppose at t = 1, the VIX falls below the down straddle's strike price, i.e. $K_{down}(0)$. In this case, we roll the straddle to the next lower strike price, selling the existing straddle and buying a new straddle at the next lower strike price, $K_{down}(1) < K_{down}(0)$. In contrast, if VIX does not fall below $K_{down}(0)$ on the next trading day, then the investor holds the existing position, i.e. $K_{down}(1) = K_{down}(0)$. By following this strategy during the calendar month, $K_{down}(j)$ tracks the lowest value of VIX attained in a given month.

Combining the down and up straddles, *LBVIX* strategy grants its owner the right to *sell* at the *highest* level of VIX seen during that month (via the put leg of the up straddle at strike price $K_{up}(j)$), and the right to *buy* at the *lowest* level of VIX seen during that month (via the call leg of the down straddle at the strike price $K_{down}(j)$). On the last trading day of the month,

[19] 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.

options that construct the *LBVIX* strategy are sold, and the same strategy is repeated the next calendar 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 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.[20] During the crisis sub-period, *LBVIX* strategy earned an average of 11.19% per month, which is 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), 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.[21]

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[20] Our definition of sub-periods is based on Edelman et al. (2012), who identify March 2009 as a structural break point associated with the end of credit crisis. Our results are robust to alternative sub-periods ending at December 2008, January 2009, and February 2009.

[21] These findings are also in line with Barnea and Hogan (2012) who document a negative variance risk premium in VIX options. Using a cross-section of VIX options, the authors find a negative average return to a long position in theoretical variance swaps on VIX futures. Furthermore, high skewness and kurtosis associated with VIX option variance swap returns imply small and regular losses to buyers of VIX variance swaps but large profits at times of market uncertainty.

One thing noteworthy is 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, which simply 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. Furthermore, Buraschi, Trojani, and Vedolin (2014) show that in a Lucas orchard with heterogeneous beliefs, there is a link between market-wide uncertainty and co-movement 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 co-movement of stock returns, and a substantial correlation risk premium generated by the endogenous optimal risk sharing among investors. Therefore, $LBVIX$ and *CR* are also expected to share a common component. To isolate the confounding effects of correlation risk, and aggregate volatility risk factors with our VOV measure, we orthogonalize *RetVIX*, and *CR* and use the orthogonalized versions of the two factors in the remainder of the analysis.

3. Time-series analysis of hedge fund performance

We start with time-series analysis of returns on hedge fund indices, and examine their exposures to VOV. Our starting benchmark is the standard Fung and Hsieh (2004) seven-factor model, in which a hedge fund's excess returns $r_{i,t}$ can be decomposed into a risk-adjusted performance component(α_i), and factor exposures to each risk component $\left(\beta_i^k\right)$. In order 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 ($LBVIX$):

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

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.[22] 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

Our main hedge fund indices are the 8 indices from Dow Jones Credit Suisse hedge fund index database. We focus on Hedge Fund Index, Convertible Arbitrage, Equity Market Neutral, Event Driven, Global Macro, Long/Short Equity, Managed Futures, and Multi-Strategy indices, which cover the major strategies implemented by hedge funds.[23] Table 2 presents factor loadings on the eight risk factors in equation (3) for eight indices as well as for the pooled sample of the indices 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 indices exhibit significantly negative VOV loadings over our sample period from April 2006 to December 2012, Furthermore, panel regressions also point towards a negative VOV exposure in the pooled hedge fund index sample providing further evidence that the hedge fund industry is significantly exposed to the VOV factor, and VOV is a critical determinant of hedge fund returns at the index level.[24]

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

[22] *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.

[23] There are originally 14 indices covered by Dow Jones Credit Suisse. We omitted 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.

[24] 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 determinant in the cross-section of hedge fund returns. Recently, Bali, Brown, and Caglayan (2014) document that hedge fund exposure to macroeconomic risk is a significant determinant of cross-sectional differences in hedge 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:

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

where $r_{i,t}$ and the first nine factors are as explained in equation (3), *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), and *UNC* is the economic uncertainty index capturing macroeconomic risk exposure of hedge funds as defined in Bali, Brown, and Caglayan (2014).[25]

<<Insert Table 3 about here>>

As can be seen from Table 3, VOV exposures at the hedge fund index level are very robust with seven out of eight indices exhibiting significant VOV loadings in the 12-factor model even after controlling for correlation, liquidity, macroeconomic, and volatility risk factors. Furthermore, pooled panel regressions confirm the previously documented negative VOV exposure in the hedge fund industry. Overall, our results point towards VOV factor being an important determinant of hedge fund returns at the index level.

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

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[25] Due to the availability of *correlation* risk factor up to June 2012, we conduct our empirical analyses of the12-factor model over the period from April 2006 to June 2012.

one of the biggest financial crises that we have witnessed in late 2000s, it is important to see if and how hedge funds' VOV exposures change during the crisis and post-crisis periods. To achieve this objective, we divide the sample period into 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 hedge 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 mostly significant loadings for seven of the eight indices 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 with an agreed debt haircut among investors, and the implementation of austerity programs throughout troubled Eurozone economies, as well as monetary easing programs by the FED, BoE, and the ECB. 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 exposures to the VOV factor. However, these negative exposures pay off during periods of low VOV when uncertainty is diminished.

We conclude our time-series analyses at the hedge fund index level by testing the explanatory power of the 12 factors in explaining the time-series variation in index returns. In particular, we conduct three different variable selection tests. The first test is a forward recursive variable selection method with the objective of identifying variables that bring the highest improvement in adjusted R^2.[26] 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, and we implement this condition both in forward stepwise and backward stepwise regressions.[27] For the sake of brevity, we only present results of variable selection tests based on improvement in adjusted R^2's.[28] The results presented in Table 5 provide us information about the factors that are more important in explaining hedge fund 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 in the model among the 8 indices, and the last column reports how many variables are selected in the model to explain the corresponding hedge fund index return.

<<Insert Table 5 about here>>

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 indices), 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 time during the full sample.

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

[27] 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 further 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 B.

[28] The results based on forward and backward stepwise regressions are very similar and are available upon request.

The time-series analyses at the index level indicate that hedge funds exhibit negative and significant VOV exposures. Furthermore, funds' VOV exposures are time-varying, which is consistent with our expectation of VOV being much more relevant in explaining fund returns during the financial crisis period when uncertainty about expected returns had peaked. However, it is important to note that hedge fund trading styles are heterogeneous and can exhibit significant cross-sectional variation within each strategy. Therefore even though time-series analysis at the hedge fund index level point towards VOV being a potentially important factor in explaining fund returns, explanatory power might result from other characteristics of individual hedge fund strategies. In the next section, we examine whether cross-sectional differences in individual hedge funds' risk-return profiles are attributable to VOV, and whether VOV is a priced risk factor in the cross section.

4. Cross-sectional analysis of hedge fund performance

In this section, we conduct parametric and nonparametric tests to examine the relationship 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 6 presents summary statistics of several fund characteristics over the full sample period from April 2006 to December 2012. 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. Furthermore, average fund age (number of months in business since inception) of 4.52 years. Average management and incentive fees are also very close to the 2-20 typical fee structure in the hedge fund industry.

<<Insert Table 6 about here>>

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:

$$r_{i,t} = \alpha_{i,t} + \beta_{i,t}^{LBVIX} LBVIX_t + \varepsilon_{i,t}\ , \qquad (5)$$

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*.[29]

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. Hence it avoids potential look-ahead bias in the estimation of VOV betas. Quintile 1 (5) contains funds with the lowest (highest) VOV betas. Next-month post-ranking value-weighted portfolio returns are calculated, and the procedure is repeated each month.[30] Table 7 reports average VOV betas, next-month returns, and 8-factor alphas of VOV beta sorted quintiles.

<<Insert Table 7 about here>>

Univariate portfolio sorts indicate a monotone and negative relationship between the VOV betas and next-month 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 7 also presents next month's risk-

[29] 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.
[30] Value-weighting scheme is based on funds' assets under management. We also conduct equally-weighted sorts, and sorts without backfill bias by omitting funds' first 24 months of return data after inception (see Fung and Hsieh (2000) for discussion of data biases). The results are essentially similar and available upon request.

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.[31]

It is important to 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 negative) VOV beta quintile. For example, when we compare returns and 8-factor alphas of portfolios 1 and 5, we observe that funds in the lowest $\beta_{i,t}^{LBVIX}$ quintile exhibit positive and significant returns, whereas returns on funds in the highest $\beta_{i,t}^{LBVIX}$ are not statistically 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 which 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 (Ang et al. (2006); Bali and Engle (2010); and Cremers, Halling, and Weinbaum (2014)). To ensure that we are not simply picking up aggregate volatility risk, we further sort hedge funds with respect to their volatility risk (VOL) and VOV exposures. We estimate each fund's volatility risk exposure by estimating the following time-series regressions over 36-month rolling windows:

$$r_{i,t} = \alpha_{i,t} + \beta_{i,t}^{MKT} MKT_t + \beta_{i,t}^{VOL} VOL_t + \varepsilon_{i,t} , \qquad (6)$$

[31] Negative and significant relationship between *LBVIX* beta sorted portfolios and next-month risk-adjusted returns is robust after controlling for jump, volatility, and correlation risk factors.

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 8 reports average next-month return and 8-factor alphas for the 25 VOL-VOV beta sorted portfolios.

<<Insert Table 8 about here>>

Bivariate portfolio sorts confirm the negative relationship between VOV betas and next month's average fund returns. Regardless of the portfolios' volatility risk exposures, the five spread portfolios which 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 command significant and negative next-month returns, with losses ranging from 1.43% to 1.95% per month. 8-factor alphas also point towards even higher negative and significant average risk-adjusted losses for the spread portfolios, ranging from –1.66% to –2.49% per month. 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 might 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 very different characteristics compared to the funds in the highest $\beta_{i,t}^{LBVIX}$quintile. To mitigate the effects of the aggregation, and to control for potential effects of other fund characteristics, we conduct multivariate cross-sectional regressions at the individual fund level in the next section.

4.3 Multivariate cross-sectional regressions

This section presents the results of Fama and MacBeth (1973) regressions conducted at the individual fund level after controlling for a large set of fund characteristics. Specifically, we estimate the following regression:

$$\begin{aligned} r_{i,t+1} = {} & \lambda_{0,t} + \lambda_{LBVIX,t}\beta_{i,t}^{LBVIX} + \lambda_{r,t}r_{i,t} + \lambda_{Size,t}Size_{i,t} + \lambda_{Age,t}Age_{i,t} \\ & + \lambda_{MgmtFee,t}MgmtFee_{i,t} + \lambda_{IncFee,t}IncFee_{i,t} \\ & + \lambda_{Redemption,t}Redemption_{i,t} + \lambda_{MinInv,t}MinInv_{i,t} + \lambda_{Lockup,t}Lockup_{i,t} \\ & + \lambda_{Delta,t}Delta_{i,t} + \lambda_{Vega,t}Vega_{i,t} + \lambda_{VOL,t}\beta_{i,t}^{VOL} + \varepsilon_{i,t+1}\,, \end{aligned} \tag{7}$$

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 equation (6).[32]

<<Insert Table 9 about here>>

Table 9 presents the 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 betas, as well as different set of fund characteristics for the period

[32] See Agarwal, Daniel, and Naik (2009) for a detailed description and construction of hedge fund's delta and vega.

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 might result from the fact that betas are estimated (hence are measured with error) in the first pass.[33] The first specification examines the cross-sectional relationship 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 provides evidence of a negative and significant relation between $\beta_{i,t}^{LBVIX}$ and one-month-ahead fund excess returns, with an average slope of –0.1770 and a *t*-statistic of –2.15.

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 fund managers' 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. The fourth specification incorporates all fund-specific characteristics. The fifth specification examines the robustness of VOV factor in the presence of volatility risk factor, and the sixth specification tests the full model presented in equation (7).

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 during our sample period. Regardless of the control variables used, all the

[33] 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 premia 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.

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.

5. VOV exposures and hedge fund characteristics

Having established a robust negative relation between VOV betas and funds' future returns, we next investigate if and whether there are cross-sectional differences in VOV betas with respect to funds' risk profiles. Specifically, we first investigate whether different fund strategies exhibit different VOV beta-return relation. Second, we examine whether negative or positive exposure to VOV is related with different fund characteristics and risk-taking behavior.[34] Third, we extend our analyses to mutual funds and investigate whether mutual funds' exposures to VOV predicts their future returns. Finally, we investigate the dollar VOV exposures at hedge fund strategy level and examine if VIX options market is deep enough to accommodate VOV exposures of hedge funds for their hedging (or risk management) needs.

5.1 Univariate portfolio sorts at hedge fund strategy level

Hedge funds have various investment strategies and different tools available to them to achieve absolute returns. For example, unlike mutual funds, they can trade options and other derivatives. Using different tools, hedge funds can choose to get direct exposure to or minimize several risks such as market, volatility, correlation, and VOV. In terms of their investment objectives, managed futures, global macro, and emerging markets are directional strategies that are subject to market risk, whereas equity market neutral, fixed income arbitrage, and convertible arbitrage funds follow non-directional investment strategies that

[34] We also test whether changes in fee structure and high-water mark (HWM) provision affect funds' VOV exposures. We use proprietary daily fee-change data from the Lipper TASS database available since 04/17/2008. Our findings indicate that funds' VOV betas increase (become more negative) after incentive fees increase, management fees decrease, and removal of HWM. These findings are consistent with the greater risk-taking behavior of funds associated with such fee changes as reported and discussed in Agarwal and Ray (2012).

aim to minimize market risk. Some funds also aim at diversifying risk by taking both long and short, diversified positions, such as long-short equity, event-driven, and multi-strategy funds.

Given the diversity of investment strategies available to hedge funds, we expect to observe cross-sectional differences in funds' VOV exposures with respect to their strategies. To investigate if and how the relation between funds' VOV exposures and returns change across strategies, we first classify funds with respect to ten distinct strategies and then each month, from March 2009 to December 2012, we sort funds within each strategy into quintile portfolios based on their $\beta_{i,t}^{LBVIX}$. Table 10 presents next-month value-weighted portfolio returns, and average $\beta_{i,t}^{LBVIX}$ for the five VOV beta sorted quintiles across each strategy. For sake of comparison, we report ex-post average excess returns of funds within each strategy during the two sub-periods: April 2006 – March 2009, and April 2009 – December 2012.

<<Insert Table 10 about here>>

We find that strategies such as managed futures, global macro, equity market neutral, fixed income arbitrage, event driven, multi-strategy, and distressed securities have lower VOV beta spreads than the other 3 strategies, i.e. emerging markets, convertible arbitrage, and long/short equity. Interestingly, the strategies with lower VOV beta spreads are the ones who lost the least (and even managed to achieve positive excess returns) during the first sub-period corresponding to the financial crisis and increase in aggregate uncertainty, with average excess returns ranging from –0.24% per month for distressed securities to 0.76% per month for managed futures. A detailed analysis among those strategies reveal that the three strategies which had positive returns during the financial crisis sub-period (i.e. managed futures, global macro, and equity market neutral) show similar VOV exposures. In particular, funds in those strategies exhibit the least negative VOV exposures in the lowest quintile (–0.044, –0.051, and –0.039) and the most positive VOV exposures in the highest quintile (0.033, 0.028, and 0.021). We further find that the three strategies with higher VOV beta spreads, i.e. emerging market, convertible arbitrage, and long/short equity, were the worst performers during the financial crisis. A common characteristic of these strategies is that they have the most negative VOV exposures compared to others across all quintiles, ranging from –0.093 for long/short equity to –0.118 for emerging markets in the lowest quintile.

What are the potential reasons behind the heterogeneity across VOV exposures and fund performance across strategies? Do some funds have better tools to manage VOV exposures? It is conceivable that managed futures and global macro strategies have more tools available to them to cope with uncertainty during the financial crisis. For example, global macro style relies heavily on currency and interest rate trading, including U.S. treasuries and other cash and debt instruments. Managed futures take long or short positions in futures contracts predominantly on commodities, but also on currency and government bond futures. All of these were asset classes that were least affected from uncertainty in expected stock returns during the crisis. Equity market neutral strategy aims to maintain market beta close to zero as well as hedge against volatility by using statistical and fundamental arbitrage. Our findings imply that funds following the equity market neutral strategy are also better at hedging against VOV and uncertainty in expected returns. To sum, our results imply that by having less negative VOV exposures, these three strategies had a clear advantage as opposed to other strategies in weathering the uncertainty during the financial storm of 2007 and 2008.

Although strategies that had high VOV exposures performed worse during the crisis sub-period, their negative VOV exposures earned them handsome profits during the second sub-period when uncertainty about expected returns had been partially resolved, and confidence in financial markets had been restored. Overall, our results indicate significant differences in VOV exposures and performance across hedge fund strategies. The next section explores whether differences in VOV exposures are attributable to funds' risk-taking behavior, and whether they are related to certain fund characteristics.

5.2 VOV exposure and fund characteristics

Previous section documents that funds with more negative VOV betas earn higher returns during normal times but lose more during periods of increased uncertainty. Funds with more positive VOV betas in the highest VOV beta quintile earn lower returns during normal times, but outperform funds with more negative betas during the crisis. Could funds' VOV betas be related to differences in their risk-taking behavior? Do funds with negative VOV betas take more risk, and funds with positive VOV betas hedge against uncertainty? Are the differences in VOV betas related to differences in certain fund characteristics? This section investigates the relation between VOV exposures, risk taking, and fund characteristics.

We use 24-month rolling windows and estimate each fund's VOV beta using the 8-factor model in equation (3). Next, we separate funds with negative and positive VOV betas during the estimation period from March 2008 to December 2012 and compare fund characteristics for the two sample of funds with distinct VOV betas. This informal test helps to discover which fund characteristics are attributable to more risk taking (negative VOV betas) and which ones are attributable to hedging uncertainty (positive VOV betas). We estimate the following multivariate logistic regression to investigate the relation between fund characteristics and VOV betas:

$$\begin{aligned} VOVDummy_{i,t} = {} & \alpha_{i,t} + \beta_{ret} r_{i,t-1} + \beta_{Size} Size_{i,t-1} + \beta_{Age} Age_{i,t-1} \\ & + \beta_{MgmtFee} MgmtFee_i + \beta_{IncFee} IncFee_i + \beta_{Redemption} Redemption_i \\ & + \beta_{MinInv} MinInv_i + \beta_{Lockup} Lockup_i + \beta_{Delta} Delta_{i,t-1} + \beta_{Vega} Vega_{i,t-1} \\ & + \beta_{Moneyness} Moneyness_{i,t-1} + \beta_{Leverage} Leverage_i + \beta_{HWM} HWM_i + \varepsilon_{i,t} \, , \end{aligned} \tag{8}$$

where $VOVDummy_{i,t}$ is an indicator variable that takes a value of 1 if VOV beta of a fund is negative, and 0 otherwise, $Moneyness_{i,t-1}$ is the moneyness of the incentive fee contract as a percentage of the strike price, i.e., (S-X)/X as of month *t-1*, $Leverage$ is an indicator variable that takes a value of 1 if the fund uses leverage and 0 otherwise, HWM is an indicator variable that takes the value of 1 if the fund has a high-water mark provision, and 0 otherwise, and other variables are as defined earlier in equation (7).

<<Insert Table 11 about here>>

Panel A of Table 11 compares the characteristics of funds with negative VOV betas with those of the funds with positive betas. It reports the difference in fund characteristics and the associated *t*-statistics assuming unequal variances for the samples. The results uncover distinct fund characteristics that are associated with funds having negative versus positive exposures to VOV. In particular, funds with negative VOV betas (i.e., those that take greater risks) have lower past performance, greater fund size, longer existence, longer redemption period, higher minimum investment requirement, longer lockup period, higher delta, higher vega, lower moneyness, higher leverage, and do not have HWM provision. These findings are consistent with the predictions from the extant theoretical literature on the risk-taking incentives from the compensation contracts of hedge fund managers. For example, Panageas and Westerfield (2009) show that the presence of HWM provision can mitigate the risk-taking behavior as it induces the manager to care about the sequence of options in the future since excessive risk taking can result in those options being out of the money if the risks do not pay off. Carpenter's (2000) theoretical model shows that manager who is compensated with an asymmetric bonus fee takes more risk when the moneyness is lower.

Panel B reports estimates of logistic regressions as specified in equation (8) for three different specifications. The first specification uses time-invariant fund characteristics (such as management fee, incentive fee, redemption period, minimum investment, lockup period, leverage, and high-water mark provision). The second specification includes lagged time-variant characteristics (returns, AUM, age, delta, vega, and moneyness), and the third specification includes all characteristics together as expressed in equation (8). Most coefficients are in line with the results reported in Panel A. For example, among time-invariant characteristics, longer lockup period and greater leverage are associated with increased risk taking, i.e. more negative VOV betas. Among time-variant characteristics, funds with longer existence, larger AUM, higher deltas, and lower moneyness are associated with more negative betas. Overall the results point towards distinct risk-taking behavior for funds that exhibit negative and positive VOV betas, and this difference is related to the fund characteristics that have been shown to be important in explaining risk taking in hedge funds.

5.3 VOV exposure and mutual funds

To gain further insight about the strong VOV exposure in the overall hedge fund industry and the distinct VOV exposure-performance relationship across different hedge fund strategies, we compare and contrast VOV exposure-performance relationship of hedge funds with mutual funds. Hedge funds and mutual funds have distinct characteristics in terms of risk taking, investment tools available to them, asymmetric performance-based incentive fees, and liquidity restrictions placed on fund investors. For example, hedge funds use much more aggressive dynamic trading strategies and employ a range of investment tools, including options, leverage, and short-selling, whereas the majority of equity mutual funds tend to use long-only buy and hold strategies. Hedge funds seek absolute returns whereas mutual funds tend to seek relative returns. Furthermore, hedge fund managers are compensated with a performance fee (usually 20% of the profits) on top of the fixed management fees (usually 2%), which is the only type of fee that most mutual fund managers receive. These differences in general result in more aggressive and risk-taking behavior of hedge funds compared to mutual funds. Previous section documents that several hedge fund strategies, such as managed futures, equity market neutral and global macro have distinct VOV exposures as opposed to the rest of the hedge fund strategies, and those three strategies performed much better than other strategies during the first sub-period. Because mutual funds do not use dynamic trading strategies and sophisticated investment tools, we do not expect mutual funds' VOV exposures to explain cross-sectional differences in mutual fund returns.

To test our hypothesis, we first estimate monthly VOV exposure of each mutual fund from the time-series regressions of equation (5) using a 36-month rolling window period.[35] We next conduct portfolio-level analysis to investigate cross-sectional predictive power of mutual funds' VOV exposures. To do that, for each month, from March 2009 to December 2012, funds are sorted into quintile portfolios based on their $\beta_{i,t}^{LBVIX}$. Quintile 1 (5) contains funds with the lowest (highest) VOV betas. Next-month post-ranking value-weighted portfolio returns are calculated, and the procedure is repeated each month.[36]

<<Insert Table 12 about here>>

Table 12 reports average VOV betas, next-month returns, 4-factor alphas of VOV beta-sorted quintiles, and the average monthly ex-post excess returns of US equity mutual funds during the two sub-periods.[37] The spread portfolio that is long in the highest VOV beta and short in the lowest VOV beta funds (high $\beta_{i,t}^{LBVIX}$– low $\beta_{i,t}^{LBVIX}$) loses on average 0.42% per month with a *t*-statistic of –1.49. The risk-adjusted return (4-factor alphas) for the same portfolio is –0.37% per month with a Newey-West adjusted *t*-statistic of –1.22. The raw returns (risk-adjusted returns) for the spread portfolio of mutual funds are much lower compared to that for hedge funds in Table 7, i.e., –0.42% vs. –1.62% (–0.37% vs. –1.89%). Further, the return of the spread portfolio is not statistically significant.

The results confirm our hypothesis that hedge funds are distinct in terms of their exposure to VOV. With the tools available to them, several hedge funds are able to generate less negative (even positive) exposure to VOV. This exposure grants them the ability to

[35] Our mutual fund data comes from the Morningstar database. Our sample is based on 8,095 funds from the US Equity category, which represents 35.69% of all funds in the database.
[36] Value-weighting scheme is based on funds' AUM. We also conduct equally-weighted sorts. The results are essentially similar and are available upon request.
[37] We use the standard four-factor model of Carhart (1997) consisting of MKT, SMB, HML, and MOM as risk factors for the US equity mutual funds.

weather uncertain turbulent times with positive returns. In contrast, US equity mutual funds show much less cross-sectional variation in VOV betas. Mutual funds as a whole exhibit a negative VOV exposure with pre-ranking average VOV betas ranging from –0.09 to –0.06. This is in stark contrast to hedge funds' VOV exposures that range from –0.09 to 0.02.

This negative exposure of mutual funds to VOV further manifests itself in average ex-post excess returns during the crisis and post-crisis period as documented in the last two columns of Table 13. Because of their inability to implement dynamic strategies and lack of sophisticated investment tools, US equity mutual funds exhibit much higher exposure to VOV compared to hedge funds, and in turn they experienced far worse returns (–1.44% per month) during the period of financial crisis when uncertainty was at its highest. In contrast, their negative exposures to VOV helped US equity mutual funds to recover their losses during the second sub-period when uncertainty in the market conditions diminished.

Our results indicate that hedge funds have distinct exposure to VOV compared to mutual funds. This difference manifests itself especially in several hedge fund strategies (such as managed futures, global macro, and equity market neutral) that exhibit less negative (and even positive) exposure to VOV. US equity mutual funds, in contrast, have indistinguishably negative exposure to VOV and their VOV exposures do not result in significant cross-sectional difference in their performances.

5.4 How deep is the VOV market?

So far we have established a clear link between VOV and hedge fund performance at the index, individual fund, and strategy levels. However, this raises the question about whether VOV strategies can be practically implemented. For example, how deep is the VIX options market? What is the overall VOV exposure of funds in dollar terms? Is the market sufficiently deep enough to accommodate funds' VOV exposure/hedging needs? We address these questions by looking at the depth of the VIX option market and by comparing it with dollar VOV exposures of funds within different strategies.

To have as much data as possible, we use 24-month rolling windows and estimate each fund's VOV exposure using equation (5). Each month we calculate dollar VOV exposure of each fund within each strategy, by multiplying each fund's monthly VOV exposure by its assets, i.e. $\beta_{i,t}^{LBVIX} \times AUM_{i,t}$. We then define average dollar VOV exposure and total dollar VOV exposure of each strategy as:

$$AvgDollarVOVExp = \frac{\sum_{t=1}^{T}\sum_{i=1}^{I}\beta_{i,t}^{LBVIX} \times AUM_{i,t}}{T \times I}, \quad i = 1, \dots, I \text{ and } t = 1, \dots, T \qquad (9)$$

$$TotalDollarVOVExp = \frac{\sum_{t=1}^{T}\sum_{i=1}^{I}\beta_{i,t}^{LBVIX} \times AUM_{i,t}}{T}, i = 1, \dots, I \text{ and } t = 1, \dots, T \qquad (10)$$

where $i = 1, \dots, I$ corresponds the funds within each strategy, and $t = 1, .., T$ corresponds to March 2008 – December 2012 period. $\beta_{i,t}^{LBVIX}$ is a fund's monthly VOV exposure estimated using equation (5), and $AUM_{i,t}$ is the assets under management of fund *i* in month *t*.

<<Insert Table 13 about here>>

Panel A of Table 13 reports both the number and dollar values of the monthly average and total open interest positions in VIX options traded on the CBOE.[38] The average open interest for VIX options (both calls and puts) during March 2008 – December 2012 period was \$1.19 million with a monthly total notional amount corresponding to \$9.11 billion. Open interest in VIX call options is almost twice as high as open interest in VIX put options. Panel B of Table 13 reports the monthly average and total dollar VOV exposure of funds within each strategy, as well as total AUM in each strategy, and percentage VOV exposure with respect to total AUM. Long/short equity, fixed income arbitrage, event driven and emerging market strategies have the highest total dollar VOV exposures. In line with $\beta_{i,t}^{LBVIX}$ spreads

[38] The multiplier for VIX options contracts is \$100.

observed in the previous section, emerging markets, convertible arbitrage and long/short equity funds have the highest percentage exposure to VOV with respect to their fund size, with 3.45%, 3.08%, and 2.69% of their total AUM exposed to the VOV factor, respectively.

When we compare Panels A and B, we observe that depth of VIX options market is not enough to accommodate VOV exposure/hedging needs of the hedge fund industry as a whole ($9.11 billion of VIX options monthly open interest vs. $13 billion of total VOV exposure). However, note that hedge funds employ sophisticated strategies and tools to achieve absolute returns, and to get exposed to different risk factors. Hence, we do not expect VIX options to be the only tool that hedge funds employ to get exposed to (or hedge) VOV. They might choose other options or asset classes which are highly correlated with *LBVIX* to obtain or mitigate VOV exposure and achieve their objectives via diverse strategies.

6. Conclusion

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 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 the highest. The results are robust to using a variety of hedge fund indexes and inclusion of a wide range of risk factors that have been documented to be important in the literature in explaining hedge fund returns.

Second, we find that hedge 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 aggregate volatility risk. Multivariate Fama and MacBeth (1973) regressions that control for individual fund characteristics further corroborate our findings and indicate that the relation between VOV exposures and hedge fund returns is negative.

We further document that the negative relation between VOV exposures and hedge fund returns is not homogeneous across fund strategies. Strategies with lower spreads in the VOV betas, and less negative VOV betas in the lowest quintile (managed futures, global macro, equity market neutral) outperform other strategies during the crisis. In contrast, funds with higher VOV beta spreads and more negative VOV betas in the lowest quintile (emerging markets convertible arbitrage, long/short equity) outperform their counterparts during the second sub-period when there was less uncertainty about overall market conditions.

Finally, we compare VOV exposure-performance relationship of hedge funds with mutual funds. We find strong support for distinct characteristics of hedge fund industry with respect to their VOV exposures. In contrast to hedge funds, mutual funds do not exhibit significant cross-sectional variation in their VOV exposures with all mutual fund quintiles exhibiting negative VOV betas. Furthermore, the dispersion in VOV exposures cannot explain mutual fund returns in the cross section. The variation in hedge funds' VOV betas is consistent with the unique dynamic trading behavior and risk-taking incentives of hedge funds arising from the different fund characteristics including their contractual features.

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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 equation (3) 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 indices 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 indices, 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	Adj.R^2
HFI	**–0.002**	**0.005**	**0.006**	**–0.098**	**0.237**	**0.216**	**–0.041**	**–0.006**	**0.001**	**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**	**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**	**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**	**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**	**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**	**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**	**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**	**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**	**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 equation (4) 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 indices 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 indices, 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	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**	**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**	**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**	**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**	**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**	**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**	**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**	**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**	**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**	**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

Subperiod analysis

This table reports the estimates of the 15-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	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**	**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**	**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**	**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**	**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**	**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**	**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**	**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**	**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**	**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**	**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**	**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**	**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**	**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**	**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**	**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**	**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

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 subperiods: 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
HFI					1	1		1			1		4
CA		1			1	1	1					1	5
MN	1				1	1		1	1				5
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		4
% 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
HFI					1	1		1			1		4
CA					1		1	1	1				4
MN	1	1					1						3
ED				1	1	1							3
GM					1		1	1		1			4
LS					1	1		1					3
MF			1			1		1			1		4
MS	1			1	1	1		1					3
% 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 A : 04/2009-06/2012													
	PTFSBD	PTFSFX	PTFSCOM	BD10RET	BAAMTSY	SNPMRF	SCMLC	LBVIX	RetVIX	LIQ	CR	UNC	Total
HFI		1				1			1		1	1	5
CA					1	1			1			1	4
MN						1	1						2
ED				1		1					1	1	5
GM	1		1			1					1		4
LS					1	1					1		3
MF	1					1	1				1		4
MS					1	1			1		1	1	5
% 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 6
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 7
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 8
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 equation (5). 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 9
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:

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

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 equation (6). 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–1		**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 10

Univariate portfolio sorts at the fund strategy level

This table reports next month's value-weighted return, and average $\beta_{i,t}^{LBVIX}$ of five VOV beta sorted quintile portfolios across the ten strategies. MF, GM, EM, MN, FA, CA, LS, ED, MS, DS stand for managed futures, global macro, emerging markets, equity market neutral, fixed income arbitrage, convertible arbitrage, long-short equity, event-driven, multi-strategy, and distressed securities strategies. 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 the 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. Last two columns present ex-post excess returns per strategy during the two sub-periods.

		QUINTILE PORTFOLIOS						Avg. excess return per month	
Strategy		1 (low)	2	3	4	5 (high)	5–1	04/06-03/09	04/09–12/12
MF	Avg. βLBVIX	–0.044	–0.013	–0.002	0.007	0.033	0.077	0.76%	0.19%
	Avg. Return	0.253	–0.014	0.024	–0.095	–0.078	–0.331		
		[0.45]	[–0.03]	[0.08]	[–0.30]	[–0.22]	[–0.75]		
GM	Avg. βLBVIX	–0.051	–0.016	–0.004	0.005	0.028	0.079	0.50%	0.52%
	Avg. Return	1.068	0.353	0.295	0.258	0.084	–0.983		
		[2.07]	[1.48]	[1.80]	[1.57]	[0.45]	[–1.80]		
EM	Avg. βLBVIX	–0.118	–0.071	–0.044	–0.024	–0.004	0.113	–0.44%	1.14%
	Avg. Return	2.356	1.559	1.137	0.553	0.243	–2.112		
		[1.77]	[1.90]	[2.06]	[1.54]	[1.45]	[–1.76]		
MN	Avg. βLBVIX	–0.039	–0.019	–0.009	–0.001	0.021	0.060	0.23%	0.45%
	Avg. Return	0.681	0.398	0.152	0.244	–0.395	–1.076		
		[2.12]	[1.19]	[0.92]	[2.57]	[–1.28]	[–1.95]		
FA	Avg. βLBVIX	–0.065	–0.029	–0.015	–0.004	0.011	0.076	–0.04%	0.88%
	Avg. Return	1.663	1.143	0.861	0.343	0.259	–1.404		
		[3.02]	[3.94]	[4.45]	[3.39]	[3.45]	[–2.54]		
CA	Avg. βLBVIX	–0.098	–0.051	–0.039	–0.030	–0.014	0.084	–0.39%	1.56%
	Avg. Return	2.148	1.381	1.166	1.219	0.708	–1.440		
		[2.01]	[2.67]	[2.93]	[3.45]	[3.51]	[–1.51]		
LS	Avg. βLBVIX	–0.093	–0.056	–0.035	–0.017	0.008	0.101	–0.25%	0.89%
	Avg. Return	1.879	1.246	0.874	0.570	0.120	–1.759		
		[1.97]	[2.17]	[2.31]	[2.68]	[2.00]	[–1.92]		
ED	Avg. βLBVIX	–0.069	–0.039	–0.025	–0.014	0.003	0.071	–0.21%	1.05%
	Avg. Return	2.133	1.242	0.830	0.592	0.358	–1.775		
		[3.22]	[2.70]	[2.72]	[2.58]	[2.10]	[–3.32]		
MS	Avg. βLBVIX	–0.046	–0.024	–0.017	–0.009	0.006	0.052	–0.12%	0.77%
	Avg. Return	0.923	0.487	0.567	0.510	0.556	–0.367		
		[2.21]	[1.89]	[3.72]	[3.79]	[3.61]	[–1.01]		
DS	Avg. βLBVIX	–0.062	–0.035	–0.024	–0.013	0.008	0.070	–0.24%	1.52%
	Avg. Return	1.881	1.323	0.995	1.126	1.204	–0.677		
		[2.73]	[3.30]	[2.67]	[4.33]	[1.85]	[–0.81]		

Table 11

VOV betas and fund characteristics

Panel A report monthly averages of characteristics of funds that exhibit negative and positive VOV betas. Third row reports the difference in fund characteristics and fourth row reports the *t*-statistics of the tests of significance whether the differences are statistically indistinguishable from zero assuming unequal variances. VOV betas are estimated using 24-month rolling window regressions of equation (3) controlling for 8 risk factors of Fung and Hsieh (2001). Panel B reports the estimates of the following multivariate logistic regression:

$$VOVDummy_{i,t} = \alpha_{i,t} + \beta_{ret} r_{i,t-1} + \beta_{Size} Size_{i,t-1} + \beta_{Age} Age_{i,t-1} + \beta_{MgmtFee} MgmtFee_i + \beta_{IncFee} IncFee_i + \beta_{Redemption} Redemption_i + \beta_{MinInv} MinInv_i + \beta_{Lockup} Lockup_i + \beta_{Delta} Delta_{i,t-1} + \beta_{Vega} Vega_{i,t-1} + \beta_{Moneyness} Moneyness_{i,t-1} + \beta_{Leverage} Leverage_i + \beta_{HWM} HWM_i + \varepsilon_{i,t}$$

where $VOVDummy_{i,t}$ is an indicator variable that takes a value of 1 if VOV beta of a fund is negative, and 0 otherwise, $r_{i,t-1}$ is the lagged excess return on fund *i* in month *t-1*, $Size_{i,t-1}$ is the monthly assets under management (AUM) as of month *t-1*, $Age_{i,t-1}$ is the number of months that fund *i* is in business since inception as of month *t-1*, *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 redemption frequency in number of days, *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 initial investment from the fund, $Delta_{i,t-1}$ is the expected dollar change in the manager's compensation for a 1% change in the fund's net asset value as of month *t-1*, $Vega_{i,t-1}$ is the expected dollar change in the manager's compensation for a 1% change in the volatility of fund's net asset value as of month *t-1*, $Moneyness_{i,t-1}$ is the moneyness of the incentive fee contract as a percentage of the strike price, i.e. (S-X)/X as of month *t-1*, $Leverage$ is an indicator variable that takes a value of 1 if the fund uses leverage and 0 otherwise, and HWM is an indicator variable that takes the value of 1 if the fund has high-water mark provision, and 0 otherwise.

Panel A: Comparison of fund characteristics based on VOV betas

	Ret_{t-1}	$Size_{t-1}$	Age_{t-1}	MgmtFee	IncFee	Redemption	MinInv	Lockup	$Delta_{t-1}$	$Vega_{t-1}$	$Moneyness_{t-1}$	Leverage	HWM
VOV Beta < 0	0.25	291.00	83.23	1.47	18.49	67.97	1.35	126.91	497.74	87.41	–0.05	0.56	0.50
VOV Beta > 0	0.57	194.00	42.24	1.50	18.22	61.00	1.20	113.22	390.83	79.77	–0.01	0.53	0.57
Difference	–0.32	97.00	40.99	–0.03	0.26	6.97	0.15	13.68	106.91	7.65	–0.04	0.03	–0.06
	[–4.56]	[3.12]	[5.08]	[–1.57]	[1.56]	[4.36]	[2.56]	[3.24]	[4.67]	[3.16]	[–6.50]	[3.42]	[–3.19]

Panel B: Logistic regressions of VOV beta dummy on different fund characteristics

Intercept	Ret_{t-1}	$Size_{t-1}$	Age_{t-1}	MgmtFee	IncFee	Redemption	MinInv	Lockup	$Delta_{t-1}$	$Vega_{t-1}$	$Moneyness_{t-1}$	Leverage	HWM	Pseudo R^2
0.9871				–1.3128	–1.0150	0.0001	0.0010	0.0003				0.0269	0.1223	4.28%
[5.94]				[–0.65]	[–1.21]	[0.75]	[1.36]	[7.52]				[1.77]	[1.07]	
0.4512	–0.0045	0.1280	0.0029						0.0894	0.0831	–0.3553			4.50%
[3.52]	[–1.51]	[2.58]	[6.00]						[4.63]	[1.05]	[–3.25]			
1.1052	–0.0037	0.0601	0.0012	–2.1516	–1.7049	0.0004	0.0171	0.0005	0.0610	0.0989	–0.3103	0.0186	0.1074	5.11%
[6.15]	[–1.40]	[1.37]	[3.36]	[–1.05]	[–0.92]	[1.72]	[3.93]	[5.21]	[3.37]	[1.22]	[–2.68]	[0.57]	[1.06]	

Table 12

Univariate portfolio sorts based on mutual fund VOV betas

This table reports next-month value-weighted return, next-month 4-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:

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

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, mutual 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						Avg. excess return per month	
	1 (low)	2	3	4	5 (high)	**5-1**	04/06-03/09	04/09-12/12
Avg. Return	**2.051**	**1.954**	**1.763**	**1.764**	**1.634**	**–0.417**	**–1.44%**	**1.64%**
	[2.42]	[2.53]	[2.48]	[2.56]	[2.70]	[–1.49]		
4-Factor Alpha	**1.960**	**1.889**	**1.700**	**1.701**	**1.588**	**–0.372**		
	[1.97]	[2.06]	[2.01]	[2.09]	[2.20]	[–1.22]		
Average βLBVIX	**–0.089**	**–0.079**	**–0.073**	**–0.069**	**–0.060**			

Table 13

VIX options open interest and fund strategy dollar VOV exposures

Panel A reports both the number and dollar amount of the monthly average and total open interest of VIX options traded on the CBOE during March 2008 – December 2012 period. Panel B reports monthly average and total dollar VOV exposure of funds within each strategy, as well as monthly average of total assets under management of each strategy, and percentage VOV exposure with respect to total assets under management.

Panel A: VIX options open interest				
	Average	Total (million)	Average ($)	Total (billion$)
Open Interest	11947.48	91.1	1194748	9.11
Call Open Interest	15606.20	59.5	1560620	5.95
Put Open Interest	8288.71	31.6	828871	3.16
Panel B: Strategy VOV exposures				
	Average Dollar Exposure	Total Dollar Exposure (billion$)	Total AUM (billion$)	% VOV Exposure
Managed Futures	–437043	–0.127	78.4	0.16%
Global Macro	–2567901	–0.801	130	0.62%
Emerging Markets	–5241578	–1.470	42.6	3.45%
Equity Market Neutral	–1652123	–0.026	4.47	0.59%
Fixed Income Arbitrage	–6152723	–1.660	160	1.04%
Convertible Arbitrage	–6772792	–0.277	8.98	3.08%
Long/Short Equity	–5731508	–5.760	214	2.69%
Event Driven	–7756090	–1.490	89.2	1.67%
Multi-Strategy	–5614923	–0.236	32.4	0.73%
Distressed Securities	–11200000	–0.761	46.2	1.65%

Appendix A

We provide a numerical example to highlight the link between uncertainty and volatility of aggregate volatility in the case of a mean-variance framework. Assume that investors have the following first-order expected utility function, $\mathrm{E}[u(\mu_S, \sigma_S)] = \mu_S - \frac{\sigma_S^2}{2}$. For the sake of simplicity, let us assume that there are two states of the economy (*S* = *2*). Investors agree on the expected returns in each state of the economy. However, uncertainty about the probability distribution of expected outcomes implies that they might differ in the probabilities that they attach to the occurrence of those states.

Based on the above assumptions, the second-order utility function in Equation (1) takes the following discrete-form representation.[39]

$$V(\mu, \sigma) = \sum_{\Delta} \pi_{\Delta} E[u(\mu_S, \sigma_S)]$$

where Δ represents the set of possible probability distributions that define the mean-variance pairs of expected outcomes in each state, and π_Δ represents investors' attitude towards uncertainty, i.e. the likelihood that the investor attaches to the occurrence of possible uncertain events. The following example establishes the link between uncertainty and volatility of aggregate volatility.

Example: Investors agree that the market portfolio can go up by 6% or go down by 2%. We first consider the case of no uncertainty about the probabilities that drive the asset price dynamics:

<u>Case 1 (No uncertainty case):</u> Let us assume that both up and down moves are equally likely. In this case, the expected return and variance of the market portfolio is given by:

$$E(R) = 0.50x0.06 + 0.50x(-0.02) = 2\%$$

$$\sigma(R) = \sqrt{0.50x(0.06 - 0.02)^2 + 0.50x(-0.02 - 0.02)^2} = 4\%$$

In the case of no uncertainty, Δ=1, therefore the value of the second-order utility function is equal to the value of the first-order expected utility function:

$$V(f) = E[u(\mu_S, \sigma_S)] = 0.02 - \frac{0.0016}{2} = 0.0192$$

<u>Case 2 (Uncertainty case):</u> Assume that investors are uncertain about the probabilities attached to up and down moves of the market portfolio and the probabilities can take either of the following 5 pairs, $\pi = (p_u, p_d)$ = ((0.10, 0.90), (0.30, 0.70), (0.50, 0.50), (0.70, 0.30), (0.90, 0.10)).

[39] The results can easily be extended to cases with multiple number of states (S > 2) and to continuous-case where the probability distribution can range between 0 and 1.

For each of the uncertain outcomes, Δ = 1, 2, 3, 4, 5, the expected return and variance of the market portfolio is given by:

<u>Δ=1:</u> $\pi_1 = (p_u, p_d) = (0.10, 0.90)$:

$E(R) = 0.10x(0.06) + 0.90x(-0.02) = -1.2\%$

$\sigma(R) = \sqrt{0.10x(0.06-(-0.012))^2 + 0.90x(-0.02-(-0.012)^2} = 2.4\%$

<u>Δ=2:</u> $\pi_2 = (p_u, p_d) = (0.30, 0.70)$:

$E(R) = 0.30x(0.06) + 0.70x(-0.02) = 0.4\%$

$\sigma(R) = \sqrt{0.30x(0.06-(0.004))^2 + 0.70x(-0.02-(0.004)^2} = 3.7\%$

<u>Δ=3:</u> $\pi_3 = (p_u, p_d) = (0.50, 0.50)$:

$E(R) = 0.50x0.06 + 0.50x(-0.02) = 2\%$

$\sigma(R) = \sqrt{0.50x(0.06-0.02)^2 + 0.50x(-0.02-0.02)^2} = 4\%$

<u>Δ=4:</u> $\pi_4 = (p_u, p_d) = (0.70, 0.30)$:

$E(R) = 0.70x(0.06) + 0.30x(-0.02) = 3.6\%$

$\sigma(R) = \sqrt{0.70x(0.06-(0.036))^2 + 0.70x(-0.02-(0.036)^2} = 3.7\%$

<u>Δ=5:</u> $\pi_5 = (p_u, p_d) = (0.90, 0.10)$:

$E(R) = 0.90x(0.06) + 0.10x(-0.02) = 5.2\%$

$\sigma(R) = \sqrt{0.90x(0.06-(0.052))^2 + 0.10x(-0.02-(0.052)^2} = 2.4\%$

The above example demonstrates that uncertainty about probability distribution of expected outcomes in a mean-variance framework results in uncertainty about expected market returns and its volatility, i.e. $\big(E(R), \sigma(R)\big) \in \{(-1.2,2.4), (0.4,3.7), (2.0,4.0), (3.6,3.7), (5.2,2.4)\}$.Uncertainty about expected returns and volatility of the market portfolio enters into investors' decision making directly. In determining their optimal portfolio allocations, investors will weigh the possible mean-variance pairs under each uncertain outcome according to their attitudes towards uncertainty.

Consider two uncertainty-averse investors, UA-1 and UA-2, who differ in their uncertainty attitudes.

<u>UA-1:</u> Assume that UA-1 attaches the following probabilities to the set of uncertain mean-variance pairs, $(\pi_1, \pi_2, \pi_3, \pi_4, \pi_5) = (0.40, 0.30, 0.20, 0.10, 0)$.

The value of her second-order utility function will be:

$$V_{UA1}(f) = 0.40\left(-0.012 - \frac{0.0006}{2}\right) + 0.30\left(0.004 - \frac{0.0014}{2}\right) + 0.20\left(0.02 - \frac{0.0016}{2}\right) + 0.10\left(0.036 - \frac{0.0014}{2}\right) = 0.0035$$

UA-2: Assume that UA-2 attaches the following probabilities to the set of uncertain mean-variance pairs, $(\pi_1, \pi_2, \pi_3, \pi_4, \pi_5) = (0, 0.10, 0.20, 0.30, 0.40)$.

The value of her second-order utility function will be:

$$V_{UA2}(f) = 0.10\left(0.004 - \frac{0.0014}{2}\right) + 0.20\left(0.02 - \frac{0.0016}{2}\right) + 0.30\left(0.036 - \frac{0.0014}{2}\right) + 0.40\left(0.052 - \frac{0.0006}{2}\right) = 0.0355$$

Suppose the risk-free rate is 1%. UA-1 will choose not to invest in the market portfolio because doing so results in lower expected utility than investing in the risk-free asset, $V_{UA1}(f) = 0.0035 < 0.01 = V_{RF}(f)$. She will invest all her wealth in the risk-free asset.

UA-2 will choose to invest in the market portfolio (or a combination of the market portfolio and the risk-free asset) because doing so results in a higher expected utility than investing in the risk-free asset, $V_{UA2}(f) = 0.0355 > 0.01 = V_{RF}(f)$. UA-2 might even allocate more weight to the market portfolio than no-uncertainty case (Case 1), because volatility of market returns and volatility of volatility together with UA-2's attitude towards uncertainty results in a higher expected utility than no-uncertainty case, $V_{UA2}(f) = 0.0355 > 0.0192 = V(f)$.

The example demonstrates that uncertainty about probability distribution of expected outcomes in a mean-variance framework implies uncertainty about expected return and volatility of the market portfolio, which manifests itself in the form of volatility in expected market returns σ(E(R)) and volatility in market volatility σ(σ(R)). In the classical Markowitz mean-variance setting, the expected return and volatility of the market portfolio are the two parameters that investors take into account in determining their optimal portfolios. However, when there is uncertainty about probability distribution of expected outcomes, in addition to those two parameters, volatility of expected market returns and volatility of market volatility also show up in the decision making process. Therefore, volatility of aggregate volatility is a strong determinant in investors' decision making under uncertainty.

Appendix B

This section presents time-series regressions estimated at index level using two alternative statistical proxies of volatility of aggregate volatility, the results of variable selection tests 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).

The first statistical VOV proxy we use is the monthly range of the VIX index, which is defined as:

$$RVIX_t = Max\{VIX_\tau\} - Min\{VIX_\tau\},\ \tau = 1, 2, \dots, T \tag{11}$$

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

The second proxy for VOV is monthly standard deviation of the VIX index, which is defined as:

$$SDVIX_t = \sqrt{\frac{1}{T}\sum_{\tau=1}^{T}(VIX_\tau - \overline{VIX}_t)^2} \tag{12}$$

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

Table B1
Summary statistics

This table reports summary statistics of two statistical measures of volatility of aggregate volatility, i.e., *RVIX* and *SDVIX*, 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. Panel B reports the correlations between the two factors.

Panel A: Summary Statistics						
VOV measure	Mean	StdDev	Min	Max	Skew	Kurt
RVIX	6.52	5.15	1.32	40.25	3.03	15.49
SDVIX	1.82	1.39	0.38	10.69	2.78	13.73
Panel B: Correlations						
	RVIX	SDVIX				
RVIX	1					
SDVIX	0.9850	1				

Table B2

Time-series results of the 8-factor model with RVIX

This table reports factor exposures of the nine-factor model in equation (3) during January 1994 – December 2013 period:

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

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 *RVIX* is defined as the monthly range of the VIX index as in equation (11). The 8 indices 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 indices, 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	RVIX	Alpha	Adj.R^2
HFI	**–0.018**	**0.013**	**0.016**	**0.061**	**0.269**	**0.220**	**0.121**	**–0.062**	**0.004**	**48.87%**
	[–2.68]	[2.32]	[2.08]	[1.11]	[4.39]	[9.05]	[4.04]	[–2.72]	[2.32]	
CA	**–0.008**	**–0.005**	**–0.008**	**0.078**	**0.533**	**0.076**	**0.023**	**–0.043**	**0.002**	**43.97%**
	[–1.27]	[–0.87]	[–1.06]	[1.48]	[9.01]	[3.23]	[0.78]	[–1.99]	[1.25]	
MN	**–0.023**	**0.020**	**0.020**	**0.022**	**0.174**	**0.125**	**0.019**	**–0.146**	**0.008**	**19.21%**
	[–1.98]	[2.12]	[1.56]	[0.24]	[1.67]	[3.03]	[0.38]	[–3.80]	[2.62]	
ED	**–0.022**	**0.008**	**0.001**	**–0.072**	**0.228**	**0.192**	**0.103**	**–0.050**	**0.005**	**61.68%**
	[–4.43]	[1.98]	[0.16]	[–1.80]	[5.06]	[9.76]	[4.66]	[–3.00]	[3.35]	
GM	**–0.015**	**0.016**	**0.020**	**0.172**	**0.263**	**0.109**	**–0.001**	**–0.065**	**0.007**	**10.47%**
	[–1.31]	[1.71]	[1.54]	[1.86]	[2.54]	[2.66]	[–0.02]	[–1.79]	[2.32]	
LS	**–0.014**	**0.010**	**0.010**	**0.037**	**0.159**	**0.388**	**0.308**	**–0.012**	**0.001**	**60.82%**
	[–1.80]	[1.47]	[1.10]	[0.58]	[2.25]	[13.79]	[8.87]	[–0.45]	[0.49]	
MF	**0.029**	**0.041**	**0.041**	**0.164**	**0.098**	**0.003**	**–0.004**	**–0.021**	**0.002**	**13.30%**
	[2.03]	[3.49]	[2.58]	[1.44]	[0.77]	[0.06]	[–0.06]	[–0.65]	[0.61]	
MS	**–0.008**	**0.006**	**–0.000**	**–0.008**	**0.350**	**0.081**	**0.035**	**–0.031**	**0.003**	**36.30%**
	[–1.31]	[1.37]	[–0.04]	[–0.17]	[7.04]	[4.10]	[1.44]	[–1.70]	[1.75]	
Pooled	**–0.009**	**0.014**	**0.012**	**0.059**	**0.233**	**0.148**	**0.069**	**–0.068**	**0.007**	**20.05%**
	[–1.90]	[4.10]	[3.14]	[2.09]	[5.87]	[9.79]	[3.83]	[–2.99]	[5.60]	

Table B3

Time-series results of the 8-factor model with SDVIX

This table reports factor exposures of the eight-factor model in equation (3) during January 1994 – December 2013 period:

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

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 *SDVIX* is defined as the monthly standard deviation of the VIX index as in equation (12). The 8 indices 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 indices, 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	SDVIX	Alpha	Adj.R^2
HFI	**–0.019**	**0.013**	**0.016**	**0.064**	**0.268**	**0.220**	**0.120**	**–0.228**	**0.004**	**48.88%**
	[–2.76]	[2.30]	[2.10]	[1.16]	[4.38]	[9.10]	[4.01]	[–2.73]	[2.35]	
CA	**–0.009**	**–0.005**	**–0.008**	**0.078**	**0.537**	**0.077**	**0.023**	**–0.140**	**0.002**	**43.75%**
	[–1.35]	[–0.88]	[–1.05]	[1.46]	[9.07]	[3.31]	[0.79]	[–1.73]	[1.06]	
MN	**–0.025**	**0.020**	**0.020**	**0.018**	**0.192**	**0.132**	**0.021**	**–0.457**	**0.007**	**17.75%**
	[–2.13]	[2.08]	[1.56]	[0.19]	[1.83]	[3.18]	[0.41]	[–3.18]	[2.13]	
ED	**–0.023**	**0.008**	**0.001**	**–0.072**	**0.232**	**0.194**	**0.103**	**–0.165**	**0.004**	**61.38%**
	[–4.54]	[1.96]	[0.17]	[–1.78]	[5.13]	1[0.84]	[4.64]	[–2.68]	[3.07]	
GM	**–0.016**	**0.016**	**0.020**	**0.178**	**0.259**	**0.109**	**–0.003**	**–0.255**	**0.008**	**10.62%**
	[–1.35]	[1.70]	[1.56]	[1.91]	[2.50]	[2.66]	[–0.05]	[–1.80]	[2.41]	
LS	**–0.014**	**0.010**	**0.010**	**0.037**	**0.159**	**0.388**	**0.308**	**–0.043**	**0.001**	**60.82%**
	[–1.82]	[1.46]	[1.10]	[0.58]	[2.25]	[13.83]	[8.85]	[–0.45]	[0.48]	
MF	**0.029**	**0.041**	**0.041**	**0.170**	**0.091**	**0.002**	**–0.006**	**–0.144**	**0.003**	**13.40%**
	[2.04]	[3.48]	[2.59]	[1.49]	[0.71]	[0.03]	[–0.09]	[–0.83]	[0.76]	
MS	**–0.008**	**0.006**	**–0.000**	**–0.006**	**0.349**	**0.081**	**0.034**	**–0.121**	**0.003**	**36.37%**
	[–1.35]	[1.35]	[–0.02]	[–0.12]	[7.01]	[4.10]	[1.41]	[–1.78]	[1.83]	
Pooled	**–0.010**	**0.014**	**0.012**	**0.061**	**0.235**	**0.149**	**0.069**	**–0.240**	**0.007**	**20.05%**
	[–1.98]	[4.07]	[3.15]	[2.15]	[5.81]	[9.83]	[3.80]	[–3.21]	[6.02]	

Table B4

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. Panel A reports the results for the full sample period (April 2006 – June 2012). Panels B and C report the results for the two subperiods: 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
HFI				**1**	**1**	**1**		**1**		**1**	**1**		**6**
CA		**1**	**1**		**1**	**1**	**1**	**1**	**1**		**1**	**1**	**9**
MN	**1**	**1**	**1**		**1**	**1**	**1**		**1**		**1**	**1**	**9**
ED				**1**	**1**	**1**		**1**			**1**		**5**
GM	**1**		**1**		**1**	**1**	**1**	**1**	**1**	**1**	**1**		**9**
LS				**1**	**1**	**1**		**1**	**1**		**1**		**6**
MF	**1**		**1**				**1**	**1**			**1**		**5**
MS	**1**			**1**	**1**	**1**		**1**			**1**		**6**
% 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
HFI				**1**	**1**	**1**		**1**		**1**			**5**
CA		**1**			**1**	**1**	**1**	**1**	**1**				**6**
MN	**1**	**1**				**1**	**1**		**1**		**1**	**1**	**7**
ED				**1**	**1**	**1**		**1**		**1**			**5**
GM					**1**		**1**	**1**		**1**			**4**
LS				**1**	**1**	**1**		**1**	**1**	**1**			**6**
MF	**1**		**1**	**1**	**1**	**1**	**1**	**1**			**1**	**1**	**9**
MS	**1**			**1**	**1**	**1**		**1**			**1**		**6**
% 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 A : 04/2009-06/2012

	PTFSBD	PTFSFX	PTFSCOM	BD10RET	BAAMTSY	SNPMRF	SCMLC	LBVIX	RetVIX	LIQ	CR	UNC	Total
HFI		**1**			**1**	**1**		**1**	**1**		**1**	**1**	**7**
CA					**1**	**1**					**1**	**1**	**4**
MN					**1**	**1**	**1**						**3**
ED		**1**	**1**	**1**	**1**	**1**			**1**	**1**	**1**	**1**	**9**
GM	**1**		**1**	**1**	**1**	**1**	**1**				**1**	**1**	**8**
LS		**1**	**1**	**1**	**1**	**1**					**1**	**1**	**7**
MF	**1**		**1**			**1**	**1**				**1**		**5**
MS				**1**	**1**	**1**					**1**	**1**	**5**
% 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 B5

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 12 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 – June 2012). Panels B and C report the results for the two subperiods: 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
HFI					**1**	**1**		**1**			**1**		**4**
CA		**1**			**1**	**1**	**1**						**4**
MN	**1**	**1**			**1**								**3**
ED					**1**	**1**		**1**					**3**
GM					**1**			**1**					**2**
LS				**1**		**1**		**1**					**3**
MF	**1**		**1**					**1**			**1**		**4**
MS					**1**	**1**		**1**					**3**
% 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
HFI				**1**	**1**	**1**		**1**			**1**		**5**
CA					**1**		**1**	**1**	**1**				**4**
MN	**1**	**1**					**1**				**1**		**4**
ED				**1**	**1**	**1**							**3**
GM					**1**		**1**	**1**		**1**			**4**
LS					**1**	**1**		**1**					**3**
MF	**1**					**1**		**1**			**1**	**1**	**5**
MS					**1**	**1**		**1**					**3**
% 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 A : 04/2009-06/2012													
	PTFSBD	PTFSFX	PTFSCOM	BD10RET	BAAMTSY	SNPMRF	SCMLC	LBVIX	RetVIX	LIQ	CR	UNC	Total
HFI		**1**				**1**		**1**			**1**	**1**	**5**
CA					**1**	**1**			**1**			**1**	**4**
MN					**1**	**1**	**1**				**1**		**4**
ED				**1**		**1**							**2**
GM	**1**		**1**			**1**					**1**		**4**
LS						**1**					**1**		**2**
MF	**1**					**1**	**1**				**1**		**4**
MS					**1**	**1**					**1**	**1**	**4**
% 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 C

This appendix presents the results of the 14-factor model that further controls for the aggregate volatility and jump risk factors of Cremers et al. (2014), which are documented to be priced risk factors in the cross-section of stock returns. The model to be tested is:

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

where $r_{i,t}$ and the eight factors are as explained in equation (3), *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 et al. (2014).[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 C1

Correlations among factors

The table reports correlations between the 1’ 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 et al. (2014).

	TFSBD	TFSFX	TFSCOM	D10RET	AAMTSY	NPMRF	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 C2

Time-series results with the 14-factor model

This table reports factor exposures of the 14-factor model in equation (13) 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 et al. (2014). The 8 indices 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 indices, 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 C3

Subperiod analysis

This table reports the estimates of the 1'-factor model for sub-periods April 2006 – March 2009 and April 2009 – March 2012. All variables are as defined in Table C2.

	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 C4

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 subperiods: 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 C5

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 subperiods: 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 C6

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 subperiods: 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%	

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