Uncertainty and Stock Returns

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Abstract

This paper investigates how firm-level uncertainty is priced in the cross-section of stock returns. Uncertainty is proxied by the volatility of option-implied volatility (vol-of-vol), with higher vol-of-vol signaling more uncertainty among investors about the dynamics of expected stock returns. We find that high vol-of-vol stocks *under*perform low vol-of-vol stocks by circa 0.77 percent over the next month, or about 9 percent a year. The negative vol-of-vol effect is stronger for larger stocks, persists for more than twelve months, and cannot be explained by exposures to many previously documented factors. At the same time, statistical tests cannot confirm that vol-of-vol is driven by arbitrage frictions and optimism bias, nor by exposures to jump risk or stochastic volatility risk. Moreover, we do not find vol-of-vol to be a priced risk factor in traditional asset pricing models, or to reflect higher-order risk. Our results seem inconsistent with rational pricing by a representative agent, and indicate strong information linkages between option and stock markets.

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"There are known knowns.
There are things we know we know.
And we also know there are known unknowns.
That is to say, we know there is some things we do not know.
But there are also unknown unknowns.
The ones we don't know we don't know."

– Donald Rumsfeld, former U.S. Secretary of Defense

1 Introduction

Uncertainty can have strong effects on behavior after controlling for risk (Ellsberg, 1961).[1] Following Knight (1921), research investigating uncertainty in asset pricing demonstrates that expected stock returns are not only risky to the extent that objective probabilities can be assigned to potential outcomes, but also uncertain in that the odds are in part unobserved (see Epstein and Schneider (2010) for a recent overview). For example, many representative-agent asset pricing models predict that assets with higher levels of uncertainty require higher expected returns (e.g., Epstein and Schneider, 2008; Leippold et al., 2008; Anderson et al., 2009). Anderson et al. (2009) confirm this empirically at the market index level using disagreement in predictions among professional forecasters as a proxy of uncertainty.

Notwithstanding the rapidly developing literature on uncertainty in asset pricing, the question of how cross-sectional variation in firm-level uncertainty affects future stock returns has yet to be explored. We take a first step in this direction by proposing a simple and innovative empirical measure to capture uncertainty in the cross-section of stocks. This paper examines the measure's ability to predict stock returns, and determines whether it is a priced risk factor in asset pricing models.

[1] Risk, traditionally measured by the volatility of stock returns, only partially explains stock price dynamics. For instance, even though the risk-return trade-off is a fundamental relationship in finance, confirming a positive link between between risk and return, as predicted by Merton (1973), is not at all straightforward. Some studies on the link between the conditional variance and the conditional expected return find a positive but mostly insignificant relation (?Baillie and DeGennaro, 1990; Campbell and Hentschel, 1992), others find a significantly negative relation (Campbell, 1987; Nelson, 1991; Brandt and Kang, 2004), and yet others find that different estimation methods predict both a positive and a negative relation (Turner et al., 1989; Glosten et al., 1993; Harvey, 2001). In fact, Ang, Hodrick, Xing and Zhang (2006) and Blitz and Van Vliet (2007) find that higher volatility coincides with *lower* future returns in the cross-section of stocks.

We postulate that time variation in beliefs about volatility, measured by the time-series volatility of option-implied volatility (vol-of-vol), can be viewed as a proxy for expected uncertainty. Although uncertainty is difficult to measure by nature, vol-of-vol is an attractive candidate for the following reasons. First, option markets are forward-looking by nature and form an appealing basis to measure uncertainty expectations *ex ante*. Furthermore, options-implied volatilities (IV) are primarily driven by expected stock price volatility (e.g., Christensen and Prabhala, 1998), and IV increases with the risks perceived by investors about future stock returns. Hence, such risks are "known unknowns"; they concern stock price dynamics that investors know they don't know. Vol-of-vol, then, captures the variation in the expectations about risk in future stock returns. Hence, vol-of-vol captures stochastic, second-order probabilities about stock returns. This approach to modeling uncertainty has been used by, among others, Segal (1987) and Klibanoff, Marinacci and Mukerji (2005). An illustrative example of a second-order probability is given by Gaifman (1986), who describes a cartoon with a forecaster making the following announcement:

> *"There is now a 60% chance of rain tomorrow, but, there is a 70% chance that later this evening the chance of rain tomorrow will be 80%."*

Hence, vol-of-vol measures "stochastic unknowns" with a higher vol-of-vol indicating greater uncertainty, or less confidence, among investors about the expected variation in future stock returns. Roughly speaking, vol-of-vol reflects the extent to which investors don't know what they don't know, or "unknown unknowns."

Remarkably, our results reveal that, compared to otherwise similar stocks in our sample from 1996 to 2009, stocks with higher vol-of-vol earn significantly lower returns. When we sorts stocks by vol-of-vol into value-weighted quintile portfolios, stocks in the highest vol-of-vol quintile underperform stocks in the lowest vol-of-vol quintile by 0.77 percent in the month following portfolio formation, equivalent to about 9 percent per year. This negative vol-of-vol effect is not explained by loadings to the market, the Fama and French (1993) size and book-to-market factors, or the Carhart (1997) momentum factor, witnessing a four-factor alpha of -0.61 percent a month for the high-minus-low vol-of-vol portfolio. Assuming that vol-of-vol captures higher-order risk or uncertainty, our results strongly suggest that uncertainty has a negative effect on stock returns in the cross-section. This finding seemingly contrasts with previous findings that uncertainty is positively priced at the index level (Anderson et al., 2009).

The vol-of-vol effect is quite robust. Portfolio sorts and firm-year regressions indicate that it is distinct from more than twenty previously documented return drivers. Negative return spreads persist after controlling for many previously documented cross-sectional stock return drivers including size (Banz, 1981), beta, book-to-market (Fama and French, 1992), momentum (Jegadeesh and Titman, 1993) and short-term reversal (Jegadeesh, 1990; Lehmann, 1990); idiosyncratic volatility (Ang et al., 2006b, 2009), past month's maximum return (Bali et al., 2011), skewness (Harvey and Siddique, 2000), and kurtosis (Dittmar, 2002); Amihud's stock liquidity (Amihud, 2002) and option liquidity; previously documented option-based return predictors such as changes in call and put implied volatilities (Ang et al., 2010), the implied-minus-realized volatility spread (Goyal and Saretto, 2009; Bali and Hovakimian, 2009), call-minus-put implied volatilities (Cremers et al., 2011; Bali and Hovakimian, 2009), and the volatility skew (Xing et al., 2010); heterogeneity in beliefs (Diether et al., 2002) and information uncertainty (Zhang, 2006); private information (Easley et al., 2002; Durnev et al., 2003); leverage (Bhandari, 1988); stock price response delay (Hou and Moskowitz, 2005); and short-sale constraints (Nagel, 2005). In contrast to previously documented return predictors, studying the interaction of vol-of-vol with size reveals that the negative returns are especially strong among large caps but seem absent for small firms. Hence, vol-of-vol is difficult to explain by liquidity or other small firm effects. Moreover, applying industry-neutral vol-of-vol portfolios yields even more significant performances of the Low, High, and High-Low portfolios. Further, effects of vol-of-vol on stock returns are robust across different holding periods; persist beyond twelve months after portfolio formation; hold for a variety of vol-of-vol definitions; and are found in value-weighted, equal-weighted, quintile and decile portfolios.

What then explains the negative vol-of-vol effect? Economic theory offers several possible explanations that are not based on uncertainty. We examine these arguments in more detail, but find that none offer a satisfactory explanation for the vol-of-vol effect. First, the effect may be caused by short-sale constraints that result in prices deviating stronger from fundamental value for high vol-of-vol stocks than for low vol-of-vol stocks. However, while this could explain underperformance, it does not explainthe significantly positive alpha's that we find for low vol-of-vol stocks. More generally, the vol-of-vol effect remains large and significant after excluding many stocks with high short-sale constraints. Second, the vol-of-vol effect could indicate the presence of a negative premium on volatility risk (Bakshi and Kapadia, 2003) or jump risk (Bali and Hovakimian, 2009; Cremers et al., 2011), with high vol-of-vol stocks having different exposures to aggregate volatility or jump risk than low vol-of-vol stocks. However, we find that the vol-of-vol effect remains economically and statistically significant after controlling for aggregate volatility or jump risk exposures. Third, exposures to vol-of-vol may be priced in a factor model as in Ross (1976)'s arbitrage pricing theory. Similarly, vol-of-vol can be a negatively priced risk factor if it provides a hedge against against deteriorating investment opportunities (Campbell, 1993, 1996; Ang et al., 2006b). We formally test whether the lower returns on higher vol-of-vol stocks reflect a priced risk factor in traditional asset pricing models, but cannot confirm this econometrically. Fourth, vol-of-vol reflects second-order probabilities and hence may capture some form of higher-order or asymetric risk not captured in measures like idiosyncratic or systematic volatility, skewness, or kurtosis. However, after studying the future returns distribution of various vol-of-vol portfolios, we find no evidence for this explanation. Hence, the vol-of-vol effect can be reconciled with little existing research in asset pricing.

While we are the first to examine how firm-level uncertainty is related to the cross-section of expected stock returns, previous work examines various forms of uncertainty. For instance, Zhang (2006) studies uncertainty about the quality of information, and finds that information uncertainty enhances other return anomalies. However, our paper is different in that vol-of-vol focuses on the uncertainty investors have about future movements of a stock, an aspect investors can directly incorporate in the pricing of a stock. Vol-of-vol also appears similar to the concept of parameter uncertainty (e.g., Pastor and Veronesi (2003); Cremers and Yan (2009); Korteweg and Polson (2009)). However, since these models incorporate Bayesian measures for information quality, research on parameter uncertainty describes probabilities of first (not second) order. Another strand of research measures uncertainty by the dispersion of beliefs among investment professionals.[2] However, vol-of-vol is calculated from (option) market prices and measures time-series variation of volatility forecasts, whereas dispersion statistics are calculated from analysts forecasts and capture cross-sectional variation in earnings forecasts.[3] One might also see kurtosis as related to vol-of-vol since it focuses on fat tails in the return distribution. Our empirical analysis confirms that the vol-of-vol effect is not affected by previously used measures for information uncertainty, parameter uncertainty, kurtosis, or dispersion in analyst forecasts. More closely related is the study by Bessembinder et al. (1996), who examine the open interest on the Standard & Poor's (S&P) 500 Index futures as a measure for disagreement in opinions. However, the open interest measure relates primarily to trading activity rather than stock returns, and does not capture second-order probabilities. Brenner et al. (2011) is perhaps most closely related to our study. They model uncertainty at the index level and find results that are consistent with ours. We complement this work by examining uncertainty at the firm-level.

Our findings indicate that the equity option market contains information that is reflected later in stock prices. This adds to previous research arguing and showing that information diffuses slowly into and across markets (Hong and Stein, 1999; Hong et al., 2007), and that the option market contributes to price discovery in the stock market (Chakravarty et al., 2004). Similarly, Bali, Ang and Cakici (2010), Goyal and Saretto (2009), Xing, Zhang, and Zhao (2010), Bali and Hovakimian (2009), Cremers and Weinbaum (2010) and Yan (2011) document a significant relation between various measures extracted from option prices and future

[2] For instance, Morgan (2002) shows that when risks are opaque, rating agencies disagree more often on the initial ratings on newly issued bonds. In the cross-section, Diether et al. (2002) show that dispersion in analysts' earnings forecasts leads to lower subsequent returns, while Qu et al. (2004) find a positive effect on expected returns. Anderson et al. (2005) construct a factor specification for short-term and long-term forecast dispersion and also find a positive price on analyst dispersion. Using *aggregate* survey forecasts, Anderson et al. (2009) find a positive price of dispersion, and argue that a variant of this measure among professional forecasters reflects model uncertainty. Harris and Raviv (1993), Shalen (1993), and Graham and Harvey (1996) find that dispersion among newsletter "forecasts" is positively related to historical volatility, implied volatility, and volume.

[3] More generally, our option-based measure has the advantage over analyst-based measures by generally being based on a larger number of agents per firm, and being observed on a daily frequency. Our option-based measure also circumvents agency problems, such as self-selection and optimism bias in analyst forecasts (McNichols and O'Brien, 1997).

stock returns. However, the vol-of-vol effect is different from, and robust to, each of these measures. Our findings suggest that understanding the joint dynamics and pricing of option and stock markets requires the modeling of such information spillovers.

This paper proceeds as follows. Section 2 describes our dataset and explains the vol-of-vol measure. Section 3 presents the vol-of-vol effect and demonstrates how vol-of-vol affects future stock returns after controlling for a series of stock characteristics by means of portfolio sorts, Fama and MacBeth (1973) regressions, performance persistence and robustness analyses. Section 4 explores several alternative explanations for our results. Finally, Section 5 discusses and concludes. The Appendix defines the explanatory variables used in this study.

2 Data and empirical measures

2.1 Data

We use data of U.S.-listed options that are written on individual stocks trading on the NYSE, AMEX, and NASDAQ exchanges. We use the standard OptionMetrics database to obtain daily implied volatilities (IVs), closing bid and ask prices, option strikes and tenors, as well as information on options' volume and open interest. For individual equity options (all of which are American), OptionMetrics provides IVs from Cox et al. (1979)'s binomial tree-based algorithm, which incorporates discrete dividend payments and early exercise. We use these IVs to calculate vol-of-vol.[4] The option data run from January 1st, 1996 (the first date in the OptionMetrics database), until September 30th, 2009, with which we analyze future returns from February 1996 until October 2009 (for monthly returns) or December 2009 (for longer horizons).

We apply the following screening criteria on all options to ensure that we select well-traded and well-priced options that contain reliable information. First, we exclude 'special' options that do not expire on the third Friday of a month to filter out non-standard option series that generally are only partially available in the sample and generally have lower liquidity. Second, we retain only those options that have positive open interest, positive best bid price, and non-missing implied volatility values between 3 percent and 500 percent. Third, we eliminate all options that have bid-ask spreads exceeding 25 percent of the average between the bid and ask price.

Since most activity for options is concentrated at the short end we require a maturity between 10 and

[4] IVs are also available through OptionMetrics' Volatility Surface file, which contains interpolated IVs for constant levels of maturity and moneyness. However, in preliminary analyses, we find that these IVs sometimes vary because of arbitrary changes in the options used to calculate the Surface. For example, the OptionMetrics 30-day at-the-money put IV is interpolated from four put options, with strike prices straddling the stock price and maturities straddling 30 days. As the included options approach expiration, one or more of the four options will be replaced by other options, often causing a spurious change in the estimated implied volatility. Since vol-of-vol relies relies on the time-series properties of IV, we choose not to use the Volatility Surface and instead rely on the individual options' database with all listed, actual implied volatility quotes.

52 trading days for our main option measures, thereby selecting options with a remaining time to maturity (TTM) of approximately one month.[5] We separate call and put options into at-the-money (ATM), out-of-the-money (OTM), and in-the-money (ITM) options following Ofek et al. (2004) and Xing et al. (2010). An option is defined as ATM when the ratio of the strike price to the stock price (strike-to-spot) is between 0.95 and 1.05. Similarly, an option is OTM when the ratio is lower than 0.95 (but higher than 0.80), and ITM when the ratio is higher than 1.05 (but lower than 1.20). Options with ratios below 0.80 and above 1.20 are dropped from the sample. When multiple options fall into the same group, we select options with moneyness closest to 1.00 (ATM), 0.95 (OTM) or 1.05 (ITM).[6]

Stock returns, stock characteristics, and market capitalization data for the whole period are obtained from the Center for Research in Security Prices (CRSP). From CRSP we select all data for ordinary common shares (CRSP share codes 10 and 11) listed on the NYSE, AMEX and NASDAQ, and exclude closed-end funds and REITs (SIC codes 6720-6730 and 6798). We exclude penny stocks with prices below $5 (Amihud, 2002; Zhang, 2006), and "micro caps" by requiring a market capitalization of at least $225mln at the end of 2009 (discounted at the risk-free rate). This eliminates stocks with difficult-to-measure prices and fundamentals, and illiquid stocks with potential market microstructure problems. Furthermore, D'Avolio (2002) shows that about one-third of these excluded stocks are difficult to short since institutional lenders generally do not have a position in them, and have high shorting costs. Hence, these criteria imply that we select stocks with relatively low short-sale constraints. We adjust the data for delisting returns (obtained from the CRSP delisting file) as suggested by Shumway (1997) and Shumway and Warther (1999), assuming a delisting return of -30 percent (for NYSE and AMEX stocks) or -55 percent (for NASDAQ stocks) if the corresponding delisting code is performance-related.

We match OptionMetrics data to monthly CRSP data using the procedure outlined by Duarte et al. (2005), and select option data on the one-but-last trading day of a month to match to stock returns over the next month(s). This one-day implementation lag avoids spurious findings caused by non-synchronous trading between options and stocks due to slightly different closing times of the exchanges (Battalio and Schultz, 2006), and takes into account the time needed for less technologically advanced investors to process the option information. Following Fama and French (1992), we match COMPUSTAT accounting data to CRSP after six months following fiscal year end. Accounting data are required to have a 3-year history to prevent survivorship bias. Realized earnings are obtained from Compustat's quarterly item 8 (income before extraordinary items) and matched to CRSP after the earnings announcement date. Analyst forecasts, dis-

[5] We have verified that results are qualitatively similar when considering option with TTMs of approximately three, six or twelve months.

[6] Unreported analysis reveals that the results are qualitatively similar when weighting all ATM options by their volume or open interest.

persion, and revision data are from Thomson Financial's Institutional Brokers Estimate System (I/B/E/S). For I/B/E/S, the U.S. unadjusted file is used to mitigate the problem of imprecise forecasts (Diether et al., 2002). Data on institutional ownership are from the Thomson Financial 13f database, and we use Kenneth French's online data library to obtain the risk-free rate, market, size, value, and momentum factors.

2.2 Volatility of implied volatility

We define vol-of-vol as the standard deviation of implied volatility (IV) over the past month. Implied volatility is calculated as the average IV of the ATM call option and ATM put option. It generally measures the risk perceived by investors about future price movements of a stock. The volatility of IV, then, captures the amount of variation in investors' assessments of these risks, or second-order probabilities about future stock price movements. In the spirit of Segal (1987) and Klibanoff et al. (2005), we therefore propose vol-of-vol as a measure for uncertainty. Since the IV of high volatility stocks changes more than the IV of low volatility stocks, and to filter the effect of risk from our uncertainty measure, we scale the standard deviation of IV with average implied volatility over the past month. We require at least 12 non-missing observations in order to compute vol-of-vol (our results are similar if we require less or more non-missing observations). In our analysis, we use a one-month window with daily data to balance time-variation in vol-of-vol against the precision of the vol-of-vol estimates.

Table 1, panel (a) provides an overview of our sample, compared against the CRSP sample as a whole. A substantial number (on average over 1,000) of stocks satisfy our screening criteria, and firms with sufficient OptionMetrics data tend to have stocks with larger market capitalization. In the first year that OptionMetrics data became available, 24 percent of the firms in the CRSP universe have sufficient listed option data availablesuch that we can construct vol-of-vol measures. This increases to over 40 percent at the end of our sample. While these numbers seem modest, the stocks represent 68 percent to 87 percent of U.S. market capitalization indicating that larger firms tend to have well-traded options listed on their stocks. Hence, our sample is tilted towards larger stocks that are generally better tracked and better investable.

Table 1, panel (b) presents summary statistics on vol-of-vol for each year in our sample. The statistics are computed by first value-weighing vol-of-vol per month for each firm, and then averaging per year. The average vol-of-vol level tends to increase during turbulent market years, and a similar pattern emerges from the median vol-of-vol. The difference between the average vol-of-vol (8.38 percent) and median vol-of-vol (7.57 percent) suggests that the distribution of vol-of-vol is positively skewed, which is confirmed by the 25th and 75th percentiles. Moreover, vol-of-vol varies substantially across firms with an average standard deviation of 4.20 percent.

[Insert Table 1 about here]

2.3 Control variables

The central result of this paper is that high vol-of-vol stocks earn lower average future returns than low vol-of-vol stocks. However, previous research has documented several variables that predict cross-sectional returns and potentially explain this effect. In this section, we discuss a range of variables that will be controlled for in the empirical analysis, classified into six categories. The variables and their abbreviations are described in full detail in the Appendix, and discussed as they are used in the analysis.

Canonical characteristics Our first set of control variables are the canonical characteristics based on firm size (Banz, 1981), beta, book-to-market (Fama and French, 1992), momentum (Jegadeesh and Titman, 1993), and short-term reversal (Jegadeesh, 1990; Lehmann, 1990). Since each of these characteristics have been associated with future returns, the cross-sectional dispersion in expected returns might be less for stocks within portfolios based on these characteristics.

Return distribution characteristics Vol-of-vol is related to return dynamics or distribution characteristics by definition, which have a well-known impact on stock returns. In addition to the systematic risk measured by a stock's beta, stock returns might also be affected by non-systematic risk (Ang et al., 2006b, 2009; Fu, 2009), and by asymmetry in the return distribution. For instance, Bali et al. (2011) show that average return difference between stocks in the lowest decile and the highest decile based on the previous month's maximum return exceeds 1 percent per month. Also, Barberis and Huang (2008) develop a behavioral setting in which positively skewed securities become overpriced and earn negative average excess returns. Finally, vol-of-vol bears resemblance to the kurtosis of a stocks' return distribution. Since each of these factors have power in explaining stock returns, we examine whether idiosyncratic volatility, the maximum return, skewness, and kurtosis can explain the negative vol-of-vol effect.[7]

[7] In addition to individual skewness and kurtosis, systematic skewness (Harvey and Siddique, 2000) and systematic kurtosis (Dittmar, 2002) affect future stock returns. Therefore, we repeat our analysis when controlling for these characteristics, as discussed in the Results section. The results are comparable to what is reported in the main tables, but are omitted to conserve space.

Liquidity characteristics The negative impact of vol-of-vol on future stock returns might relate to a liquidity effect. In general, stocks with relatively high liquidity require lower expected returns (Amihud and Mendelson, 1986). Therefore, we control for a stock's liquidity by using the Amihud illiquidity measure (Amihud, 2002) and a stock's turnover (Datar et al., 1998). Furthermore, higher levels of vol-of-vol might be the result of stronger bid-ask bounces in option prices, implying that high vol-of-vol stocks might be subject to more measurement error in their vol-of-vol statistic than low vol-of-vol stocks. To control for this possibility we also include option liquidity,measured by the average ATM option bid-ask spread, as a control variable.

Option-based characteristics The negative vol-of-vol effect might also be explained by other option-based characteristics that predict future equity returns. Specifically, Bali and Hovakimian (2009) and Cremers et al. (2011) find that stocks with a low spread between the IVs of ATM put and call options (i.e., ATM volatility skew) outperform stocks with a high spread. Measuring investor concerns about negative price movements, Xing et al. (2010) find that stocks with the largest spread between OTM put IV and ATM call IV (i.e., OTM volatility skew) underperform stocks with the smallest OTM skew (see also Yan (2011)). Furthermore, Bali and Hovakimian (2009) and Goyal and Saretto (2009) find that a strategy that buys (sells) stocks with the lowest (highest) spread between IV and past month realized volatility yields positive returns. Finally, Ang et al. (2010) find that large monthly increases in call IV precede positive stock returns over the following month, and increases in put IV precede negative returns.[8]

Uncertainty-related characteristics Since we propose that vol-of-vol captures firm-level uncertainty, we should control for several other previously documented uncertainty-related measures. The literature on parameter uncertainty (e.g., Pastor and Veronesi, 2003; Cremers and Yan, 2009) proxies uncertainty by market capitalization and firm age. Similarly, Zhang (2006) uses size and age as proxies for information uncertainty, together with for example analyst coverage, forecast dispersion, and return volatility. Related, Diether et al. (2002) find that a smaller degree of consensus among analysts predicts negative average returns. Moreover, calling it "information risk," Easley et al. (2002) find that the existence of private information that cannot be inferred from prices, either about a common component of asset returns or about a single asset in a finite asset economy, should affect asset prices. Considering the lack of consensus in this literature, we control for all of these alternative measures.

[8]In addition, one might argue that vol-of-vol is related to IV, which reflects the expected volatility of a stock, and which might also relate to a stock's uncertainty. However, Bali and Hovakimian (2009)find that IV has no reliable predictive power for future stock returns. Nevertheless, we analyse if and confirm that our results are robust to including IV as a control variable as reported in the Results section. These results are omitted from the paper to conserve space.

Other characteristics In addition to the above, we control for leverage, information delay and short-sale constraints. Since equityholders' claim on firm value is limited in levered firms, higher debt levels increasingly transmit variations in total firm value to the equity holders (Black and Scholes, 1973). As a consequence, stock prices might be more uncertain for highly levered firms. Since empirically more levered firms have been shown to be are associated with higher returns (Bhandari, 1988), we control for leverage. Further, Hou and Moskowitz (2005) show that the delay with which information is reflected in a stock's price affects future stock returns. Since, stocks surrounded with more uncertainty might incorporate information more slowly into their prices we also control for price delay. Finally, Miller (1977) argues that, in the presence of short-sale constraints, pessimistic investors may not be able to price high short-sale constrained stocks, leading to overpricing and more negative future returns on these stocks than on low short-sale constrained stocks. Empirically, Nagel (2005) shows that short-sale constraints affect future stock returns. To investigate whether the vol-of-vol effect is driven by the effects of short-sale constraints, we control for this variable as well.

3 The vol-of-vol effect

3.1 Single portfolio sorts

We start analyzing the effect of vol-of-vol on future stock returns using simple portfolio sorts. At the end of each month, we rank all stocks in ascending order based on vol-of-vol at the end of month t, taking into account a one-day implementation lag, and sort the stocks into quintile portfolios. The first portfolio ("Low") contains the stocks with the lowest vol-of-vol values, the fifth portfolio ("High") contains the stocks with the highest vol-of-vol values. For each of these portfolios we compute the value-weighted and equal-weighted return over the following month. In addition, we form a high-minus-low ("High-Low") vol-of-vol portfolio that buys the high vol-of-vol portfolio and sells the low vol-of-vol portfolio, holding this position for one month.

Figure 1 provides the results and persistence of this sorting procedure. Depicted are for each of the five portfolios, the value-weighted average of vol-of-vol from twelve months before until twelve months after portfolio formation. The cross-sectional dispersion in vol-of-vol is highest around portfolio formation. Moreover, the relative ranking of the portfolios is persistent over time, witnessing positive cross-sectional dispersion between the high vol-of-vol and low vol-of-vol portfolios from twelve months before portfolio formation until twelve months thereafter. This also holds for the the other quintile portfolios, which all keep their rank during twelve months before until twelve months after portfolio formation.

[Insert Figure 1 about here]

Table 2 reports the average monthly excess and risk-adjusted returns of the quintile and High-Low portfolios, calculated after sorting stocks in our universe on vol-of-vol. We report the time-series mean of the cross-sectional weighted average vol-of-vol ("Vol-of-vol"), average excess returns ("Excess return"), and the intercepts from the regression of excess portfolio returns on: i) a constant and the excess market return ("CAPM alpha"), ii) the previous model augmented by the SMB size and HML book-to-market factor following Fama and French (1993) ("3F alpha"), and iii) the previous model augmented by the momentum factor following Carhart (1997) ("4F alpha"). All t-statistics reported in Table 2 (in parentheses) are computed with robust Newey-West corrected standard errors. The asterisks *, ** and *** indicate the significance of the excess returns and alphas at a 10 percent, 5 percent and 1 percent level, respectively.

[Insert Table 2 about here]

Panel (a) of Table 2 contains the results after value-weighting stocks within each portfolio. During our sample period, low vol-of-vol stocks earn on average 0.56 percent per month in excess of the risk free rate, whereas high vol-of-vol stocks earn -0.21 percent. The difference as implemented in the High-Low portfolio equals an economically substantial -0.77 percent per month, with a highly significant t-statistic of -2.50. A similar negative profit is observed for the alphas in the CAPM and three-factor Fama and French (1993) model, indicating that the market, value, and size factors do not drive the return spread on the high-low vol-of-vol portfolio. Similarly, the alpha in the four-factor regression is economically highly important, with a return differential of -0.62 percent per month and a significant t-value of -2.14. This indicates that vol-of-vol is also distinct from exposures associated with momentum.

As also illustrated in Figure 2, the portfolio returns decrease monotonically from quintile 1 (Low) to quintile 5 (High). The average raw and risk-adjusted returns are positive for quintile 1 to 3. In quintile 4, average excess returns are still slightly positive but risk-adjusted returns are negative, and average excess and risk-adjusted returns are negative in quintile 5. We note that the drop in monthly returns from quintile 3 to 4 (0.28 percent in returns vs. 0.24 percent in 4F alpha) and from quintile 4 to 5 (0.37 percent in returns vs. 0.30 percent in 4F alpha) is stronger than the drop in returns from quintile 1 to 2 (0.10 percent in returns vs. 0.03 percent in 4F alpha) or quintile 2 to 3 (0.02 percent in returns vs. 0.04 percent in 4F alpha). Strikingly, this pattern is similar to the increase in average vol-of-vol for each quintile presented in the top row of panel (a). By construction, the portfolios increase monotonically in vol-of-vol from quintile 1 to 5, but the increase is more dramatic for quintile 4 (0.03) and especially quintile 5 (0.05), as compared to quintile 2 (0.02) and quintile 3 (0.01).

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[Insert Figure 2 about here]

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The results for equal-weighted portfolios, presented in panel (b) of Table 2, are similar. Excess returns and alphas are economically smaller, but still of substantial economic magnitude and statistically stronger. More specifically, the average excess return difference between the low vol-of-vol and high vol-of-vol portfolios is -0.50 percent per month with a t-statistic of -3.09.

We focus on value-weighted returns in the remainder of this paper since equal-weighted portfolios are tilted towards smaller stocks, which are generally more difficult to buy or sell and economically less important. Moreover, equal-weighted returns may be biased upwards in the presence of bid-ask bounces (Blume and Stambaugh, 1983) and other forms of microstructure noise (Asparouhova et al., 2010). Specifically, Asparouhova et al. (2010, 2012) show that if security-level explanatory variables are positively correlated with the amount of microstructure noise, portfolio-sorted returns and coefficients in empirical asset pricing tests may be overstated, with equally weighted portfolios being especially sensitive to this bias. By inducing a negative correlation between returns and microstructure noise, the value-weighting of stocks tends to offset the microstructure noise-induced upward bias in returns (Asparouhova et al., 2012).

3.2 Characteristics of vol-of-vol portfolios

Hence, stocks with higher levels of vol-of-vol experience lower future returns. We continue by examining what characterizes high vol-of-vol stocks and low vol-of-vol stocks, and investigate how the variables from

Section 2.3 vary across the vol-of-vol quintiles described above. For each month and each quintile portfolio, we compute the value-weighted average of each of the variables (except for size, which is computed on an equal-weighted basis). Next, we compute the time-series average and t-statistic over the months in our sample. In addition, we compute the average number of stocks in each portfolio and the percentage of stocks that stays in the portfolio from one month to the next. The results are presented in Table 3.

Canonical characteristics High vol-of-vol stocks have larger market capitalization ("Size"), suggesting that firms surrounded with high uncertainty are larger than firms surrounded with low uncertainty. High vol-of-vol stocks also have higher beta ("Beta"). Further, high vol-of-vol stocks have earned significantly lower returns over the year prior to portfolio formation excluding the most recent month ("Momentum"), suggesting that negative past returns coincide with more uncertainty. However, no significant pattern is found between vol-of-vol and the book-to-market ratio ("Book-to-market") and returns over the most recent month ("Short-term reversal").

Return distribution characteristics In addition to higher beta, high vol-of-vol stocks also tend to have higher idiosyncratic volatility ("Idiosync. volatility"), higher past month maximum returns ("Maximum return"), and a more positively skewed ("Skewness") and leptokurtic ("Kurtosis") return distribution. This implies that the lower returns of the high vol-of-vol portfolios are potentially related to each of the return distribution characteristics.

Liquidity characteristics Vol-of-vol does not have a univocal relation with liquidity. The Amihud illiquidity measure ("Amihud illiquidity") reveals that high vol-of-vol are more illiquid than low vol-of-vol stocks. By contrast, high vol-of-vol stocks are more liquid in terms of stock turnover ("Turnover"). We do not find a significant link between vol-of-vol and option liquidity, as reflected in the option bid-ask spread ("Option bid-ask spread").

Option-based characteristics When looking at the interaction of vol-of-vol with the previously documented option measures, average at-the-money skew ("ATM Skew"), change in call IV ("Change in call IV"), and change in put IV ("Change in put IV") are not significantly different across the vol-of-vol portfolios. However, as vol-of-vol increases across the quintiles, the volatility skew ("OTM Skew") increases, suggesting that stocks surrounded with more uncertainty are also surrounded with more downside jump concerns. Similarly, vol-of-vol relates negatively with the spread between implied volatility and historical, realized volatility ("IV-RV spread"). This suggests that firms surrounded with more uncertainty are actually less exposed to negatively priced volatility risk premia.

Uncertainty-related characteristics Turning to uncertainty-related characteristics, high vol-of-vol stocks tend to belong to younger firms ("Age"), although the relation with age is not monotonic. This suggests that vol-of-vol relates weakly to parameter uncertainty (Pastor and Veronesi, 2003) or information uncertainty (Zhang, 2006). High vol-of-vol stocks also have higher forecast dispersion ("Forecast dispersion") and higher volatility ("Volatility"), which are indicative of higher information uncertainty (Zhang, 2006) or more heterogeneity in beliefs (Diether et al., 2002). These results also suggest that higher vol-of-vol firms have higher risk and less agreement among future analyst earnings forecasts. At the same time, high vol-of-vol stocks tend to be larger and have better analyst coverage ("Analyst coverage"), characteristics that are generally associated with *lower* uncertainty (Zhang, 2006). Hence, the relationship of vol-of-vol with uncertainty measures from previous studies is unclear, suggesting that vol-of-vol captures a distinct part of uncertainty that is not reflected in previously proposed measures.

Other characteristics Vol-of-vol has no relationship with leverage ("Leverage"), the private information proxy ("Private information") and information delay ("Price response delay"). However, the highest quintile of vol-of-vol stocks have lower (residual) institutional ownership than the other vol-of-vol firms, suggesting that these firms face larger short-sale constraints.[9]

Portfolio characteristics To further analyze the coverage and persistency of vol-of-vol we compute the average number of stocks in each portfolio ("Avg. number of stocks/month") and the percentage of stocks that stay in the portfolio from one month to the next ("Fraction in portfolio next month"). The one-but last row of Table 3 indicates that each portfolio-month combination consists of a substantial number of stocks (more than 220 stocks on average). The same holds when studying the number of stocks in each vol-of-vol portfolio over time (unreported); it is smallest at the start of our sample (1996), but yet more than 130 stocks are in each portfolio. Finally, the last row of Table 3 shows that extreme levels of vol-of-vol tend to persist from one month to another. On average, 33 percent (32 percent) of the stocks in the lowest (highest) vol-of-vol quintile stay in that quintile during the next period, a percentage substantially bigger than the 20 percent expected under random allocation.

[9]Unreported analysis reveals that vol-of-vol also tend relate positively to firm aspects that are generally associated with higher uncertainty about the future. High vol-of-vol firms tend to have higher R&D (as a proportion of assets), more intangible capital (measured by property, plant and equipment over total assets), and higher expect long-term growth than low vol-of-vol firms. By contrast, vol-of-vol does not reliably relate to profitability (as measured by return-on-equity), the ratio of external financing to assets, or past one or five years sales growth. None of these measures affect subsequent conclusions, but are omitted from the paper to conserve space.

[Insert Table 3 about here]

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3.3 Double sorts

To verify that the vol-of-vol effect is not explained by any of the characteristics discussed above, we next examine the excess returns and four-factor alphas of vol-of-vol sorted portfolios after controlling for each of them. To this end, we form quintile portfolios at the end of each month by sorting on the variables that potentially explain the negative vol-of-vol effect. Next, we further sort each quintile portfolio into five additional vol-of-vol portfolios, which results in a total of 25 portfolios. Subsequently, we average each of the vol-of-vol portfolios across the five quintiles that could explain the vol-of-vol effect, in order to produce portfolios with dispersion in vol-of-vol but similar exposure to the explanatory variables. Note that this procedure allows us to control for each characteristic, while assuming no parametric form on the relationship with vol-of-vol and of vol-of-vol with returns. In addition, we form a high-minus-low ("High-Low") vol-of-vol portfolio that buys the resulting high vol-of-vol portfolio and sells the resulting low vol-of-vol portfolio. For each of these portfolios, we compute average value-weighted excess returns and alphas over the following month. The results of these double sorts are presented in Table 4.

Canonical characteristics Panel (a) of Table 4 demonstrates that the negative relation between vol-of-vol and future stock returns is affected by the size characteristic. When controlling for size, the average High-Low excess return (4F alpha) more than halves from -0.77 percent (-0.61 percent) to -0.32 percent (-0.27 percent), which is now only marginally significant at the 10 percent level. Hence, since the high vol-of-vol quintile contains relatively few small stocks, the negative vol-of-vol effect can partially be explained by the small firm effect. However, when we focus on the NYSE stocks (NYSE only), generally the larger stocks in our sample, we find that the average excess return (4F alpha) on the High-Low portfolio equals -0.74 percent (-0.58 percent) with a t-statistic of -2.63 (-2.12). We further examine the relationship between size and vol-of-vol by a more detailed look into the size quintiles, which is also presented in panel (a) of Table 4. Unlike many other anomalies, the vol-of-vol effect is especially pronounced for the largest stocks. In the lowest two size quintiles the vol-of-vol effect is absent, while in the largest 60 percent of stocks we observe a economically meaningful and statistically significant vol-of-vol effect. The High-Low columns show average excess returns (4F alphas) for the largest three size quintiles of -0.55 percent, -0.45 percent, and -0.73 percent (-0.51 percent, -0.38 percent, and -0.65 percent) per month, respectively, with significant t-statistics of -2.01, -2.06, -2.13 (-1.86, -1.90, and -2.08). This leads us to conclude that size cannot account for the vol-of-vol effect.

The negative vol-of-vol effect also remains economically and statistically significant after controlling for the beta, book-to-market, momentum, and short-term reversal characteristics. The average excess return (4F alpha) on the High-Low portfolio decreases most when controlling for beta and equals -0.43 percent (-0.41 percent) per month, with a t-statistic of -2.22 (-1.98). The average excess return (4F alpha) equals -0.63 percent (-0.59 percent) when controlling for book-to-market, -0.84 percent (-0.74 percent) when controlling for momentum, and -0.76 percent (-0.69 percent) when controlling for short-term reversal. All excess returns and four-factor alphas remain statistically significant. Hence, even though high vol-of-vol stocks have significant negative momentum (see the previous subsection), this does not mitigate the vol-of-vol effect. In fact, when studying the (unreported) interaction between momentum and vol-of-vol, we observe that the vol-of-vol effect is more pronounced among loser and winner stocks than among stock with a more neutral past performance. Most notably, past year loser stocks with low vol-of-vol experience substantial positive average excess returns (4F alphas) of 0.95 percent (0.61 percent). Hence, the vol-of-vol effect is not subsumed by return effects related to the common factor characteristics.

Return distribution characteristics Panel (b) of Table 4 presents results on whether idiosyncratic volatility, maximum return, skewness, and kurtosis explain the vol-of-vol effect. Despite the strong linkages between vol-of-vol and each of these characteristics, the negative relation between vol-of-vol and the stock returns persists after controlling for each of them. More specifically, the excess return (4F alpha) of the High-Low vol-of-vol portfolio ranges from -0.76 percent to -0.83 percent (-0.63 percent to -0.75 percent) per month, with corresponding t-statistics of -2.72 and -3.02 (-2.37 and -2.99). Hence, none of these characteristics are able to explain the vol-of-vol effect. This finding is of particular interest for kurtosis that focuses on fat tails in the return distribution, and therefore may naturally relate to vol-of-vol.[10]

Liquidity characteristics In panel (c) of Table 4, we can see whether stock liquidity explains the lower returns for high vol-of-vol stocks relative to low vol-of-vol stocks. Since the most liquid stocks tend to be the most relevant from an investment perspective, we will look into the vol-of-vol effect for the most liquid stocks (as opposed to the average over five quintiles in the other panels in Table). The negative vol-of-vol effect remains of similar magnitude and stays significant for the most liquid of stocks as measured by the Amihud illiquidity measure ("Most liquid (Amihud)"), with a High-Low excess return (4F alpha) of -0.72 percent (-0.59 percent) and corresponding t-statistics of -2.22 (-2.09). Moreover, the vol-of-vol effect becomes substantially stronger when focusing on the stocks with the highest turnover ("Most liquid (turnover)"), judging from a

[10] In unreported double-sorts, we also find a persistent negative and significant vol-of-vol effect after controlling for co-skewness (Harvey and Siddique, 2000), co-kurtosis (Dittmar, 2002), and downside beta (Ang et al., 2006a).

1.71 percent (1.52 percent) average excess return (4F alpha) per month for the High-Low portfolio, with t-statistics of -3.80 (-3.40). Next, we control for option liquidity in the bottom rows of panel (c) by averaging over the option liquidity quintile portfolios. The vol-of-vol effect is hardly affected by option liquidity, with High-Low average excess returns (4F alphas) equal to -0.68 percent (-0.54 percent) per month and t-statistics of -2.46 (-2.14). These results indicate that the vol-of-vol effect is not explained by stock liquidity or bid-ask noise in option prices.

Option-based characteristics In panel (d) of Table 4, we examine are ATM volatility skew, OTM volatility skew, IV-RV spread, first monthly differences in call IVs, and first monthly differences in put IVs. In particular, Table 3 shows that average OTM volatility skew changes positively, and IV-RV spread changes negatively, with changes in the to vol-of-vol quintiles. However, it can be seen that the average excess returns (4F alphas) in the High-Low portfolios continue to be of similar magnitude and significance, ranging between -0.66 percent and -0.80 percent (-0.63 percent and -0.70 percent) per month with corresponding t-statistics of -2.75 and -2.44 (-2.28 and -2.45). Thus, for none of these portfolios do average excess return spreads decrease more than 11 basis points, and 4F alphas are in fact slightly higher than for single-sorted returns. This indicates that the vol-of-vol effect is not explained by previously documented, option-related characteristics.[11]

Uncertainty-related characteristics Panel (e) presents results on whether the lower returns on high vol-of-vol stocks can be explained by the previosuly proposed measures for uncertainty and heterogeneity in beliefs. Controlling for age continues to generate negative average excess returns (4F alphas) in the High-Low portfolio, which amounts to -0.73 percent (-0.55 percent) per month with a t-statistic of -2.67 (-2.32). Similarly, after controlling for analyst coverage, the High-Low difference in excess returns (4F alphas) remains large at -0.71 percent (0.64 percent) per month with significant t-statistics of -2.99 (2.65 percent). The High-Low portfolio return differential on analyst forecast dispersion is -0.75 percent (-0.57 percent) per month, with a t-statistic of -2.80 (-2.06). Controlling for volatility does not mitigate the High-Low difference either, with excess returns (4F alphas) at -0.73 percent (-0.61 percent) per month and t-statistics of -3.06 (-2.37). Hence, none of previously documented forms of uncertainty explain the negative vol-of-vol effect.

[11] In unreported double-sorts, we also find a persistent negative and significant vol-of-vol effect after controlling changes in ATM skew (Cremers and Weinbaum, 2010). Moreover, one may argue that vol-of-vol is related to IV, which reflects the expected volatility of a stock, and which may also relate to a stock's uncertainty. However,Bali and Hovakimian (2009)find that IV has no predictive power for future stock returns using a slighlty different sample and shorter sample period. Nevertheless, our results are robust to including IV as a control variable, witnessing an average excess return (4F alpha) of the High-Low vol-of-vol portfolio of -0.73 percent (-0.57 percent), with t-statistics of -2.75 (-2.07). These results are not presented in the tables for sake of brevity, but available from the authors upon request.

Other characteristics Similar results emerge after controlling for leverage, private information, price response delay, and short sale constraints. Average excess returns (4F alpha) decrease to 0.44 percent (0.40 percent) per month at most, and remain significant with t-statistics ranging between -2.24 and -3.24 (-2.06 and -2.98).[12]

3.4 Regression tests

The previous sections indicate that portfolios formed by sorting on vol-of-vol generate substantial profits that are not explained by any single control variable. In this section, we estimate Fama and MacBeth (1973) regressions to simultaneously control for a range of control variables, to avoid the specification of breakpoints, and to take more advantage of the cross-sectional variation in vol-of-vol and the control variables. Each month, we conduct cross-sectional regressions of firm returns on vol-of-vol and one or more control variables, each of which is winsorized at the 1 percent and 99 percent level to limit the effect of outliers. The regressions are estimated using OLS and take the following form:

$$r_{it+1} = \alpha + \beta X_{it} + \varepsilon_{it+1},$$

where r_{it+1} is the realized return on stock i in month $t+1$, X_{it} is a collection of predictor variables at time t for stock i, and ε_{it+1} is the prediction error which is assumed to be normally distributed with mean zero.

Next, we conduct tests on the time-series averages of the slope coefficients from the regressions. To account for potential autocorrelation and heteroskedasticity in the coefficients, we compute Newey and West (1987)-adjusted t-statistics based on the time-series of the coefficient estimates. Since slope coefficients obtained by OLS regression of observed returns on security-specific attributes may be biased upwards if individual stock prices contain microstructure noise that is correlated to the independent variable, we value-weigh stocks in each regression (Asparouhova et al. (2012)). Table 5 shows the results, classified in the same categories as before.

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[Insert Table 5 about here]

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[12] In unreported double-sorts, we also find a persistent negative and significant vol-of-vol effect after controlling for various other potential return drivers including the return on equity, the expected earnings-reporting month effect, I/B/E/S forecast revisions over the previous month, the Altman distress score, I/B/E/S long-term growth expectations, historical sales growth , R&D/total assets, growth in capital expenditures, property, plant and equipment(PPE) to total assets, net payout yield, and change in institutional ownership.

Canonical characteristics In panel (a) of Table 5, model (1) regresses the next month's return against current vol-of-vol. The coefficient on vol-of-vol is 0.042 with a t-statistic of -3.34, which is of substantial economic importance. Since the sample-wide standard deviation of vol-of-vol equals 4.2 percent (Panel (b) in Table 1), a two-standard deviation increase in vol-of-vol is associated with lower returns of 0.35 percent over the following month. Regressions (2)-(6) add the five canonical characteristics (beta, book-to-market, size, momentum, and short-term reversal) to regression (1). None of the coefficients on the canonical cross-sectional stock return predictors are significantly different from zero, whereas the coefficients on vol-of-vol effect remain economically large and highly significant. Regression (7) adds all risk factors jointly, with similar results. Hence, the vol-of-vol effects seems not subsumed by the canonical characteristics. In panels (b)-(f), we use this regression (7) as the base specification.

Return distribution characteristics In panel (b) of Table 5, coefficients on idiosyncratic volatility, maximum return, and skewness are significant when added individually (see models (1)-(3)). The coefficient on skewness is not significant (see model (4)). The coefficients on vol-of-vol range from -0.030 to -0.068 and are slightly smaller than those in panel (a). Still, the vol-of-vol effect remains economically substantial and highly significant in all models with t-statistics ranging between -2.44 and -2.96. When all return distribution characteristics are added jointly in model (5), the coefficient on idiosyncratic volatility remains significant while the coefficients on maximum return and skewness do not. But more importantly, the coefficient on vol-of-vol is of similar size and remains highly statistically significant. Hence, the vol-of-vol effect seems not explained by returns distribution characteristics.

Liquidity characteristics In panel (c) of Table 5, the coefficients on Amihud illiquidity and stock turnover are not significant in any specification. Interestingly, the coefficient on option liquidity is substantial and highly significant, either when added individually or with the stock liquidity variables. This suggests that stocks with relatively illiquid options require a premium. Consistent with the previous results, the coefficient on vol-of-vol is of similar magnitude and significance in all four models, indicating that stock and option liquidity characteristics cannot explain the vol-of-vol effect either.

Option-based characteristics In panel (d) of Table 5, the only significant coefficient is on change in put IV of Ang et al. (2010), indicating that higher demand for put options over the past month predicts negative future stock returns. The lack of statistical significance on the other option characteristic variables may be caused by a sharply reduced sample size, as the option characteristics require the availability of multiple option contracts. Nevertheless, in each model, the coefficient on vol-of-vol continues to be economically strong and statistically significant. Since it is especially the OTM Skew variable that decreases the number of observations, we have re-run the regressions after omitting the OTM Skew variable (unreported). The resulting vol-of-vol coefficients have similar size and significance levels. Hence, option characteristics that have been shown to predict cross-sectional stock returns in previous studies cannot explain the vol-of-vol effect either.

Uncertainty-related characteristics; Other characteristics Finally, in panel (e) of Table 5, the coefficients on analyst coverage, private information, and short-sale constraints are statistically significant when added individually, or in combination with the other characteristics. The coefficients on age, forecast dispersion, volatility, leverage, and price response delay are not significantly different from zero. The coefficients on vol-of-vol, again, remain economically large and range from -0.030 to -0.069, with t-statistics between -2.58 and -2.99. Hence, other uncertainty-related characteristics and a series of other characteristics cannot explain the vol-of-vol effect either.

In summary, vol-of-vol has consistent predictive power for future stock returns with a strongly negative coefficient in each specification. This is in line with the patterns observed in Tables 2 and 4. Hence, we confirm the previous findings that higher vol-of-vol stocks subsequently have lower average returns, and a considerable portion of the vol-of-vol effect remains unexplained.

3.5 Robustness

In the previous two subsections, we have shown that the negative cross-sectional relation between vol-of-vol and future monthly stock returns is robust to a range of control variables. In this subsection, we investigate whether the vol-of-vol effect is resistant to a series of robustness checks in which we change the portfolio breakpoints, the sample screening criteria, the procedure of calculating vol-of-vol, and the vol-of-vol definition. Table 6 presents the results in terms of average excess returns and four-factor alphas on the Low vol-of-vol quintile portfolio, the High vol-of-vol portfolio, and the corresponding High-Low portfolio. To facilitate comparison, the top row re-states this information for the vol-of-vol portfolio from Table 2.

[Insert Table 6 about here]

First, we examine whether our results are driven by the selection of portfolio breakpoints. We partition the sample into ten portfolios ("Deciles") instead of five and find that the average excess return (4F alpha) of the High-Low portfolio increases to -0.89 percent (-0.77 percent) per month, with a t-statistic of -2.57 (-2.42).

Second, we previously excluded stocks with prices below \$5 and stocks with a market capitalization smaller than \$225mln at the end of 2009 (discounted at the risk-free rate). To verify that our results are not driven by this sample screen we repeat our analyses without excluding these stocks ("No sample screen"). The average excess return (4F alpha) of the High-Low portfolio become slightly stronger with values of -0.83 percent (-0.68 percent), and a t-statistic of -2.70 (-2.31).

Third, our results may be driven by the way we construct of vol-of-vol. Therefore, in the next four rows, we examine whether the vol-of-vol effect is robust to changes in its definition. If we do not scale vol-of-vol by the average past month implied volatility ("Unscaled") we observe a larger High-Low return spread of -0.99 percent that is marginally significant with a t-statistic of -1.75. However, since the unscaled vol-of-vol measure has a higher correlation with market beta (which had an almost flat risk premium over our sample period), the four-factor alpha is similar but highly significant (-1.00 with a t-statistic of -2.79). Similarly, calculating vol-of-vol using OTM puts ("OTM puts") yields a slightly stronger vol-of-vol effect, with an average excess return (4F alpha) of the High-Low portfolio of -0.84 percent (-0.76 percent) and a t-statistic of -2.28 (-2.05).

Fourth, by forming vol-of-vol portfolios that follow procedures that are standard in the literature, we ignore possible industry clustering within the portfolios. However, one could argue that high or low vol-of-vol stocks might be clustered in certain industries at various points in time, and that therefore the vol-of-vol effect is driven by industry effects. Therefore, we next construct vol-of-vol portfolio within each two-digits SIC code industry, and average each vol-of-vol portfolio over the various industries ("Industry neutral"). The results reveal that vol-of-vol effect is similar in magnitude as before, witnessing an average excess return (4F alpha) of the High-Low portfolio of -0.64 percent (-0.61 percent). Due to eliminating movements in the vol-of-vol portfolios that are the result of industry-wide movements, the t-statistic increases to -4.16 (-4.01). Moreover, both the Low and High vol-of-vol portfolio now have significant four-factor alphas. Further, unreported analysis reveals that the vol-of-vol effect is present in most industries, as defined by the two-digits SIC code.

Finally, the negative vol-of-vol effect could be clustered in specific time periods. In Figure 3, we plot the average excess return of the High-Low portfolio for each month in our sample period from January 1996 to October 2009. The negative vol-of-vol effect is present in around 60 percent of the months, and negative returns tend to be larger (in absolute terms) than positive returns for any given year throughout the sample period. Overall, it seems unlikely that the vol-of-vol effect is driven by any particular sub-period.

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[Insert Figure 3 about here]

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To conserve space, we do not report results for a series of additional robustness checks. Specifically, the negative vol-of-vol effect also persists if we compute vol-of-vol exclusively from ATM put implied volatilities; ATM call implied volatilities; equal weighted, open-interest weighted or volume weighted average implied volatilities within the ATM call and/or put and OTM put category, or standardize vol-of-vol by the implied volatility measured at the beginning or end of the month. Results are also similar if require three, ten, or twenty non-missing implied volatility observations when calculating vol-of-vol (the four-factor alphas of the High-Low portfolio are -0.87, -0.65, and -0.67 respectively, and all highly significant). The same holds when using implied volatilities for options with longer maturities. For example, for options with twelve months to maturity, the High vol-of-vol portfolio earns average excess returns (4F alpha) of 0.66 percent (0.32 percent) with a t-statistic of 1.83 (2.28), while the Low vol-of-vol portfolio earns average excess returns (4F alpha) of -0.08 percent (-0.32 percent) with a t-statistic of -0.16 (-1.57). The resulting High-Low portfolio achieves an average excess return (4F alpha) of -0.74 percent (-0.64 percent) with a t-statistic of -2.38 (-2.32).

3.6 Return Persistence

The previous sections show that vol-of-vol has a robust negative relationship with stock returns over the following month in the cross-section. This begs the question as to how long such predictability persists? To evaluate return persistence, we proceed by tracking the average excess returns and 4F alphas of vol-of-vol portfolios after extending the holding period to three, six, nine, twelve or twenty-four months after portfolio formation. Table 7 presents the results for the High, Low, and High-Low vol-of-vol portfolios.

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[Insert Table 7 about here]

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The vol-of-vol effect remains present for longer holding periods. Similar to the one-month holding period results, the High-Low difference in excess returns (4F alphas) is highly significant for the three month holding period, with values of -1.66 percent (-1.37 percent) and t-statistics -2.30 (-2.03). For longer holding periods, the negative vol-of-vol effect becomes increasingly more negative in economic terms at a slowly decreasing rate. This is illustrated in Figure 4. The statistical significance decreases as the holding period gets longer, with the 4F alphas of the High-Low portfolio becoming marginally significant for the nine-month and twelve-month holding period. For example, the four-factor alpha on a portfolio that is not updated for a full year is 3.78 percent with t-statistic of -1.82. The four-factor alpha becomes insignificant for the 24-month holding period.

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[Insert Figure 4 about here]

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Looking at the performance of the Low vol-of-vol and High vol-of-vol portfolios separately, it becomes clear that it is the Low vol-of-vol portfolio that earn significantly positive excess returns and four-factor alphas over longer holding periods, whereas High vol-of-vol stocks earns four-factor alphas that are close to, and indistinguishable from, zero. The average excess return on the Low (High) vol-of-vol stocks increases at an almost linear rate up to 8.35 percent (3.64 percent) for a twelve-month holding period, with a t-statistic of 1.92 (0.66). We see a similar pattern for four-factor factor alphas that increase linearly up to 3.73 percent (-0.05 percent) for a twelve-month holding period with a t-statistic of 3.63 (-0.03). In fact, unreported analyses reveal that the Low vol-of-vol portfolio earns positive average excess returns of almost similar magnitude the first eleven months after portfolio formation. By contrast, the High vol-of-vol portfolio earns a negative average excess return over the month following portfolio formation, a small positive average return over the month thereafter, and more pronounced positive average returns in the months thereafter. As a consequence, the High-Low vol-of-vol portfolio has average excess returns that are negative in the individual months up to eleven months after portfolio formation, but which become sometimes positive and sometimes more negative thereafter.

4 Potential explanations

The previous sections have shown that high vol-of-vol stocks achieve lower future returns than low vol-of-vol stocks, suggesting the presence of a negative uncertainty premium when we assume that investors are ambiguity-averse. This result is opposite to the more intuitive idea that a cross-sectional uncertainty factor is compensated for by *higher* stock returns. In this section, we will discuss several explanations for the negative vol-of-vol effect. We first consider optimism bias and, more generally, deviations from fundamental value. Next, we examine whether vol-of-vol relates to stochastic volatility and jump risk premia. Subsequently, we investigate whether vol-of-vol reflects a priced risk factor which explains the negative relation between vol-of-vol and future stock performance. Finally, we examine the effect of vol-of-vol on the future stock return distribution in order to examine to what extent the vol-of-vol effect is explained by an omitted higher-order or asymmetric risk-based explanation.

4.1 Does vol-of-vol relate to deviations from fundamental value?

The lower future returns on stocks with higher vol-of-vol could indicate that high vol-of-vol stock prices are higher than justified by their fundamental value, or the negative vol-of-vol effect could reflect an optimism bias. Miller (1977) and Chen et al. (2001) argue that prices reflect a more optimistic valuation if short-sale constraints prevent pessimistic investors from holding a short position in a stock. They argue that when disagreement about the profitability of a stock increases, market prices rise relative to the true value of a stock and expected returns are negative. Since uncertainty and disagreement may be related (i.e. Zhang (2006); Anderson et al. (2009)), vol-of-vol could also (partly) reflect disagreement among investors. Therefore, the negative vol-of-vol effect might be explained by the same mechanism in the presence of short sales constraints, causing lower returns on stocks with higher vol-of-vol.

To investigate this explanation, we repeat the double-sorting procedure from Section 3.3. Specifically, we first sort stocks into quintile portfolios based on short-sale constraints (proxied by residual institutional ownership), and then into quintile portfolios based on vol-of-vol. Panel (a) of Table 8 presents the average excess returns of the resulting 25 portfolios and the High-Low portfolios (expressed in returns and 4F alphas) for the short-sale constraints and vol-of-vol quintiles.

The magnitude of the vol-of-vol effect, presented in the "High-Low" and "High-Low (4F alpha)" columns, increases almost monotonically with short-sale constraints. When moving from "Low short-sale constraints" to "High short-sale constraints", the vol-of-vol effect increases by 1.41 percent (1.18 percent) in terms of average excess return (4F alpha). In the "Low short-sale constraints" quintile, the vol-of-vol effect is smallest in magnitude (-0.39 percent) and statistically not distinguishable from zero.[13] This suggests that the vol-of-vol effect is more pronounced among stock held less by professional investors.

[13] As an additional (unreported) check we also ran the above double sort using the percentage of institutional ownership instead of orthogonolized ownership as in Nagel (2005), and find similar results.

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[Insert Table 8 about here]

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Although this seems in line with an optimism bias and a short-sale constraints based explanation, several other results suggest that this explanation is unlikely to fully explain the vol-of-vol effect. First, in the presence of higher short-sale constraints, the vol-of-vol effect is substantially driven by significantly *positive* abnormal returns in the Low vol-of-vol portfolio. That is, the portfolios in the "Low" column labeled "4" and "High short-sale constraints" have average excess returns of 1.10 percent and 0.88 percent, respectively. Second, the effect of short-sale constraints on low vol-of-vol stocks is directly opposite to that on high vol-of-vol stocks. In the final row labeled "High-Low", the negative effect of short sale constraints in the Low vol-of-vol portfolio mirrors the positive impact on the High vol-of-vol portfolio (-0.73 percent versus 0.68 percent). This pattern cannot be explained by an optimism bias, which only has implications for the higher vol-of-vol portfolios (which then might reflect the most optimistic investors) in the presence of short-sale constraints.

Several bits of evidence throughout this paper seem to corroborate this view. For instance, in contrast to the effect of analyst dispersion, the vol-of-vol effect is present (absent) among large firms (small firms), firms for which disagreement and short-sale constraints tend to be smaller (larger). Also, especially for longer holding periods, the alphas are significantly positive at the long side of the trade, while optimism bias only predicts underperformance. We also document a strong vol-of-vol effect in a sample that excludes stocks with price below $5 and small market values, suggesting that short-sale constraints are in fact relatively low (D'Avolio, 2002). In light of these differences, we conclude that the vol-of-vol effect is at best only partially explained by optimism bias.

More generally, if vol-of-vol is driven by pricing errors of *any* kind, we expect such errors to be larger when arbitrage is more difficult. For instance, De Long et al. (1990) and Shleifer and Vishny (1997) argue that financial markets might not always be informationally efficient when arbitrage capital is scarce and arbitrage is risky or costly. Arbitrage risk deters arbitrageurs from exploiting pricing errors, thereby preventing relevant information from being incorporated into stock prices. We explore this explanation by first sorting stocks into quintile portfolios based on arbitrage risk, proxied by idiosyncratic volatility, followed by sorting stocks into quintile portfolios based on vol-of-vol. An increase in idiosyncratic risk generally makes arbitrage more risky, and results in smaller optimal positions by arbitrageurs. In fact, previous papers argue that idiosyncratic risk deters arbitrage activity (Shleifer and Vishny, 1997; Pontiff, 2006), and amplifies anomalies such as book-to-market, post-earnings announcement drift, accounting accruals, and momentum (Ali et al., 2003; Mendenhall, 2004; Mashruwala et al., 2006).

Panel (b) of Table 8 shows the performance of the 25 resulting portfolios and the High-Low portfolios (all expressed in returns and 4F alphas) for the arbitrage risk and vol-of-vol quintiles. The effect of vol-of-vol is significant for stocks with low to moderate arbitrage risk. By contrast, the vol-of-vol effect is indistinguishable from zero when arbitrage risk is the highest. Hence, the vol-of-vol effect is not more pronounced for stocks surrounded by high arbitrage risk, which seems inconsistent with a mispricing-based explanation.

4.2 Does vol-of-vol relate to exposures to stochastic volatility and jump risk?

The negative vol-of-vol effect potentially reflects a compensation for systematic stochastic volatility risk or jump risk. Higher vol-of-vol indicates increased IV dynamics, so that the vol-of-vol statistic might simply capture systematic volatility risk. Further, higher vol-of-vol might reflect higher risk of price jumps in option prices. Andersen et al. (2002) argue that discrete jump components account for extremely high or low returns, and find that only those specifications that incorporate stochastic volatility *and* jump diffusion deliver acceptable option prices. Their result is consistent with theoretical option pricing models in which implied volatilities of options across various strike prices reflect volatility and jump risk (e.g., Pan, 2002). However, some preliminary evidence against this explanation can be found in Table 3 , which shows that high vol-of-vol stocks have significantly lower IV-RV spreads than low vol-of-vol stocks, suggesting lower volatility risk exposures for high vol-of-vol stocks (Bali and Hovakimian, 2009).

We examine this explanation in more detail using four measures of systematic stochastic volatility risk and jump risk. Specifically, since delta-hedged straddles (involving the simultaneous purchase of a delta-hedged call and put option) do well when volatility increases, Cremers et al. (2011) measure volatility risk using the return on at-the-money, market-neutral straddles on S&P 500 index options. They further argue that, from several proxies, the change in the slope of the implied volatility skew on S&P 500 index options performs best in empirical tests and is backed by asset pricing theory (Yan, 2011).[14] We will use these measures as our main proxies. However, earlier research proxies volatility risk by the first differences in the CBOE volatility index (VIX) (Ang et al., 2006b), and jump risk by the returns on out-of-the-money index puts on the S&P 500, which perform well (poorly) when crash fears increase (subside) (Cremers et al., 2011). We will use these measures to conform to previous research and corroborate our results. While several other measures could be used, Cremers et al. (2011) show that these measures yield the highest priced stochastic volatility and jump risk premia in the cross-section of stocks.

[14] Yan (2011) shows that option skew is approximately proportional to jump intensity times jump size. Hence, the change in the skew captures time-variation in jumps (i.e., jump risk).

To evaluate whether stochastic volatility and jump risk explain our results, we we first estimate jump and volatility risk factor loadings at the individual stock level following Cremers et al. (2011). Specifically, we regress daily returns on the excess equity market return and either an aggregate volatility risk measure or an aggregate jump risk measure. We also include their first lags in the regression to control for potential issues of infrequent trading (Dimson, 1979). We run rolling regressions on daily data using a one-year time window and requiring at least 12 degrees of freedom, and compute stochastic volatility or jump risk exposures as the sum of the current and the lagged coefficients. Subsequently, we double-sort stocks into 25 portfolios by first sorting based on the estimated volatility or jump risk loadings, and further sorting based on vol-of-vol. We average the resulting portfolios over the vol-of-vol sort, as before, to construct vol-of-vol portfolios with similar stochastic volatility or jump risk exposure.

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Table 9 presents the results for each vol-of-vol quintile and the High-Low portfolio, expressed in average excess returns and 4F alphas. In panel (a), individual stocks' exposure to market-neutral S&P index straddles ("S&P500 straddle betas") explains only a small fraction of the vol-of-vol effect, with High-Low excess returns (4F alphas) going from -0.77 percent to -0.66 percent (0.61 percent to 0.56 percent) per month and an increased t-statistic of -2.71 (-2.40). High-Low differences in returns (4F alphas) after sorting on the first differences in the CBOE volatility index ("ΔVIX betas") remain economically and statistically significant with values of -0.57 percent (-0.47 percent) per month, with a t-statistic of -2.42 (-2.03). Hence, none of the measures for volatility risk exposure drives out the negative vol-of-vol effect.

In panel (b), controlling for the change in the slope of the implied volatility skew ("Δoption skew betas") increases average High-Low returns (4F alphas) to 0.78 percent (0.64 percent) per month with a t-statistic of -2.70 (-2.30). Differences in excess returns (4F alphas) become even more pronounced after sorting based on out-of-the-money puts on S&P 500 futures ("OTM put betas") to -0.89 percent (-0.78 percent) per month with a t-statistic of -3.17 (-2.71). These results reject an explanation of the negative vol-of-vol effect based on individual stocks' systematic volatility risk or jump risk exposures.

4.3 Is vol-of-vol a priced risk factor?

Finding lower returns on stocks with higher vol-of-vol could reflect a risk factor that is systematically priced in a factor model as in Ross (1976)'s arbitrage pricing theory. Similarly, vol-of-vol can be a negatively priced risk factor if it provides a hedge against against an aggregate decrease in investment opportunities (Campbell, 1993, 1996; Ang et al., 2006b). We estimate *ex ante* factor exposures to examine this explanation. Following common procedures, we first construct a monthly vol-of-vol factor by taking the High-Low portfolio of the vol-of-vol sorted quintile portfolios. Then, requiring at least 12 degrees of freedom and using a one-year rolling window, we regress each stock's daily returns on the vol-of-vol factor, the market factor, and their first lags to control for infrequent trading (Dimson, 1979). Next, we take the sum of the coefficients on the vol-of-vol factor and its lag, and use it as an instrument for the future expected factor loadings (i.e. vol-of-vol betas). If our vol-of-vol result reflects exposures to a systematically priced risk factor, then a stock with a high vol-of-vol factor loading should have a lower average return than a stock with a low vol-of-vol factor loading.

Panel (a) of Table 10 presents results from single sorts. To facilitate comparison, the top row labeled "Vol-of-vol characteristic" re-states the single-sort result on the vol-of-vol characteristic from Table 2. The row labeled "Vol-of-vol beta" reports average excess returns of five portfolios, formed after sorting stocks each month on the vol-of-vol factor loading. While the decrease in excess returns over the vol-of-vol beta quintiles is slightly larger than for the vol-of-vol characteristic, the High-Low differences in excess returns and four-factor alphas are statistically insignificant with t-statistics of -1.40 and -1.31, respectively. Hence, single sorts do not indicate a significant factor explanation of the vol-of-vol effect.[15]

The sort on the vol-of-vol beta may correlate with the vol-of-vol characteristic, which may increase noise in the resulting portfolio returns. Therefore, we next follow the approach used by Daniel and Titman (1997), Daniel et al. (2001), and Davis et al. (2000), and construct portfolios based on a stock's expected future loading on a vol-of-vol factor *within* each vol-of-vol quintile. More specifically, we form 25 portfolios by equally dividing each of the vol-of-vol quintiles into five value-weighted portfolios based on the estimated vol-of-vol factor loadings. Next, we average each of the vol-of-vol factor loading portfolios over the vol-of-vol quintiles, as before. This results in sets of portfolios that consist of stocks with similar levels of vol-of-vol, but with different loadings on the vol-of-vol factor. If the vol-of-vol result reflects exposures to a systematically priced risk factor, then a stock with a high vol-of-vol factor loading should have a lower average return than a stock with a low vol-of-vol factor loading but a similar vol-of-vol characteristic.

[15] When we use a monthly (instead of annual) window to estimate the vol-of-vol factor loadings, we obtain very weak results for the vol-of-vol beta sort, with High-Low returns (4F alphas) of -0.08 percent (0.11 percent) and a t-statistic as low as -0.12 (0.14).

Panel (b) of Table 10 reports the results from this procedure. Each portfolio in the top row ("Vol-of-vol betas") represents the High-Low excess return averaged over the quintiles that are based on the vol-of-vol characteristic. As we move from portfolio "Low" to "High", we are moving from portfolios with low average loadings on the vol-of-vol factor to portfolios with high loadings. Returns for factor-sorted portfolios decrease in this direction, as do four-factor alphas. However, High-Low differences in excess returns and four-factor alphas are not significant with t-statistics of -1.14 and -0.89, respectively, consistent with the result of the single portfolio sorts reported in panel (a). Hence, we find no significant relation between vol-of-vol factor loadings and average returns.[16]

The insignificant link between the vol-of-vol loadings and returns potentially reflects the fact that *ex ante* loadings are weak predictors of *ex post* loadings. To verify that this is not the case, the bottom half of panel (b) demonstrates that both average *ex ante* vol-of-vol factor loadings ("*Ex ante* vol-of-vol beta") and average *ex post* factor loadings ("*Ex post* vol-of-vol beta") increase monotonically across the portfolios. This indicates that the Daniel and Titman (1997) method does in fact achieve considerable dispersion in the *ex post* factor loadings. Furthermore, we verify that this procedure causes little to no variation in the average vol-of-vol characteristic ("Vol-of-vol characteristic"). Hence, our sorting procedure produces substantial variation in the vol-of-vol factor loadings that is independent of the vol-of-vol characteristic. In unreported results, we double-check the predictive power of the *ex ante* vol-of-vol betas following Daniel, Titman, and Wei (2001), by calculating returns for the characteristic-balanced portfolio that has a long position in the high vol-of-vol betas portfolio and a short position in the low vol-of-vol betas portfolio. We regress these excess returns on excess returns on the market index and the vol-of-vol factor, and find a vol-of-vol factor loading of 0.95, with a t-statistic of 6.92. This too indicates that the *ex ante* factor loadings are strong predictors of *ex post* factor loadings. Collectively, we cannot confirm econometrically that the vol-of-vol effect is explained by factor exposures. Rather, the findings indicate that the vol-of-vol effect is driven by firm characteristics that are unrelated to common risk exposures.

4.4 Does vol-of-vol reflect higher-order or asymmetric risk?

Vol-of-vol might also reflect higher-order or asymmetric risk that is not captured in measures like idiosyncratic or systematic volatility, skewness or kurtosis. For example, low vol-of-vol stock stocks or portfolios may carry substantial downside or lower-tail risk, to which investors are generally averse and that is compensated for with higher future returns. Alternatively, high vol-of-vol stocks or portfolios may have more upside potential (e.g., one of them might be the 'new Google') and a more attractive upper tail in expectation, a return

[16] The results are similar when we use contemporaneous vol-of-vol exposures, monthly estimation windows, or equal- weighted portfolios.

property that investors generally like and that is compensated for with lower future returns. To explore this possibility, we examine the distribution of future monthly returns in more detail for each of the five quintile portfolios.

Table 11 describes the returns distribution for each of the vol-of-vol quintiles constructed previously. In panels (a) and (b), the first data column ("Avg") re-states the average excess returns on the five vol-of-vol portfolios from Table 2. Panel (a) contains the time-series average of statistics from the cross-sectional, value-weighted distribution of future stock returns. Each statistic is calculated from the stocks within each quintile portfolio. We also report the difference in statistics between the High vol-of-vol portfolio and the low vol-of-vol portfolio ("High-Low"). Panel (b) presents statistics that describe the time-series return distribution of each of the quintile portfolios themselves, the difference in statistics between the high vol-of-vol portfolio and the low vol-of-vol portfolio ("High-Low"), and the return distribution of the High-Low quintile portfolio described in previous Sections ("Buy-Sell").

Panel (a) reveals that up to the 90th percentile, the return distribution of the "High" portfolio is more negative than the "Low" portfolio. Hence, high vol-of-vol stocks have more negative returns than low vol-of-vol stocks for almost all individual stocks included in these portfolios. Additionally, the below-median High-Low return differences are larger (in absolute value) than above-median differences, which indicates that downside risk exceeds upside potential. Above the 90th percentile, higher vol-of-vol stocks generally achieve higher returns. In fact, when focusing on stocks with the highest returns ("Max"), the High-Low return differential ("High-Low") is positive with average returns increasing monotonically in vol-of-vol. However, the upside potential seems limited, with a difference of 6.23 percent in monthly returns on the best performing individual stocks for the High versus Low vol-of-vol portfolios.

In panel (b), we confirm the findings from panel (a) by examining the returns distribution of vol-of-vol portfolios. Higher vol-of-vol portfolios have lower returns over time for the 75th percentile and below (columns "Min" to "P75"), which contradicts a risk-based explanation. As before, below-median return differences ("High-Low") are generally larger in absolute value than above-median differences, indicating downside risk that exceeds upside potential. However, for the 90th percentile and up, the higher vol-of-vol portfolios generally achieve higher returns. When focusing on the maximum monthly return for each quintile portfolio ("Max"), we note that the High-Low return differential ("High-Low") is positive, but limited with a value of 7.67 percent. Furthermore, when we look at the future return distribution of the High vol-of-vol minus Low vol-of-vol portfolio (Buy-Sell), negative returns tend to be larger (in absolute values) than positive returns, even when correcting for the average return of the High-Low portfolio of 0.77 percent. For example, the Min, P1, P5, and P25 equal -19.91 percent, -16.55 percent, -6.42 percent, and -2.52 percent, well below the Maximum (15.43 percent), P99 (11.16 percent), P95 (3.62 percent), and P75 (1.20 percent), respectively.

Hence, when studying the future stock or portfolio returns distributions of the various vol-of-vol portfolios, we find little evidence for a higher-order or asymmetric risk based explanation.

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5 Conclusion

A large stream of academic literature shows different behavioral responses to risky problems where objective probabilities are given, and (fundamentally) uncertain problems where the odds are unobserved (Knight, 1921; Ellsberg, 1961). This extends directly to the asset management industry after the market crash of fall 2008, where a well-heard remark was that "markets look attractively priced, but the vol-of-vol, or uncertainty is too high." This article investigates the implications of stock-level uncertainty for the cross-section of future stock returns.

We postulate that the volatility of option-implied volatility (vol-of-vol) can be viewed as a proxy for such uncertainty. From finance theory, one would expect that agents are uncertainty-averse so that stocks trade at a discount when returns are more uncertainty, leading to positive expected returns. However, our results indicate that stocks earn significantly *lower* future returns if our proxy for uncertainty, the vol-of-vol, is higher. Specifically, in terms of excess returns (four-factor alphas), a value-weighted portfolio of stocks in the highest vol-of-vol quintile underperforms a portfolio of stocks in the lowest vol-of-vol quintile by about 9 (7) percent per year, which is very substantial, especially given the fact that the requirements on our sample biases it towards larger stocks. For comparison, the canoninal book-to-market and momentum effects amount to 4 percent per year over our sample period.

We demonstrate that the negative relationship between vol-of-vol and future stock returns is of a distinctly different nature than previously documented return drivers. The negative effect persists after controlling for size, beta, value, momentum and short-term reversal factors; idiosyncratic volatility, skewness, kurtosis, and the past month's maximum return; stock liquidity and option liquidity; previously documented option-based return predictors; information uncertainty, parameter uncertainty or heterogeneity in beliefs proxied by size, age, analyst coverage, forecast dispersion, total volatility, and private information; leverage, stock price response delay, and short-sale constraints. Furthermore, we find that effects of vol-of-vol on stock returns persist beyond 12 months, are robust across different holding periods, hold for a variety of vol-of-vol definitions, and are found in value-weighted, equal-weighted, quintile and decile portfolios, as well as Fama-MacBeth regressions. Moreover, unlike most previously documented cross-sectional stock return predictors, the relationship between vol-of-vol and future stock returns is especially strong among large caps but seem absent for the smaller firms. Finally, applying industry-neutral vol-of-vol portfolios yields even more significant performance of the Low, High, and Low-High portfolios.

This begs the question as to what drives the vol-of-vol effect. We examine several possible explanations for the negative vol-of-vol effect that are not related to uncertainty. For instance, the low returns on high vol-of-vol stocks might be due to prices of high vol-of-vol stocks deviating more from fundamental value, possibly due to the presence of short-sale constraints. However, we make several observations that are inconsistent with this view. Furthermore, stocks with high vol-of-vol migth have different exposures to aggregate volatility or jump risk than stocks with low vol-of-vol. But, the exposures account for very little evidence of the lower returns for higher vol-of-vol stocks. In addition, exposures to vol-of-vol may be priced in a factor model as in Ross (1976)'s arbitrage pricing theory. Vol-of-vol can be a negatively priced risk factor if it provides a hedge against against deteriorating investment opportunities (Campbell, 1993, 1996; Ang et al., 2006b). To test the validity of this explanation, we construct a factor to mimic vol-of-vol, and sort stocks into subportfolios on the basis of their past sensitivity to the vol-of-vol factor while controlling for the vol-of-vol characteristic. These subportfolios are minimally correlated with vol-of-vol. While we find strong patterns in pre-formation and post-formation loadings, we do not find significant High-Low differences in returns or alphas, suggesting that vol-of-vol underperformance cannot be explained by a factor pricing model either. Finally, vol-of-vol may capture some form of higher-order or asymmetric risk not reflected in measures such as idiosyncratic or systematic volatility, skewness or kurtosis. However, after studying the future returns distributions of various vol-of-vol portfolios, we find little evidence for an explanation based on risk characteristics. Hence, the documented vol-of-vol effect does not fit a positive uncertainty-return relationship (assuming ambiguity-averse investors), or any of these alternative explanations.

Our empirical findings are consistent with models where information diffuses gradually from option into stocks markets, but seemingly contradict the mainstream literature on uncertainty and asset pricing. Nevertheless, it is possible to reconcile the negative vol-of-vol effect with recent models in which a negative uncertainty premium occurs if investors differ in their uncertainty preferences (e.g., (Cao et al., 2005), Bossaerts et al. (2010)). This literature follows Dow and Werlang (1992) who demonstrate that when an investor's uncertainty aversion is sufficiently high, she will not hold a risky asset. Cao et al. (2005) extend this result, arguing that such limited participation can lead to a lower equity premium when investors are heterogeneous. If multiple agents differ sufficiently in their aversion against uncertainty, the more uncertainty-averse investors may shy away from stocks surrounded with high uncertainty. As a consequence, the risky asset is held – and priced – only by investors who are sufficiently less uncertainty-averse and who require low uncertainty premiums.[17] Bossaerts et al. (2010) examine limited participation at the portfolio level and use it to explain the low return on growth stocks, which are likely to be more uncertain securities. Experimental evidence has confirmed heterogeneous uncertainty preferences (Ahn et al., 2007), as well as the impact on participation in asset markets (Bossaerts et al., 2010). Alternatively, investors may actually have ambiguity-*loving* preferences if they feel competent about in making investment decisions (Heath and Tversky, 1991). Similarly, Brenner and Izhakian (2012) use a different measure for uncertainty in an aggregate time series context and, consistent with our results, present empirical evidence of uncertainty having a negative effect on future index returns.

The analysis in this paper is straightforward, and future research is needed to identify the precise mechanism that underlyies the vol-of-vol effect. This is a challenging task, since any empirical investigation is hampered by the unobservable nature of uncertainty. Therefore, it would be interesting to develop other stock-level measures for uncertainty in the future and compare them with vol-of-vol. Moreover, studying the effects of vol-of-vol and future stock earnings and analysts expectations could provide additional insights. Additionally, several studies show that investors' responses to uncertainty is conditional on their general knowledge of the financial context (Heath and Tversky, 1991) and fear for the unfamiliar (Cao et al., 2011). Hence, the implications of ambiguity deserve further studying as a possible driver of stock returns.

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[17] The idea is similar to Amihud and Mendelson (1986) who study a "clientele effect" of having different types of investors with different expected holding periods, and find that each type trades assets with different relative spreads.

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6 Appendix: Variable Definitions

This section describes the variables used in the text, their respective sources, and their abbreviations in the tables.

- **Beta** ("Beta") is estimated for each individual stock i at the end of month t using a CAPM regression over one year of weekly returns. Specifically, we estimate $r_{i\tau} - r^f_\tau = \alpha_i + \beta_{it} r^M_\tau + \varepsilon_{i\tau}$, where $r_{i\tau}$ is the return on stock i over week τ, r^M_τ is the market return in week τ, and r^f_τ is the risk-free rate in week τ. We proxy r^M_τ by the CRSP daily value-weighted index and r^f_τ by the Ibbotson risk-free rate. Beta equals the coefficient β_{it}.

- **Book-to-market** (Polk et al., 2006; "Book-to-market") is book equity divided by market capitalization at the end of the previous fiscal year, and is updated every 12 months beginning in July. Book equity is for the fiscal year ending in the preceding calendar year and equals the sum of stockholders' equity plus deferred taxes, investment tax credit, post-retirement benefit assets net of liabilities, minus preferred stock.

- **Size** (Banz, 1981; "Size") is the natural logarithm of equity market capitalization (price times shares outstanding) at the end of the previous month.

- **NYSE Only** ("NYSE Only") is a dummy variable equal to one for stocks traded on the NYSE, and zero otherwise

- **Momentum** (Jegadeesh and Titman, 1993; "Momentum") is the cumulative stock return over the previous 11 months, i.e., starting at time $t-12$ and ending at time $t-1$ to isolate momentum from the short-term reversal effect.

- **Short-term reversal** (Jegadeesh, 1990; Lehmann, 1990; "Short-term reversal") is last month's stock return (i.e., from time $t-1$ to t).

- **Idiosyncratic volatility** (Ang et al., 2006b; Bali et al., 2011; "Idiosync. volatility") for each stock i is computed as the standard deviation of the daily residuals from the Fama and French (1993) three-factor model. Specifically, we estimate $r_{i\tau} - r^f_\tau = \alpha + \beta_{it} r^M_\tau + h_{it} HML_\tau + s_{it} SMB_\tau + \varepsilon_{i\tau}$, where r^M_τ is the market return over period τ, HML_τ is the return of the Value-minus-Growth portfolio over period τ, SMB_τ is the return on the Small-minus-Big portfolio over period τ, and $\varepsilon_{i\tau}$ is the idiosyncratic return on stock i over period τ using daily returns over rolling annual periods. Subsequently, we compute idiosyncratic volatility as the standard deviation of $\varepsilon_{i\tau}$ over the past year .

- **Maximum return** (Bali et al., 2011; "Maximum return") of each stock is the maximum daily return over the past month (i.e., from time $t-1$ to t).

- **Skewness** (Xu, 2007; "Skewness") is the historical third-order centralized moment calculated as $E\left(x-\mu\right)^m/\sigma^m = 1/N\sum_{t=1}^{n}\left(x_i-\bar{x}\right)^m/\hat{\sigma}_x^m$, where $\bar{x}$ and $\hat{\sigma}_x$ are the sample mean and standard deviation of daily returns on stock i over the past year, and $m=3$.

- **Kurtosis** ("Kurtosis") is the fourth-order centralized moment calculated similarly with $m=4$.

- **Amihud illiquidity** (Amihud, 2002; "Amihud illiquidity") is computed as the absolute value of daily returns divided by daily dollar volume (in millions) measured annually. For NASDAQ firms, volume is divided by two to account for inter-dealer double-counting.

- **Turnover** (Datar et al., 1998; "Turnover") equals last month's number of shares traded in stock i as a percentage of total shares outstanding.

- **Option bid/ask spread** ("Option bid-ask spread") is computed as the previous month's average of the bid-ask spreads on at-the-money options.

- **At-the-money skew** (Bali and Hovakimian; Cremers and Weinbaum; "ATM Skew") is the difference between implied volatilities of the ATM call and put options at time t.

- **Out-of-the-money skew** (Xing et al., 2010; "OTM Skew") is the difference between the implied volatility of the OTM put options and the average of the implied volatilities of the ATM call and put options at time t.

- **Implied volatility - realized volatility spread** (Bali and Hovakimian, 2009; Goyal and Saretto, 2009; "IV-RV spread") is the difference between the average of the implied volatilities of the ATM call and put options at time t, and last month's realized volatility computed from daily returns.

- **Change in the ATM call IV** or **Change in ATM put IV** (Ang et al., 2010; "Change in the call IV," "Change in put IV") equal the monthly first difference between time t and $t-1$ in the implied volatilities of the ATM call or put options.

- **Age** (Pastor and Veronesi, 2003; Zhang, 2006; "Age") equals the number of years up to time t since a firm first appeared on the CRSP tapes.

- **Analyst coverage** (Zhang, 2006; "Analyst coverage") is the number of analysts following the firm over the last month.

- **Forecast dispersion** (Diether et al., 2002; Zhang, 2006; "Forecast dispersion") is the standard deviation in analysts' next fiscal year's I/B/E/S earnings forecasts, scaled by price, all measured at time t.

- **Volatility** (Zhang, 2006; "Volatility") is the standard deviation of weekly returns of each stock i over the past year ending at the end of month t.

- **Leverage** (Bhandari, 1988; "Leverage") is defined as 1 minus book equity (see the variable definition of Book-to-market) divided by total assets (COMPUSTAT item code: AT), updated every twelve months beginning in July.

- **Private information** (Durnev et al., 2003; "Private information") is calculated after running a regression of each stock's excess return on the excess returns of the market index and the index for industry j to which stock i belongs; $r_{it} - r_t^f = \alpha_i + \beta_{it}(r_\tau^M - r_\tau^f) + \gamma_{it}(r_{j\tau} - r_\tau^f) + \varepsilon_{it}$. Private information is measured as $1 - R^2$ obtained from this regression. The regression are run on weekly data over the past year up to time$t$ using the the CRSP value-weighted market index, the value-weighted industry index based on a firm's two-digit SIC industry classification, and r_t^f from Ibbotson.

- **Stock price delay** (Hou and Moskowitz, 2005; "Stock price delay") is calculated after running a regression of the weekly excess returns of stock i on contemporaneous and four weeks of lagged returns on the market portfolio over the past year up to time t, $r_{it} - r_t^f = \alpha_i + \beta_{it}(r_\tau^M - r_\tau^f) + \sum_{n=1}^{4} \delta_i^{(-n)}(r_{\tau-n}^M - r_\tau^f) + \varepsilon_{it}$. Price delay equals one minus the ratio of the R^2 from the regression restricting $\delta_i^{(-n)} = 0, \forall n \in [1,4]$ to the R^2 from the regression without restrictions, $1 - \frac{R_{R,it}^2}{R_{U,it}^2}$.

- **Short-sale constraints** (Nagel, 2005; "Short-sale constraints") are measured by "residual" institutional ownership (low institutional ownership indicates high short sale constraints), calculated as institutional ownership corrected for size effects. Following (Nagel, 2005), we use the residual from cross-sectional regressions of institutional ownership against firm sizeduring each quarter. Institutional ownership is measured as the fraction of shares of stock i held by institutional investors during the quarter prior to the latest earnings announcement, as reported on Thomson Financial's CDA/Spectrum Institutional (13f) Holdings. We set institutional ownership to zero if no ownership data are available for a firm-quarter during the 180 days prior to the earnings announcement.

- **Stochastic volatility** ("S&P500 straddle betas" (Cremers et al., 2011) or "ΔVIX betas" (Ang et al., 2006b)) **and jump risk** (Cremers et al., 2011; "Δoption skew betas" or "OTM put betas") are the factor loadings of stock i at time t (f_{it}) that are estimated from the following regression:

$$r_{i\tau} - r_\tau^f = \alpha + \beta_{it} r_\tau^M + f_{it}\Delta F_\tau + \varepsilon_{i\tau},$$

where r_τ^M is the excess equity market return (proxied by the CRSP value-weighted index), r_τ^f is the Ibotson risk-free rate, and f_{it} captures firm i's exposure to returns of the at-the-money, market-neutral S&P index straddles (Cremers et al., 2011) or to daily changes in the VIX (Ang et al. (2006b); Cremers et al. (2011)) as proxies for systematic stochastic volatility risk, or the returns on OTM puts on S&P 500 options (Cremers et al., 2011) or the change in the slope of the implied volatility skew (Yan, 2011; Cremers et al., 2011) as proxies for systematic jump risk. More precisely:

- **Market-neutral straddle returns** (Cremers et al., 2011; "S&P 500 Straddle") are computed by constructing zero-beta straddles using nearest to ATM and one month maturity index options on the S&P 500 by solving the problem

$$\begin{gathered} r_{MN} = \theta r_c + (1 - \theta r_p) \\ \theta\beta_c + (1-\theta)\beta_p = 0, \end{gathered}$$

  where r_{MN} is the market-neutral straddle return, r_c (r_p) is the return on the call (put), β_c (β_p) is the market beta of the call (put), and θ is the weight invested in the call. To implement this, Cremers et al. (2011) solve for θ using Black-Scholes option betas following Coval and Shumway (2001).

- **Changes in VIX** (Ang et al., 2006b; "ΔVIX") equal first daily differences in the VIX from the Chicago Board Options Exchange.

- **OTM put return on the S&P 500 options** is the daily return on the out-of-the money put S&P500 index option that is nearest to a 0.95 strike-to-spot ratio and one-month maturity.

- **Change in the slope of the implied volatility skew** (Yan, 2011; Cremers et al., 2011) is calculated as the daily change in the difference between the implied volatilities of the out-of-the money put option (nearest to 0.95 strike-to-spot ratio) and the average of the implied volatilities of the nearest to at-the-money call and put options, where the options are nearest to one-month maturity S&P500 index options.

We estimate the factor loadings by running the above regressions on daily data over an annual rolling window. In order to control for potential issues of infrequent trading, we also include the factors lagged one day (as proposed by Dimson (1979)) and use the sum of the betas estimated for the contemporaneous and the one period lagged risk factors as the estimated factor loading, following Cremers et al. (2011).

Figure 1: Vol-of-vol portfolios

This figure plots the average vol-of-vol of each vol-of-vol portfolio from one year before ($t - 12$) till one year after ($t + 12$) portfolio formation. Vol-of-vol is past month's volatility of option-implied volatility (IV) standardized by average IV (see Section 2.2), and IV is calculated from at-the-money call and put options with maturity closest to 30 days. Each month we sort stocks in ascending order into quintile portfolios (Low, 2, 3, 4, and High) on the basis of vol-of-vol. We use a one-day implementation lag and value-weight stocks in each portfolio. The sample period runs from January 1996 to October 2009.

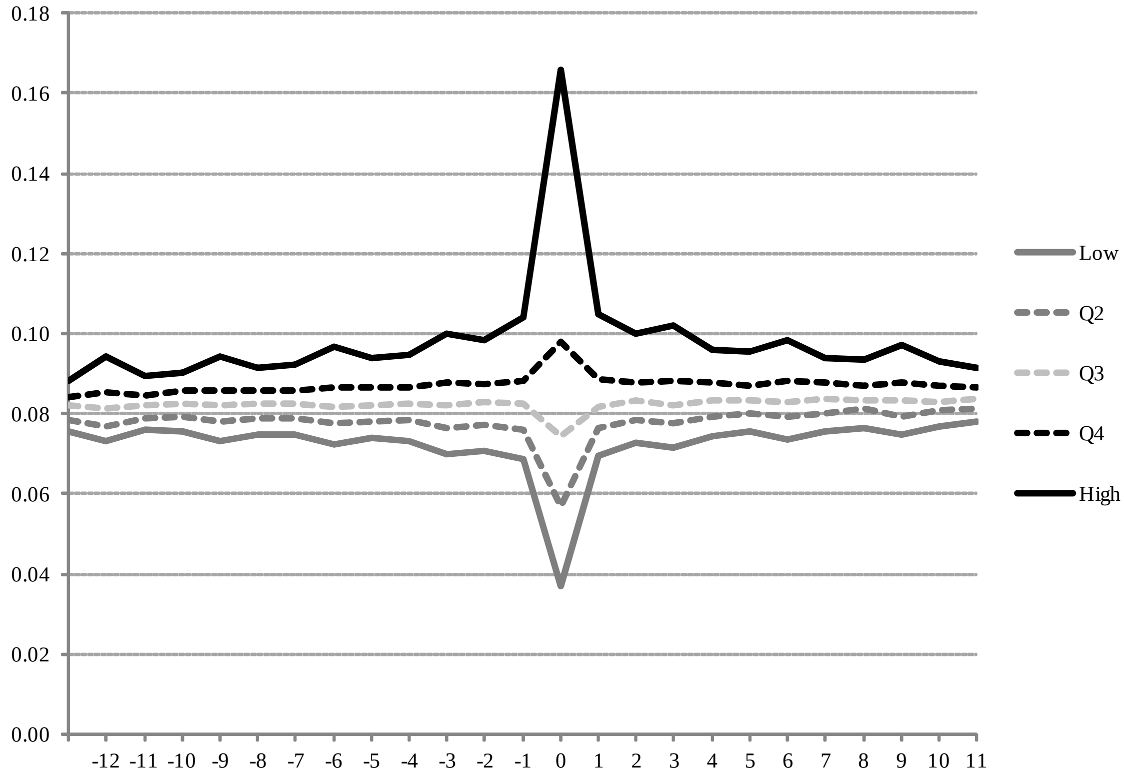

Figure 2: Monthly returns on vol-of-vol portfolios

This figure shows the average monthly excess returns of portfolios sorted on vol-of-vol. Vol-of-vol is past month's volatility of option-implied volatility (IV) standardized by average IV (see Section 2.2). IV is calculated from at-the-money call and put options with maturity closest to 30 days. Each month we sort stocks in ascending order into quintile portfolios (Low, 2, 3, 4, and High) on the basis of vol-of-vol. We use a one trading day implementation lag and value-weight stocks in each portfolio. We then plot the average excess return (Return; black bars) and four-factor alpha (4F alpha; grey bars) of each portfolio, and the High vol-of-vol minus low vol-of-vol portfolio (High-Low), over the subsequent month. The sample period runs from January 1996 to October 2009.

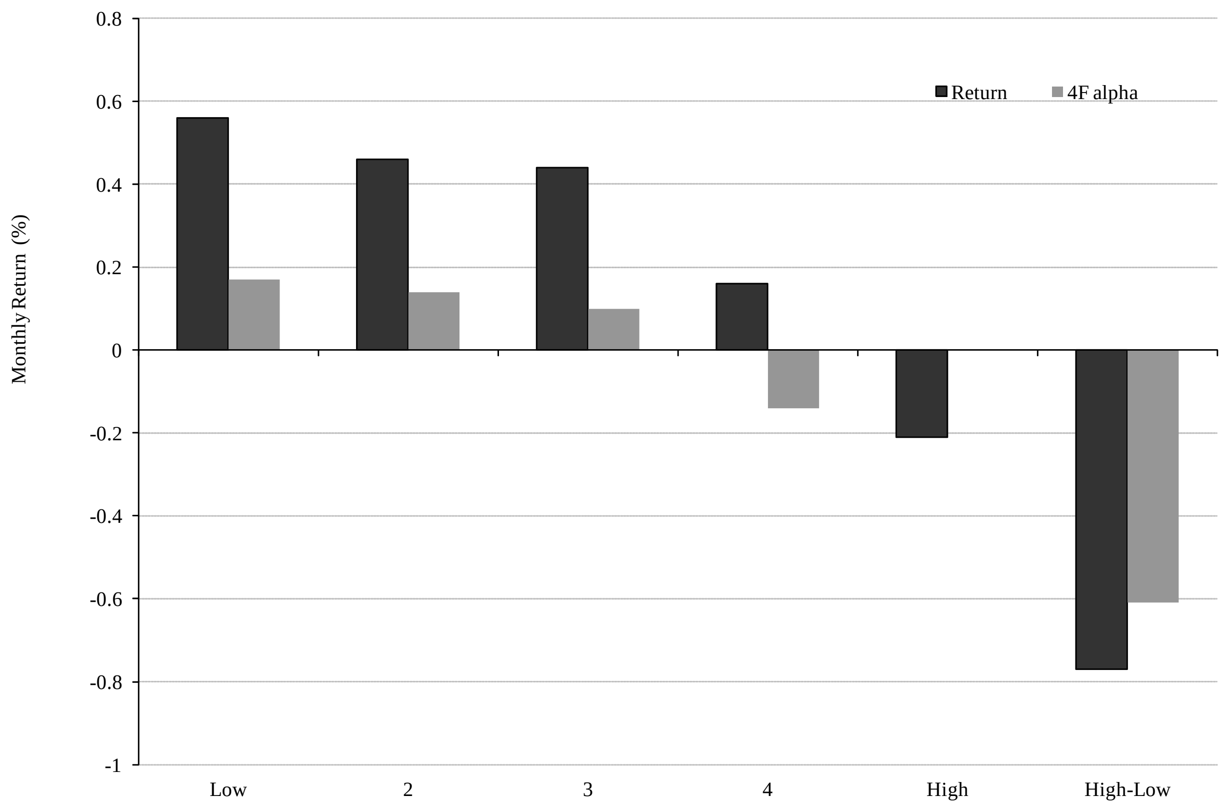

Figure 3: Performance High-Low vol-of-vol portfolio over time

This figure shows the average month-by-month excess returns on the High-Low portfolio that buys the top quintile portfolio and sells the bottom quintile portfolio. Vol-of-vol is past month's volatility of option-implied volatility (IV), standardized by average IV (see Section 2.2). IV is calculated from at-the-money call and put options with maturity closest to 30 days. Each month we sort stocks in ascending order into quintile portfolios (Low, 2, 3, 4, and High) on the basis of vol-of-vol. We use a one trading day implementation lag and and value-weigh stocks in each portfolio. We then buy the High portfolio and sell the Low portfolio, and hold this position over the subsequent month. The graph plots the average monthly returns on this strategy over our sample period from January 1996 to October 2009.

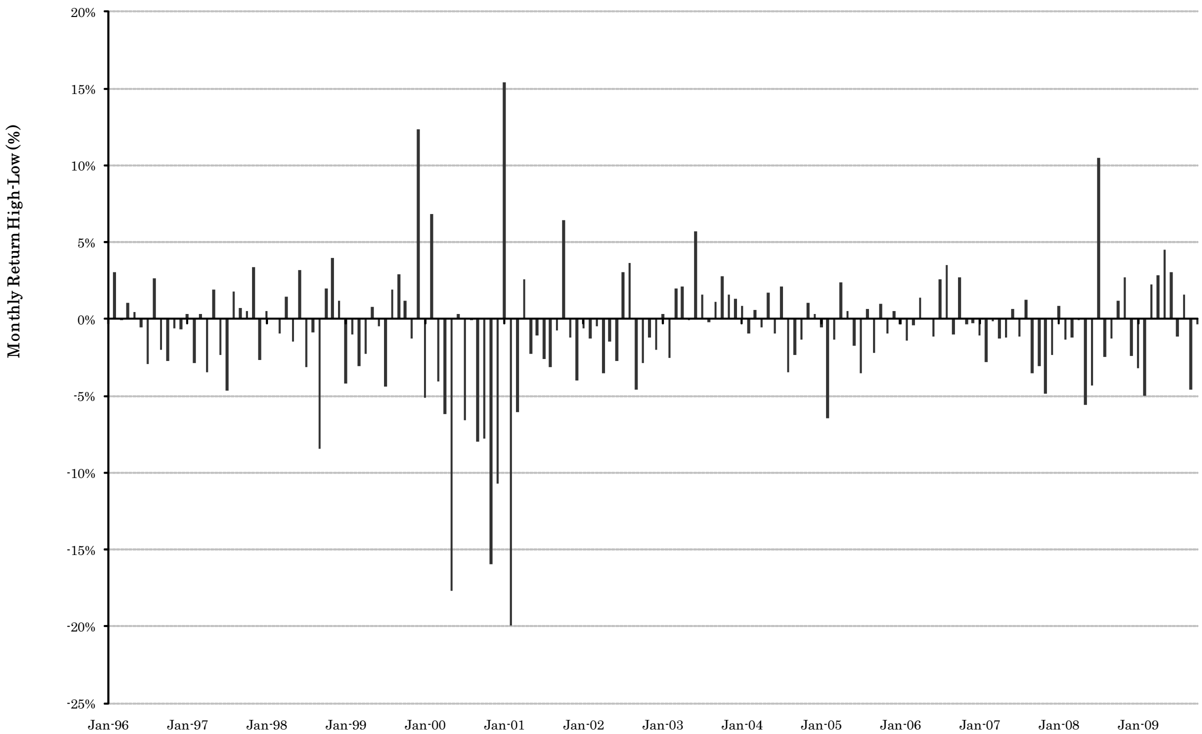

Figure 4: Performance persistence of the High-Low vol-of-vol portfolio

This figure shows the average cumulative returns on the High-Low vol-of-vol portfolio that buys the top quintile portfolio and sells the bottom quintile portfolio. Vol-of-vol is past month's volatility of option-implied volatility (IV), standardized by average IV (see Section 2.2). IV is calculated from at-the-money call and put options with maturity closest to 30 days. Each month we sort stocks in ascending order into quintile portfolios (Low, 2, 3, 4, and High) on the basis of vol-of-vol. We use a one trading day implementation lag and and value-weigh stocks in each portfolio. We then buy the High portfolio and sell the Low portfolio, and hold this position for the next one to 24 months. The graph plots the average excess returns (black line) and four-factor alphas (grey line) of this strategy, with dotted lines delineating the 95% confidence interval. The sample period runs from January 1996 to October 2009.

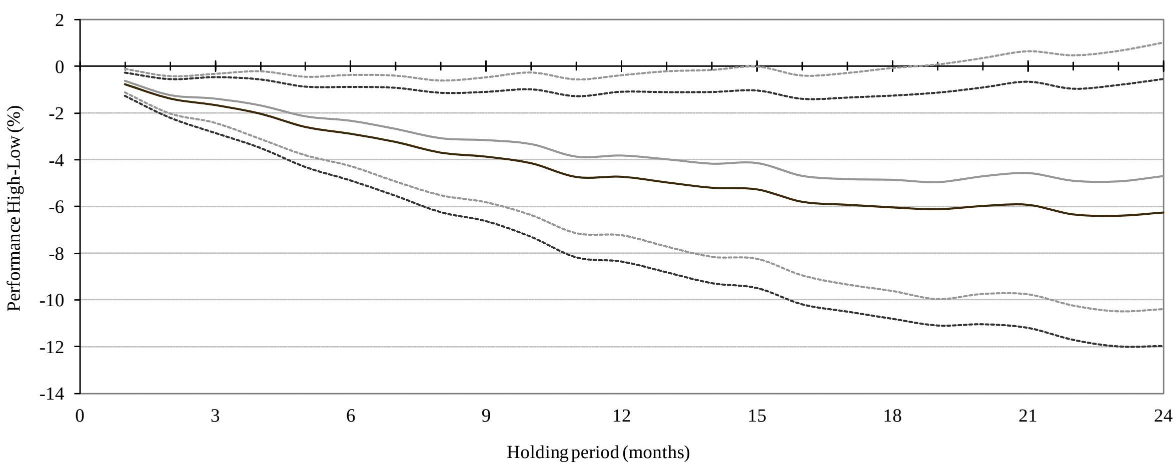

Table 1: Descriptive statistics vol-of-vol sample

This table reports descriptive statistics for vol-of-vol over our sample period from January 1996 to October 2009. Vol-of-vol is past month's volatility of option-implied volatility (IV), standardized by average IV (see Section 2.2). Implied volatility is calculated from at-the-money call and put options with maturity closest to 30 days. Panel (a) reports the coverage statistics of our sample versus the CRSP sample. The first three data columns show the number of CRSP stocks included in our analysis (Nr. of stocks), the number of CRSP stocks for which we could compute our vol-of-vol measure (Nr. of stocks with vol-of-vol), and the number of stocks for which we could compute vol-of-vol as a percentage of the number of CRSP stocks (Nr. of stocks with vol-of-vol (%)). The last three columns show the average market capitalization of CRSP stocks (MV of stocks ($mln)), the stocks for which we can compute vol-of-vol (MV of stocks with vol-of-vol ($mln)), and the stocks for which we can compute vol-of-vol as a percentage of the total market capitalization of CRSP stocks (MV of stocks with vol-of-vol (%)). Panel (b) reports year-by-year summary statistics of vol-of-vol. It presents the sample averages of the monthly value-weighted mean, standard deviation, 25th, 50th, and 75th percentiles of vol-of-vol, grouped per annum. The bottom row shows the grand average over our total sample.

(a) Coverage statistics

Year	Nr. of stocks	Nr. of stocks with vol-of-vol	Nr. of stocks with vol-of-vol (%)	MV ofstocks ($mln)	MV of stocks with vol-of-vol ($mln)	MV of stocks with vol-of-vol (%)
1996	3,414	829	24%	1,975	5,631	68%
1997	3,583	1,154	32%	2,398	6,061	80%
1998	3,498	1,279	37%	3,046	7,137	84%
1999	3,213	1,284	40%	4,047	8,900	87%
2000	3,172	1,270	40%	4,867	10,754	87%
2001	2,700	1,081	40%	4,741	10,258	85%
2002	2,476	987	40%	4,441	9,356	82%
2003	2,485	900	36%	4,242	9,649	81%
2004	2,793	1,061	38%	4,600	10,264	83%
2005	2,832	1,100	39%	4,930	10,802	84%
2006	2,889	1,198	41%	5,219	10,806	85%
2007	2,847	1,283	45%	5,853	11,356	86%
2008	2,365	1,059	45%	5,838	11,299	85%
2009	1,969	806	41%	5,101	9,602	75%

Descriptive statistics vol-of-vol sample (continued)

(b) Summary statistics of vol-of-vol

Year	Mean	Std. deviation	25-th percentile	50-th percentile	75-th percentile
1996	0.076	0.034	0.047	0.066	0.092
1997	0.072	0.049	0.043	0.059	0.085
1998	0.076	0.037	0.049	0.067	0.092
1999	0.064	0.040	0.041	0.056	0.077
2000	0.072	0.045	0.044	0.063	0.088
2001	0.089	0.041	0.063	0.083	0.109
2002	0.102	0.043	0.072	0.096	0.123
2003	0.080	0.033	0.059	0.076	0.094
2004	0.079	0.040	0.055	0.072	0.093
2005	0.086	0.048	0.056	0.076	0.105
2006	0.085	0.044	0.058	0.077	0.101
2007	0.093	0.049	0.064	0.082	0.111
2008	0.112	0.050	0.083	0.102	0.130
2009	0.089	0.036	0.067	0.084	0.104
Average	0.084	0.042	0.057	0.076	0.100

Table 2: Returns on portfolios sorted by vol-of-vol

This table reports average monthly returns on portfolios sorted on vol-of-vol over our sample period from January 1996 to October 2009. Vol-of-vol is past month's volatility of option-implied volatility (IV), standardized by average IV (see Section 2.2). IV is calculated from at-the-money call and put options with maturity closest to 30 days. Each month we sort stocks in ascending order into quintile portfolios (Low, 2, 3, 4, and High) on the basis of vol-of-vol. We use a one trading day implementation lag. The table presents average returns of each portfolio over the subsequent month, as well as the difference in monthly returns between portfolio High and portfolio Low (High-Low). The top row (Vol-of-vol) shows the average vol-of-vol of each portfolio. The remaining rows present excess returns (Excess return) and alphas from the Sharpe-Lintner model (CAPM alpha), from the Fama-French three-factor model (3F alpha), and from the Fama-French-Carhart four-factor model (4F alpha). Panel (a) presents results for value-weighted portfolios, and panel (b) for equal-weighted portfolios. We report t-values in parentheses that are Newey-West corrected. *, ** and *** indicate significance at the 10%, 5%, and 1% level, respectively.

(a) Value-Weighted Returns

	Low	2	3	4	High	High-Low
Vol-of-vol	0.04	0.06	0.07	0.10	0.15	0.12
Excess return	0.56	0.46	0.44	0.16	-0.21	-0.77**
	(1.52)	(1.25)	(1.10)	(0.36)	(-0.43)	(-2.50)
CAPM alpha	0.26*	0.16	0.10	-0.20	-0.60***	-0.87***
	(1.69)	(1.16)	(0.90)	(-1.51)	(-3.13)	(-2.84)
3F alpha	0.23	0.17	0.15	-0.13	-0.49***	-0.71***
	(1.55)	(1.39)	(1.38)	(-0.94)	(-2.77)	(-2.65)
4F alpha	0.17	0.14	0.10	-0.14	-0.44**	-0.62**
	(1.07)	(1.15)	(0.99)	(-1.03)	(-2.35)	(-2.14)

(b) Equal-Weighted Returns

	Low	2	3	4	High	High-Low
Vol-of-vol	0.04	0.06	0.07	0.10	0.15	0.12
Excess return	0.40	0.46	0.24	0.06	-0.10	-0.50***
	(0.81)	(0.91)	(0.49)	(0.12)	(-0.19)	(-3.09)
CAPM alpha	-0.01	0.04	-0.17	-0.36**	-0.51***	-0.51***
	(-0.04)	(0.28)	(-1.05)	(-2.17)	(-3.09)	(-3.04)
3F alpha	-0.08	-0.05	-0.26**	-0.43***	-0.59***	-0.51***
	(-0.66)	(-0.42)	(-2.27)	(-3.11)	(-4.66)	(-3.17)
4F alpha	-0.10	-0.02	-0.24**	-0.39***	-0.53***	-0.43***
	(-0.79)	(-0.13)	(-2.18)	(-2.84)	(-4.39)	(-2.63)

Table 3: Stock characteristics of portfolios sorted by vol-of-vol

This table reports average characteristics for portfolios sorted on vol-of-vol over our sample period from January 1996 to October 2009. Vol-of-vol is past month's volatility of option-implied volatility (IV), standardized by average IV (see Section 2.2). IV is calculated from at-the-money call and put options with maturity closest to 30 days. Each month we sort stocks in ascending order into quintile portfolios (Low, 2, 3, 4, and High) on the basis of vol-of-vol. We use a one trading day implementation lag and (except for Size which is equal-weighted) value-weight stocks in each portfolio. The table presents average characteristics at the end of month, as well as the difference in means between portfolio High and portfolio Low (High-Low). The top row (Vol-of-vol) shows the average vol-of-vol in each portfolio. Subsequent rows present averages for stock characteristics, each of which is defined in the Appendix. The final two rows present each portfolio's average number of stocks per month, and the fraction of stocks that remain in the same portfolio from one month to the next. We report t-statistics in parentheses that are Newey-West corrected. *, ** and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Category	Variable	Low	2	3	4	High	High-Low	t(High-Low)
	Vol-of-vol	0.04	0.06	0.07	0.10	0.15	0.12	
Canonical characteristics:	Beta	0.96	0.97	1.01	1.03	1.05	0.09***	(4.15)
	Book-to-market	0.37	0.34	0.33	0.33	0.36	0.00	(-0.59)
	Size ($bln)	7.43	10.07	10.39	10.72	8.56	1.13***	(2.63)
	Momentum	3.06	2.19	1.95	1.43	-0.17	-3.23***	(-3.68)
	Short-term reversal	3.03	3.42	3.53	3.50	4.87	1.85	(1.48)
Return distribution characteristics:	Idiosync. volatility (%)	1.82	1.75	1.77	1.79	1.91	0.08***	(3.86)
	Maximum return (%)	4.30	4.30	4.47	4.70	5.61	1.31***	(10.73)
	Skewness	0.14	0.10	0.16	0.13	0.20	0.06***	(3.97)
	Kurtosis	3.44	3.36	3.39	3.80	5.37	1.92***	(12.67)
Liquidity characteristics:	Amihud illiquidity (%)	0.07	0.05	0.05	0.07	0.10	0.03***	(3.16)
	Turnover	1.18	1.14	1.17	1.21	1.46	0.28***	(9.92)
	Option bid-ask spread	0.19	0.18	0.18	0.17	0.19	0.00	(-0.60)

Table 3: Stock characteristics of portfolios sorted by vol-of-vol (Continued)

Category	Variable	Low	2	3	4	High	High-Low	t(High-Low)
	Vol-of-vol	0.04	0.06	0.07	0.10	0.15	0.12**	(67.54)
Options-based characteristics:	ATM skew (%)	-0.52	-0.48	-0.40	-0.40	-0.26	0.26	(1.22)
	OTM skew (%)	3.41	3.57	3.85	3.96	4.01	0.60**	(2.52)
	IV-RV spread (%)	2.29	1.09	0.36	-0.38	-2.99	-5.27***	(-11.85)
	Change in call IV (%)	-0.04	-0.01	-0.03	-0.02	0.20	0.24	(0.34)
	Change in put IV (%)	-0.03	0.04	-0.06	0.18	0.15	0.19	(0.28)
Uncertainty-related characteristics:	Age	34.89	38.98	37.92	36.23	32.97	-1.92**	(-2.47)
	Analyst coverage	19.10	20.58	20.74	20.79	19.85	0.74***	(3.17)
	Forecast dispersion (%)	0.21	0.21	0.21	0.21	0.25	0.04***	(3.06)
	Volatility	2.15	2.14	2.19	2.26	2.45	0.30***	(7.74)
	Private information	0.27	0.26	0.24	0.24	0.26	-0.01	(-1.42)
Other characteristics:	Leverage	0.27	0.26	0.24	0.24	0.26	-0.01	(-1.42)
	Stock price delay	0.57	0.53	0.52	0.52	0.55	-0.01	(-1.44)
	Short sale constraints	0.17	0.17	0.24	0.19	-0.01	-0.18***	(3.30)
Portfolio characteristics:	Avg. number of stocks/month	221	222	222	222	221		
	Fraction in portfolio next month	0.33	0.24	0.22	0.23	0.32		

Table 4: Returns of portfolios sorted by stock characteristics and vol-of-vol

This table reports average monthly returns of portfolios sorted on stock characteristics and vol-of-vol over our sample period from January 1996 to October 2009. Vol-of-vol is past month's volatility of option-implied volatility (IV), standardized by average IV (see Section 2.2). IV is calculated from at-the-money call and put options with maturity closest to 30 days. Each month we sort stocks in ascending order into quintile portfolios on the basis of one of the characteristics described in Section 2. Each characteristic is defined in the Appendix. Within each characteristic quintile, we sort stocks into five additional portfolios (Low, 2, 3, 4, and High) based on vol-of-vol and compute the returns on the corresponding portfolios over the subsequent month. We use a one trading day implementation lag and value-weigh stocks in each portfolio. For Size, the table presents average excess returns of each of the twenty-five resulting portfolios (Small size, 2, 3, 4, Large size; Low, 2, 3, 4, High), as well as the difference between portfolio High and portfolio Low (High-Low). The column labeled "High-Low (4F alpha)" presents the difference in four-factor alphas between portfolio High and portfolio Low. For the remaining characteristics excluding liquidity characteristics, the table presents the return of each vol-of-vol quintile, averaged over the five characteristic-sorted portfolios. For liquidity characteristics, the table presents returns of the most liquid portfolios. We report t-statistics in parentheses that are Newey-West corrected. *, ** and *** indicate significance at the 10%, 5%, and 1% level, respectively.

(a) Canonical characteristics

	Low	2	3	4	High	High-Low	High-Low (4F alpha)
Size	0.30	0.50	0.11	0.15	-0.02	-0.32*	-0.27*
	(0.59)	(0.96)	(0.22)	(0.27)	(-0.04)	(-1.76)	(-1.67)
NYSE only	0.58*	0.47	0.55	0.14	-0.16	-0.74***	-0.58**
	(1.65)	(1.34)	(1.54)	(0.34)	(-0.36)	(-2.63)	(-2.12)
Small size	-0.08	0.42	-0.19	-0.11	0.17	0.25	0.22
	(-0.11)	(0.56)	(-0.26)	(-0.15)	(0.24)	(0.54)	(0.46)
2	0.23	0.47	-0.22	0.19	0.09	-0.14	-0.09
	(0.34)	(0.74)	(-0.33)	(0.29)	(0.15)	(-0.42)	(-0.29)
3	0.40	0.55	0.14	-0.01	-0.15	-0.55**	-0.51*
	(0.69)	(1.00)	(0.25)	(-0.02)	(-0.28)	(-2.01)	(-1.86)
4	0.47	0.51	0.41	0.29	0.01	-0.45**	-0.38*
	(1.02)	(1.01)	(0.81)	(0.57)	(0.02)	(-2.06)	(-1.90)
Large size	0.50	0.57	0.43	0.37	-0.23	-0.73**	-0.60*
	(1.47)	(1.55)	(1.16)	(0.89)	(-0.46)	(-2.13)	(-1.88)
Beta	0.39	0.36	0.54	0.25	-0.04	-0.43**	-0.41**
	(0.93)	(0.89)	(1.27)	(0.56)	(-0.09)	(-2.22)	(-1.98)
Book-to-market	0.56	0.61	0.43	0.26	-0.07	-0.63***	-0.59***
	(1.45)	(1.61)	(1.05)	(0.61)	(-0.17)	(-2.84)	(-2.64)
Momentum	0.65*	0.51	0.51	0.28	-0.19	-0.84***	-0.74***
	(1.66)	(1.30)	(1.18)	(0.60)	(-0.39)	(-3.41)	(-2.94)
Short-term reversal	0.55	0.43	0.48	0.09	-0.21	-0.76***	-0.69***
	(1.41)	(1.05)	(1.12)	(0.20)	(-0.42)	(-2.97)	(-2.80)

Table 4: Returns of portfolios sorted by stock characteristics and vol-of-vol (Continued)

(b) Return distribution characteristics

	Low	2	3	4	High	High-Low	High-Low (4F alpha)
Idiosync. volatility	0.32	0.37	0.26	0.07	-0.51	-0.83***	-0.72***
	(0.63)	(0.67)	(0.47)	(0.11)	(-0.82)	(-3.02)	(-2.69)
Maximum return	0.50	0.34	0.30	0.21	-0.32	-0.82***	-0.75***
	(1.09)	(0.76)	(0.63)	(0.44)	(-0.65)	(-3.51)	(-2.99)
Skewness	0.46	0.53	0.41	0.21	-0.31	-0.76***	-0.63**
	(1.17)	(1.38)	(0.99)	(0.46)	(-0.62)	(-2.72)	(-2.37)
Kurtosis	0.62	0.49	0.39	0.30	-0.18	-0.80***	-0.69**
	(1.62)	(1.30)	(0.95)	(0.69)	(-0.36)	(-2.84)	(-2.40)

(c) Liquidity characteristics

	Low	2	3	4	High	High-Low	High-Low (4F alpha)
Most liquid (Amihud)	0.57	0.52	0.50	0.17	-0.16	-0.72**	-0.59**
	(1.62)	(1.46)	(1.30)	(0.38)	(-0.31)	(-2.22)	(-2.09)
Most liquid (turnover)	0.71	0.89	0.47	0.10	-1.00	-1.71***	-1.52***
	(1.08)	(1.28)	(0.65)	(0.14)	(-1.30)	(-3.80)	(-3.40)
Option bid-ask spread	0.61	0.43	0.50	0.51	-0.07	-0.68**	-0.54**
	(1.59)	(1.12)	(1.25)	(1.18)	(-0.14)	(-2.46)	(-2.14)

(d) Option-based characteristics

	Low	2	3	4	High	High-Low	High-Low (4F alpha)
ATM skew	0.48	0.56	0.56	0.22	-0.32	-0.80**	-0.70**
	(1.29)	(1.40)	(1.35)	(0.48)	(-0.60)	(-2.44)	(-2.45)
OTM skew	0.31	0.40	0.15	0.12	-0.46	-0.76**	-0.64**
	(0.53)	(0.70)	(0.25)	(0.20)	(-0.69)	(-2.39)	(-2.04)
IV-RV spread	0.50	0.49	0.37	0.30	-0.20	-0.71**	-0.63**
	(1.29)	(1.20)	(0.89)	(0.67)	(-0.42)	(-2.58)	(-2.28)
Change in call IV	0.51	0.60	0.38	0.29	-0.15	-0.66***	-0.65**
	(1.18)	(1.40)	(0.90)	(0.67)	(-0.33)	(-2.75)	(-2.49)
Change in put IV	0.62	0.61	0.32	0.24	-0.06	-0.68***	-0.64**
	(1.46)	(1.44)	(0.78)	(0.59)	(-0.15)	(-2.69)	(-2.40)

Table 4: Returns of portfolios sorted by stock characteristics and vol-of-vol (Continued)

(e) Uncertainty-related characteristics

	Low	2	3	4	High	High-Low	High-Low (4F alpha)
Age	0.44	0.41	0.49	0.11	-0.29	-0.73***	-0.55**
	(1.04)	(0.85)	(1.04)	(0.21)	(-0.52)	(-2.67)	(-2.32)
Analyst coverage	0.33	0.32	0.24	-0.25	-0.38	-0.71***	-0.64***
	(0.71)	(0.65)	(0.44)	(-0.47)	(-0.71)	(-2.99)	(-2.65)
Forecast dispersion	0.59	0.70*	0.38	0.21	-0.16	-0.75***	-0.57**
	(1.45)	(1.77)	(0.89)	(0.44)	(-0.34)	(-2.80)	(-2.06)
Volatility	0.45	0.47	0.40	0.10	-0.28	-0.73***	-0.61**
	(0.89)	(0.92)	(0.79)	(0.18)	(-0.53)	(-3.06)	(-2.37)

(f) Other characteristics

	Low	2	3	4	High	High-Low	High-Low (4F alpha)
Private information	0.45	0.36	0.40	0.12	-0.01	-0.46**	-0.42**
	(1.24)	(0.97)	(1.07)	(0.30)	(-0.02)	(-2.31)	(-2.06)
Leverage	0.50	0.48	0.36	0.22	-0.22	-0.72***	-0.55**
	(1.29)	(1.22)	(0.85)	(0.48)	(-0.48)	(-2.95)	(-2.39)
Price response delay	0.50	0.38	0.51	0.24	0.06	-0.44**	-0.40**
	(1.32)	(1.08)	(1.38)	(0.59)	(0.14)	(-2.24)	(-2.11)
Short sale constraints	0.62*	0.54	0.49	0.26	-0.28	-0.90***	-0.78***
	(1.66)	(1.35)	(1.14)	(0.58)	(-0.57)	(-3.24)	(-2.98)

Table 5: Fama-MacBeth regression results

This table presents coefficient estimates from monthly Fama and MacBeth (1973) regressions over our sample period from January 1996 to October 2009. We regress excess stock returns over month $t+1$ against a constant, vol-of-vol, and a series of stock characteristics, all measured at the end of month t using a one-day implementation lag. The variable definitions are described in the Appendix. Vol-of-vol is past month's volatility of option-implied volatility (IV), standardized by average IV (see Section 2.2). IV is calculated from at-the-money call and put options with maturity closest to 30 days. All regressions are value-weighted as suggested by Asparouhova et al. (2010) to remediate microstructure noise. We report t-statistics in parentheses that are Newey-West corrected. *, ** and *** indicate significance at the 10%, 5%, and 1% level, respectively.

(a) Canonical characteristics

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Constant	0.008*	0.011***	0.006	0.003	0.006	0.008*	0.010
	(1.73)	(3.75)	(1.26)	(0.26)	(1.32)	(1.87)	(1.33)
Vol-of-vol	-0.041***	-0.036***	-0.041***	-0.036***	-0.041***	-0.039***	-0.030***
	(-3.34)	(-3.49)	(-3.42)	(-2.68)	(-3.45)	(-3.27)	(-2.80)
Beta		-0.002					-0.003
		(-0.75)					(-0.99)
Book-to-market			0.004				0.001
			(1.26)				(0.52)
Size				0.001			0.000
				(0.70)			(-0.05)
Momentum					0.000		-0.004
					(0.03)		(-1.31)
Short-term reversal						-0.003	-0.107*
						(-0.54)	(-1.76)
Adjusted R^2	0.002	0.050	0.011	0.019	0.017	0.013	0.081
Observations	170,720	170,720	170,720	170,720	170,720	170,720	170,720

Table 5: Fama-MacBeth regression results (Continued)

(b) Distribution-related characteristics

	(1)	(2)	(3)	(4)	(5)
Constant	0.028***	0.015**	0.011	0.011	0.028***
	(3.66)	(2.04)	(1.39)	(1.35)	(3.73)
Vol-of-vol	-0.030***	-0.068**	-0.030***	-0.031***	-0.031***
	(-2.79)	(-2.44)	(-2.81)	(-2.96)	(-3.19)
Beta	-0.001	-0.002	-0.003	-0.003	-0.000
	(-0.31)	(-0.75)	(-0.97)	(-0.98)	(-0.17)
Book-to-market	-0.001	0.001	0.001	0.001	-0.001
	(-0.31)	(0.28)	(0.57)	(0.51)	(-0.32)
Size	-0.101*	-0.000	-0.000	-0.000	-0.051**
	(-1.93)	(-0.48)	(-0.11)	(-0.07)	(-2.01)
Momentum	-0.004	-0.004	-0.004	-0.004	-0.003
	(-1.22)	(-1.28)	(-1.27)	(-1.35)	(-1.17)
Short-term reversal	-0.007*	-0.005	-0.107*	-0.107*	-0.007
	(-1.65)	(-1.21)	(-1.75)	(-1.77)	(-1.55)
Idiosync. volatility	-0.392**				-0.407**
	(-2.49)				(-2.46)
Maximum return		-0.140*			-0.005
		(-1.80)			(-0.28)
Skewness			-0.101*		-0.001
			(-1.91)		(-1.52)
Kurtosis				0.000	0.000
				(0.12)	(1.47)
Adjusted R^2	0.091	0.085	0.083	0.082	0.096
Observations	170,102	170,102	170,102	170,102	170,102

Table 5: Fama-MacBeth regression results (Continued)

(c) Liquidity characteristics

	(1)	(2)	(3)	(4)
Constant	0.016**	0.019**	0.004	0.003
	(2.07)	(2.56)	(0.52)	(0.42)
Vol-of-vol	-0.067**	-0.068**	-0.070***	-0.070**
	(-2.25)	(-2.14)	(-2.58)	(-2.36)
Beta	-0.003	-0.003	-0.003	-0.003
	(-1.01)	(-0.97)	(-1.09)	(-1.03)
Book-to-market	0.001	0.002	0.002	0.003
	(0.60)	(0.79)	(0.91)	(1.14)
Size	-0.001	-0.001	-0.001	-0.001
	(-0.88)	(-1.21)	(-0.90)	(-0.78)
Momentum	-0.005	-0.004	-0.106*	-0.105*
	(-1.51)	(-1.44)	(-1.86)	(-1.78)
Short-term reversal	-0.108*	-0.107*	-0.108*	-0.108*
	(-1.90)	(-1.73)	(-1.96)	(-1.89)
Amihud illiquidity	0.107			0.106
	(0.73)			(0.77)
Turnover		-0.001		-0.001
		(-1.09)		(-1.05)
Option bid-ask spread			0.050***	0.052***
			(6.08)	(6.32)
Adjusted R^2	0.084	0.088	0.085	0.095
Observations	163,439	163,439	163,439	163,439

Table 5: Fama-MacBeth regression results (Continued)

(d) Options-based characteristics

	(1)	(2)	(3)	(4)	(5)	(6)
Constant	0.002	0.002	-0.001	-0.001	0.001	0.000
	(0.17)	(0.18)	(-0.09)	(-0.08)	(0.07)	(0.02)
Vol-of-vol	-0.097**	-0.142**	-0.100**	-0.104**	-0.109**	-0.146**
	(-2.17)	(-2.05)	(-2.23)	(-2.35)	(-2.54)	(-2.03)
Beta	-0.002	-0.002	-0.002	-0.002	-0.002	-0.002
	(-0.55)	(-0.52)	(-0.47)	(-0.54)	(-0.61)	(-0.64)
Book-to-market	0.001	0.001	0.001	0.001	0.001	0.001
	(0.12)	(0.17)	(0.16)	(0.27)	(0.30)	(0.27)
Size	0.001	0.001	0.001	0.001	0.001	0.001
	(1.04)	(1.06)	(1.31)	(1.30)	(1.22)	(1.15)
Momentum	0.002	0.002	0.002	0.002	0.002	0.002
	(0.48)	(0.43)	(0.47)	(0.55)	(0.43)	(0.55)
Short-term reversal	-0.000	-0.001	0.000	0.000	-0.001	-0.001
	(0.00)	(-0.21)	(0.04)	(0.02)	(-0.11)	(-0.12)
ATM skew	0.024					-0.030
	(0.69)					(-0.95)
OTM skew		-0.027				-0.035
		(-1.06)				(-0.73)
IV-RV spread			0.002			0.003
			(0.29)			(0.39)
Change in call IV				-0.021		0.031
				(-1.49)		(0.94)
Change in put IV					-0.079**	-0.161*
					(-2.16)	(-1.93)
Adjusted R^2	0.104	0.103	0.103	0.105	0.104	0.118
Observations	42,867	42,867	42,867	42,867	42,867	42,867

Table 5: Fama-MacBeth regression results (Continued)

(e) Uncertainty characteristics and other characteristics

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Constant	0.010	0.014*	0.011	0.018**	0.011	0.028***	0.016**	0.011	0.034***
	(1.21)	(1.73)	(1.46)	(2.58)	(1.42)	(3.08)	(2.22)	(1.45)	(3.98)
Vol-of-vol	-0.031***	-0.030***	-0.030***	-0.069***	-0.028***	-0.030***	-0.031***	-0.030***	-0.067***
	(-2.92)	(-2.83)	(-2.81)	(-2.58)	(-2.68)	(-2.84)	(-2.99)	(-2.86)	(-2.60)
Beta	-0.003	-0.003	-0.002	-0.001	-0.003	-0.004	-0.004	-0.003	-0.003
	(-0.87)	(-1.01)	(-0.82)	(-0.62)	(-0.90)	(-1.22)	(-1.09)	(-0.94)	(-1.12)
Book-to-market	0.001	0.001	0.002	0.000	0.001	-0.000	0.001	0.001	0.000
	(0.38)	(0.41)	(0.76)	(0.18)	(0.30)	(-0.11)	(0.26)	(0.45)	(-0.08)
Size	-0.000	-0.001	-0.000	-0.001	-0.000	-0.001	0.000	0.000	-0.052**
	(-0.38)	(-0.93)	(-0.21)	(-0.90)	(-0.18)	(-1.30)	(-0.42)	(-0.20)	(-2.37)
Momentum	-0.004	-0.003	-0.004	-0.003	-0.004	-0.003	-0.003	-0.004	-0.004
	(-1.17)	(-1.10)	(-1.22)	(-1.09)	(-1.28)	(-1.13)	(-1.09)	(-1.17)	(-1.26)
Short-term reversal	-0.007	-0.007	-0.107*	-0.006	-0.007*	-0.006	-0.006	-0.007	-0.007
	(-1.61)	(-1.56)	(-1.70)	(-1.49)	(-1.65)	(-1.50)	(-1.52)	(-1.61)	(-1.62)
Age	-0.001								0.000
	(-1.14)								(-0.47)
Analyst coverage		0.000*							0.000*
		(1.82)							(1.87)
Forecast dispersion			-0.166						-0.193
			(-1.33)						(-1.63)
Volatility				-0.171					-0.104
				(-1.53)					(-1.04)
Leverage					-0.001				-0.002
					(-0.20)				(-0.52)
Private information						-0.061**			-0.060**
						(-2.08)			(-2.14)
Price response delay							-0.004		0.000
							(-1.10)		(0.15)
Short sale constraints								0.000***	0.000***
								(2.90)	(2.80)
Adjusted R^2	0.085	0.085	0.085	0.091	0.087	0.086	0.085	0.083	0.106
Observations	166,748	166,748	166,748	166,748	166,748	166,748	166,748	166,748	166,748

Table 6: Robustness checks

This table reports robustness results on the vol-of-vol effect. Vol-of-vol is past month's volatility of option-implied volatility (IV), standardized by average IV (see Section 2.2). IV is calculated from at-the-money call and put options with maturity closest to 30 days. The row labeled "Vol-of-vol" is taken from Table 2 and presents the average monthly excess returns (Excess returns) and four-factor alphas (4F alphas) on portfolio Low and portfolio High, after sortings stock in ascending order into quintile portfolios on the basis of vol-of-vol. Excess returns and alphas are calculated using a one trading day implementation lag and after value-weighing stocks in each portfolio. We also present the difference in excess returns and four-factor alphas between portfolio High and portfolio Low (High-Low). The row named "Deciles" presents excess returns and four-factor alphas after sorting stocks into ten portfolios instead of five. The row named "No sample screening" presents excess returns and four-factor alphas after including stocks with prices below \$5 and market capitalization below \$225 million. The row "Unscaled" presents excess returns and four-factor alphas without scaling vol-of-vol by average implied volatility. The row "OTM puts" presents excess returns and four-factor alphas after calculating vol-of-vol from out-of-the-money put options. The row "Industry neutral" presents excess returns and four-factor alphas after constructing industry-neutral vol-of-vol portfolios. We report t-statistics in parentheses that are Newey-West corrected. *, ** and *** indicate significance at the 10%, 5%, and 1% level, respectively.

	Excess returns			4F alphas		
	Low	High	High-Low	Low	High	High-Low
			Vol-of-vol			
	0.56	-0.21	-0.77**	0.17	-0.44**	-0.62**
	(1.52)	(-0.43)	(-2.50)	(1.07)	(-2.35)	(-2.14)
			Sample criteria			
Deciles	0.55	-0.34	-0.89**	0.12	-0.65***	-0.77**
	(1.40)	(-0.65)	(-2.57)	(0.69)	(-2.99)	(-2.42)
No sample screening	0.60	-0.22	-0.83***	0.22*	-0.45**	-0.68**
	(1.63)	(-0.46)	(-2.70)	(1.68)	(-2.43)	(-2.31)
			Vol-of-vol definitions			
Unscaled	0.47	-0.52	-0.99*	0.14	-0.86***	-1.00***
	(1.59)	(-0.73)	(-1.75)	(0.99)	(-3.35)	(-2.79)
OTM puts	0.60	-0.25	-0.84**	0.26	-0.51**	-0.76**
	(1.32)	(-0.43)	(-2.28)	(1.04)	(-2.08)	(-2.05)
Industry neutral	0.65*	0.01	-0.64***	0.23**	-0.38***	-0.61***
	(1.74)	(0.03)	(-4.16)	(1.99)	(-3.41)	(-4.01)

Table 7: The vol-of-vol effect across holding periods

This table presents average monthly excess returns and four-factor alphas after formation of portfolios sorted on vol-of-vol over our sample period from January 1996 to October 2009. Vol-of-vol is past month's volatility of option-implied volatility (IV), standardized by average IV (see Section 2.2). IV is calculated from at-the-money call and put options with maturity closest to 30 days. Each month we sort stocks in ascending order into quintile portfolios (Low, 2, 3, 4, and High) on the basis of vol-of-vol, and we hold these portfolios for 3 to 24 months. We use a one trading day implementation lag and value weight stocks in each portfolio. The table presents average portfolio excess returns (Excess return) and four-factor alphas (4F alpha) over these holding periods for portfolio Low and portfolio High, as well as the difference between portfolio High and portfolio Low (High-Low). We report t-statistics in parentheses that are Newey-West corrected. *, ** and *** indicate significance at the 10%, 5%, and 1% level, respectively.

	Excess return			4F alpha		
	Low	High	High-Low	Low	High	High-Low
Holding period 3 months	2.00*	0.34	-1.66**	0.81**	-0.56	-1.37**
	(1.86)	(0.24)	(-2.30)	(2.39)	(-1.36)	(-2.03)
Holding period 6 months	4.37**	1.47	-2.90**	2.04***	-0.28	-2.33**
	(-2.00)	(0.53)	(-2.38)	(3.55)	(-0.40)	(-1.98)
Holding period 9 months	6.59**	2.74	-3.85**	3.17***	0.03	-3.14*
	(2.03)	(0.67)	(-2.30)	(4.03)	(0.03)	(-1.94)
Holding period 12 months	8.35*	3.64	-4.71**	3.73***	-0.05	-3.78*
	(1.92)	(0.66)	(-2.13)	(3.63)	(-0.03)	(-1.82)
Holding period 24 months	14.17	7.92	-6.26*	5.28***	0.59	-4.69
	(1.64)	(0.76)	(-1.80)	(2.76)	(0.22)	(-1.35)

Table 8: Can deviations from fundamental value explain low returns on high vol-of-vol stocks? This table reports average monthly excess returns and four-factor alphas of portfolios sorted on short sale constraints or arbitrage risk and vol-of-vol, over our sample period from January 1996 to October 2009. Vol-of-vol is past month's volatility of option-implied volatility (IV), standardized by average IV (see Section 2.2). IV is calculated from at-the-money call and put options with maturity closest to 30 days. Short-sale constraints are proxied by residual institutional ownership and arbitrage risk is proxied by idiosyncratic volatility. Both are defined in the Appendix. Each month we sort stocks in ascending order into quintile portfolios on the basis of short-sale constraints (Low short-sale constraints, 2, 3, 4, High short-sale constraints; see panel (a)) or arbitrage risk (Low arbitrage risk, 2, 3, 4, High arbitrage risk; see panel (b)). Within each quintile, we further sort stocks into five additional portfolios based on vol-of-vol (Low, 2, 3, 4, High). We use a one-trading day implementation lag and value-weigh stocks in each portfolio. The table presents average excess returns of the twenty-five resulting portfolios, as well as the difference in monthly returns between portfolio High and portfolio Low (High-Low). The columns labeled "High-Low (4F alpha)" present the High-Low difference in four-factor alphas. We report t-statistics in parentheses that are Newey-West corrected. *, ** and *** indicate significance at the 10%, 5%, and 1% level, respectively.

(a) Short-sale constraints

	Low	2	3	4	High	High-Low	High-Low (4F alpha)
Low short-sale	0.15	0.42	0.17	-0.05	-0.24	-0.39	-0.38
constraints	(0.35)	(0.85)	(0.38)	(-0.10)	(-0.48)	(-1.08)	(-1.00)
2	0.36	0.61	0.21	0.11	-0.40	-0.76*	-0.57*
	(0.90)	(1.57)	(0.45)	(0.24)	(-0.74)	(-1.89)	(-1.67)
3	0.62	0.47	0.77*	0.34	0.00	-0.62*	-0.56*
	(1.55)	(1.18)	(1.71)	(0.70)	(0.00)	(-1.81)	(-1.71)
4	1.10**	0.90*	1.15**	0.88*	0.16	-0.94**	-0.81**
	(2.27)	(1.76)	(2.33)	(1.72)	(0.28)	(-2.16)	(-2.00)
High short-sale	0.88**	0.28	0.13	0.03	-0.92	-1.80***	-1.56***
constraints	(1.97)	(0.63)	(0.26)	(0.06)	(-1.51)	(-3.81)	(-3.56)
High-Low	-0.73**	0.14	0.04	-0.09	0.68*	1.41***	1.18***
	(-2.32)	(0.38)	(0.11)	(-0.21)	(1.73)	(3.04)	(2.67)

(b) Arbitrage risk

	Low	2	3	4	High	High-Low	High-Low (4F alpha)
Low arbitrage risk	0.63	0.31	0.76	0.45	-0.29	-0.92***	-0.91***
	(2.00)	(0.91)	(2.27)	(1.18)	(-0.80)	(-3.19)	(-3.17)
2	0.53	0.68	0.70	0.04	0.08	-0.45	-0.31
	(1.37)	(1.57)	(1.76)	(0.07)	(0.14)	(-1.12)	(-0.72)
3	0.76	0.91	0.36	0.51	-0.63	-1.39***	-1.17**
	(1.43)	(1.62)	(0.63)	(0.77)	(-1.06)	(-3.13)	(-2.53)
4	0.29	0.51	-0.01	0.34	-0.68	-0.97**	-1.00**
	(0.39)	(0.68)	(-0.01)	(0.43)	(-0.79)	(-2.21)	(-2.37)
High arbitrage risk	-0.61	-0.57	-0.51	-0.99	-1.02	-0.41	-0.20
	(-0.63)	(-0.58)	(-0.52)	(-0.92)	(-0.93)	(-0.67)	(-0.33)
High-Low	-1.24	-0.88	-1.27	-1.43	-0.73	0.51	0.71
	(-1.39)	(-1.04)	(-1.45)	(-1.54)	(-0.78)	(0.75)	(1.07)

Table 9: Can volatility risk exposure or jump risk exposure explain low returns on high vol-of-vol stocks? This table reports average monthly excess returns and four-factor alphas of portfolios sorted on exposures to jump risk or volatility risk and vol-of-vol, over our sample period from January 1996 to October 2009. Vol-of-vol is past month's volatility of option-implied volatility (IV), standardized by average IV (see Section 2.2). IV is calculated from at-the-money call and put options with maturity closest to 30 days. Each month we sort stocks in ascending order into quintile portfolios on the basis of jump risk exposure or volatility risk exposure. We use two proxies for volatility risk exposure and two proxies for jump risk exposure, each of which is defined in the Appendix. Within each quintile, we sort stocks into five additional portfolios based on vol-of-vol (Low, 2, 3, 4, High). We use a one trading day implementation lag and value-weigh stocks in each portfolio. The table presents the excess return of each vol-of-vol quintile over the subsequent month, averaged over the five volatility risk exposure or jump risk exposure portfolios. It also presents the difference between portfolio High and portfolio Low in excess returns (High-Low) and in four-factor alphas (High-Low (4F alpha)). We report t-statistics in parentheses that are Newey-West corrected. *, ** and *** indicate significance at the 10%, 5%, and 1% level, respectively.

(a) Volatility risk exposure

	Low	2	3	4	High	High-Low	High-Low (4F alpha)
S&P500 straddle betas	0.47	0.45	0.38	0.20	-0.18	-0.66***	-0.56**
	(1.18)	(1.12)	(0.88)	(0.45)	(-0.37)	(-2.71)	(-2.40)
ΔVIX betas	0.41	0.42	0.43	0.13	-0.17	-0.57**	-0.47**
	(1.01)	(1.05)	(1.04)	(0.28)	(-0.33)	(-2.42)	(-2.03)

(b) Jump risk exposure

	Low	2	3	4	High	High-Low	High-Low (4F alpha)
Δoption skew betas	0.50	0.46	0.28	0.30	-0.29	-0.78***	-0.64**
	(1.27)	(1.18)	(0.67)	(0.66)	(-0.57)	(-2.70)	(-2.30)
OTM put betas	0.61	0.44	0.43	0.10	-0.27	-0.89***	-0.78***
	(1.54)	(1.13)	(1.00)	(0.22)	(-0.54)	(-3.17)	(-2.71)

Table 10: Empirical test of vol-of-vol as a priced risk factor

This table presents test results on whether exposures to a vol-of-vol factor explain stock returns during our sample period from January 1996 to October 2009. Vol-of-vol is past month's volatility of option-implied volatility (IV), standardized by average IV (see Section 2.2). IV is calculated from at-the-money call and put options with maturity closest to 30 days. Each month we sort stocks into quintiles on the basis of vol-of-vol. We use a one trading day implementation lag and value-weigh stocks in each portfolio. We construct a monthly vol-of-vol factor from the difference between the High vol-of-vol portfolio and the Low vol-of-vol portfolio. Next, requiring at least 12 degrees of freedom, we measure exposure to the vol-of-vol factor as the sum the coefficients $\beta^V_{t-1} + \beta^V_{t-2}$ from the following regression:

$$r_{it} - r^f_t = \alpha + \beta^V_t r^V_t + \beta^V_{t-1} r^V_{t-1} + \beta^M_t (r^M_t - r^f_t) + \beta^M_{t-1}(r^M_{t-1} - r^f_{t-1}),$$

where r_{it} is the return of stock i, r^f_t is the risk-free rate, r^V_t is the daily return on the vol-of-vol factor, and r^M_t is the daily excess return on the market. Panel (a) reports the results of the single-sort portfolio analysis. Each month we sort stocks in ascending order into quintile portfolios (Low, 2, 3, 4, High) on the basis of the vol-of-vol characteristic as in Table 2 (Vol-of-vol characteristic), or on the basis of the estimated vol-of-vol exposure $\beta^V_{t-1} + \beta^V_{t-2}$ (Vol-of-vol beta). The table reports average excess returns of each portfolio over the subsequent month, as well as the difference in returns between portfolio High and portfolio Low (High-Low). The columns labeled "High-Low (4F alpha)" present the difference in four-factor alphas between portfolio High and portfolio Low. Panel (b) reports the results of the double sorts analysis. Each month we sort stocks in ascending order into quintile portfolios on the basis of the vol-of-vol characteristic. Within each quintile, we sort stocks into five additional portfolios based on the vol-of-vol beta. The row labeled "Average excess returns" presents the monthly excess return of each vol-of-vol quintile, averaged over the five vol-of-vol beta-sorted portfolios. The rows labeled "Portfolio averages" report the average *ex ante* vol-of-vol beta, the average *ex post* vol-of-vol beta, and the average *vol-of-vol* characteristic of each vol-of-vol quintile. We report t-statistics in parentheses that are Newey-West corrected. *, ** and *** indicate significance at the 10%, 5%, and 1% level, respectively.

(a) Single sorts analysis

	Low	2	3	4	High	High-Low	High-Low (4F alpha)
Vol-of-vol	0.56	0.46	0.44	0.16	-0.21	-0.77**	-0.61**
characteristic	(1.52)	(1.25)	(1.10)	(0.36)	(-0.43)	(-2.50)	(-2.01)
Vol-of-vol beta	0.63*	0.36	0.43	0.22	-0.27	-0.90	-0.68
	(1.70)	(1.08)	(1.12)	(0.46)	(-0.38)	(-1.40)	(-1.31)

(b) Double sorts analysis

	Low	2	3	4	High	High-Low	High-Low (4F alpha)
	Portfolio performance						
Vol-of-vol beta	0.58	0.43	0.24	0.27	-0.18	-0.77	-0.48
	(1.44)	(1.31)	(0.59)	(0.52)	(-0.23)	(-1.14)	(-0.89)
	Portfolio characteristics						
Ex ante vol-of-vol beta	-0.59	-0.20	0.07	0.32	0.83	1.43	
Ex post vol-of-vol beta	-0.26	-0.09	0.00	0.14	0.44	0.70	
Vol-of-vol characteristic	0.08	0.08	0.08	0.08	0.08	0.00	

Table 11: Distribution of monthly stock returns associated with varying levels of vol-of-vol

This table presents distribution characteristics for portfolios sorted on vol-of-vol over our sample period from January 1996 to October 2009. Vol-of-vol is past month's volatility of option-implied volatility (IV), standardized by average IV (see Section 2.2). IV is calculated from at-the-money call and put options with maturity closest to 30 days. Each month we sort stocks in ascending order into quintile portfolios (Low, 2, 3, 4, and High) on the basis of vol-of-vol. We use a one trading day implementation lag and value-weigh stocks in each portfolio. Panel (a) presents the mean (Avg), standard deviation (Std), minimum (Min), percentiles (P1-P99), and maximum (Max) of individual stock returns within each portfolio, as well as the difference in returns between portfolio High and portfolio Low (High-Low). Panel (b) presents the mean (Avg), standard deviation (Std), minimum (Min), percentiles (P1-P99), and maximum (Max) of the vol-of-vol quintile portfolios, as well as the difference in returns between portfolio High and portfolio Low (High-Low). The rows labeled "Buy-Sell" describe the returns distribution of the High-Low vol-of-vol portfolio (that buys the top quintile and sells the bottom quintile).

Panel (a): Cross-sectional distribution of individual stock returns

	Avg	Std	Min	P1	P5	P10	P25	P50	P75	P90	P95	P99	Max
Low	0.56	12.45	-40.63	-20.79	-12.42	-9.00	-4.26	0.42	5.32	10.41	13.89	23.17	49.42
2	0.46	12.35	-41.39	-20.44	-11.98	-8.95	-4.15	0.36	5.02	9.81	13.45	22.28	50.36
3	0.44	12.46	-42.80	-20.55	-12.46	-9.05	-4.21	0.35	5.15	9.94	13.35	22.33	50.93
4	0.16	12.53	-42.70	-20.56	-12.71	-9.64	-4.83	0.02	5.03	10.24	14.05	22.55	54.12
High	-0.21	12.87	-47.24	-23.42	-13.63	-10.21	-5.38	-0.30	5.02	10.25	14.39	23.24	55.65
High-Low	-0.77	0.41	-6.62	-2.63	-1.21	-1.21	-1.12	-0.72	-0.31	-0.16	0.50	0.08	6.23

Panel (b): Time-series distribution of portfolio returns

	Avg	Std	Min	P1	P5	P10	P25	P50	P75	P90	P95	P99	Max
Low	0.56	4.62	-18.43	-12.32	-6.38	-4.51	-2.01	0.97	4.35	6.24	7.57	9.40	10.46
2	0.46	4.56	-15.78	-10.91	-7.68	-4.59	-1.94	1.50	3.34	6.60	7.86	9.06	9.67
3	0.44	4.90	-15.59	-14.74	-8.33	-5.95	-1.88	0.76	4.10	6.32	8.24	9.28	11.53
4	0.16	5.30	-16.59	-14.15	-9.46	-6.71	-2.27	0.81	3.89	6.68	7.80	10.03	10.69
High	-0.21	6.06	-22.41	-17.45	-10.92	-7.07	-3.05	0.71	3.54	6.53	7.85	11.56	18.14
High-Low	-0.77	1.44	-3.98	-5.14	-4.54	-2.56	-1.05	-0.26	-0.81	0.29	0.27	2.15	7.67
Buy-Sell	-0.77	4.07	-19.91	-16.55	-6.42	-4.59	-2.52	-0.60	1.20	2.85	3.62	11.16	15.43