The VIX Premium

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May 2018

Ex-ante estimates of the volatility premium embedded in VIX futures, known as the VIX premium, fall or stay flat when ex-ante measures of risk rise. This is not an artifact of mismeasurement: 1) Ex-ante premiums reliably predict ex-post returns to VIX futures with a coefficient near one, and 2) Falling ex-ante premiums predict increasing ex-post market and investment risk, creating profitable trading opportunities. Falling hedging demand helps explain this behavior, as premiums and trader exposures tend to fall together when risk rises. These facts provide a puzzle for theories of why investors hedge volatility.

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I thank the editor (Stijn Van Nieuwerburgh), two anonymous referees, Jonathan Lewellen, Tobias Adrian, Hui Chen, Ian Dew-Becker, Thomas Eisenbach, Kenneth French, Harrison Hong, Nikunj Kapadia, Ian Martin, Scott Mixon, Philippe Mueller, Tyler Muir, Stefan Nagel, Martin Schmalz, Wei Xiong, and Fan Yang for several helpful comments. I also thank conference and seminar participants at Dartmouth College, Hong Kong University, Hong Kong University of Science and Technology, University of Massachusetts-Amherst, University of Utah, Financial Intermediary Research Society Meetings, Michigan Mitsui Finance Symposium, Northern Finance Association Meetings, and University of Connecticut Risk Management Conference. This draft subsumes a previous draft titled "The Expected Returns to Fear." This work was supported by research funds from the Tuck School of Business, Dartmouth College.

How much are people willing to pay to hedge fluctuations in stock market volatility? A growing body of research on the *variance risk premium* (VRP) suggests that the answer is a lot (Coval and Shumway, 2001; Bakshi and Kapadia, 2003). Figure 1 plots two sets of VRP estimates from Bollerslev, Tauchen and Zhou (2009) and Bekaert and Hoerova (2014), calculated as the risk-neutral (Q) minus physical (P) expectation of the 30-day variance of S&P 500 returns. The estimated premiums are positive on average and tend to be high around periods of market stress such as the 2008 financial crisis.

The dynamics of estimated premiums, however, contain a puzzle: during periods of market turmoil, sharp increases in realized variance have driven estimated premiums downwards, sometimes to negative levels, before rebounding (Bekaert and Hoerova, 2014). Because it is counter-intuitive for risk appetite to increase during these periods, the natural explanation for this behavior is that estimates of the VRP contain error from misspecified variance forecast models. Yet, as Bekaert and Hoerova point out, this puzzling behavior occurs in VRP estimates across many leading forecast models. This raises the question of whether this behavior is more systematic and whether it reflects mismeasurement.

This paper studies the *VIX premium*, which I define as the risk premium for uncertainty in the Chicago Board Options Exchange (CBOE) Volatility Index (VIX), a benchmark gauge of S&P 500 volatility. The VIX premium equals the risk-neutral minus physical expectation of the future value of the VIX. One important reason to study the VIX premium is that it governs pricing for what has become a major avenue for investors to hedge and speculate on volatility in practice: the VIX derivatives market. A second important reason is that readily available data allow me to jointly assess the link between ex-ante and ex-post behavior in premiums, risk, and market participants' positions. I use this to show not only that estimated VIX premiums have exhibited puzzling behavior akin to that above, but more importantly, that the evidence suggests this has reflected true variation in premiums, risk, and hedging demand.

Figure 2 plots estimated VIX premiums. Section 1 shows that, when several ex-ante measures of risk have risen, the estimated VIX premium has tended to fall or stay flat before rising later, behavior that I term the "low premium-response" puzzle. Section 2 provides two pieces of evidence that this has reflected true variation in ex-post premiums and risk. First, ex-ante estimated premiums reliably predict ex-post realized premiums with a coefficient near one: Low estimated premiums are typically followed by low realized premiums, and vice versa. If some estimated premiums are erroneously low when true premiums are high, or if there is uncorrelated measurement error, this should bias the coefficient towards zero. Instead, I find that VIX premiums predict ex-post monthly excess returns to VIX futures with a coefficient of 0.92 and standard error of 0.29. I use only out-of-sample information to estimate the VIX forecast model needed to calculate premiums. Results are similar across a wide range of forecast models, are robust to excluding the financial crisis, and hold at monthly, weekly, and daily frequencies. The sample is relatively short—2004 to 2015—but is sufficient to pick up the benchmark Bollerslev, Tauchen, and Zhou (2009) result that the 30-day VRP predicts stock market returns.

Second, falling estimated premiums predict increases in subsequent realized risk, both in the stock market and in VIX futures. That is, the low premium-response puzzle is not due to mismeasurement of ex-ante risk. This relationship has created opportunities for trading strategies to profitably exploit the low premium-response puzzle by using estimated VIX premiums as a signal of low-premium, high-risk situations. For an investor who is short VIX futures, reducing exposure when the estimated premium becomes negative has generated higher Sharpe ratios and alphas than a short-only strategy.

Section 3 provides evidence for an explanation of the low premium-response puzzle: risk shocks have acted to reduce volatility hedging demand. In the VIX futures market, hedging demand comes from the long side (who pays the premium), which the data suggest has been composed mainly of dealers in aggregate since the financial crisis. The short side supplies liquidity and earns the premium. Data on trader positions shows that premiums and market participants' futures exposures tend to fall together in response to risk shocks, suggesting a fall in hedging demand when risk rises. Dealer exposures and premiums also positively co-move, consistent with large movements in hedging demand in the sample. These patterns are consistent with extant evidence that demand movements influence premiums in derivatives markets (Barras and Malkhozov, 2016; Fan, Imerman, and Dai, 2016; Gârleanu, Pedersen, and Poteshman, 2009).

Section 4 shows that the VIX premium is related to the traditionally-studied 30-day VRP. The VIX premium compensates for uncertainty in future values of the VIX, which approximates (risk-neutral) conditional volatility. Consistent with this, options strategies that load on forward volatility hedge a substantial portion of VIX futures returns. However, the approximation error in the VIX clouds the exact relationship between estimates of the 30-day VRP and VIX premium, as the error can be significant (Aït-Sahalia, Karaman, and Mancini, 2015; Martin, 2017) and affects the interpretations of both estimates.

To make progress, I take a pragmatic approach. First, I show that, for the relevant short-term horizons, the VIX premium and 30-day VRP share a source of uncertainty, as uncertainty in future conditional volatility partially overlaps with uncertainty about realized volatility. Second, I show that VIX premium estimates directly correlate with leading estimates of the 30-day VRP. Finally, I show that the VIX premium, like the 30-day VRP, has explanatory power for other asset prices. The VIX premium shares some of the VRP's predictive power for market returns (Bollerslev, Tauchen, and Zhou, 2009), although the short sample is a significant caveat for drawing any stronger conclusions. The VIX premium is also correlated with corporate bond yields, sovereign CDS spreads, and foreign exchange carry returns, settings where research has shown the VIX or VRP is important.

A burgeoning line of previous work focuses on the properties of the synthetically estimated 30-day VRP such as those in Figure 1 (e.g., Carr and Wu, 2006, 2009; Drechsler and Yaron, 2011, in addition to several aforementioned papers). These estimates often rely on the squared VIX as an approximation to risk-neutral expected variance, and different forecast models for physical conditional variance. Testing whether ex-ante VRP estimates reflect ex-post returns to claims on realized variance (known as *variance swaps*) would shed light on the importance of error in explaining anomalous premium behavior. Observing more hedging demand as risk increases would provide further clues about the behavior of true premiums. However, there is scarce data on prices, returns, and positions in the over-the-counter variance swap market.

The main contribution of studying the VIX premium is to pull together evidence from return predictability, trading strategies, and trader positions from a central market for volatility to show that the low premium-response puzzle has reflected true variation in premiums and risk, rather than the null of mismeasurement, and that the behavior is associated with falling hedging demand. The evidence challenges our understanding of volatility premiums. Theories of why investors hedge volatility, including theories of long-run risk and rare disasters, predict that increases in risk in the economy (such as volatility, volatility-of-volatility, or jump risk) should drive up volatility premiums (Bollerslev, Tauchen, and Zhou, 2009; Dew-Becker, Giglio, Le, and Rodriguez, 2017; Drecshler and Yaron, 2011). Yet the estimated VIX premium has often initially fallen before subsequently rising in response to shocks to realized volatility, measures of volatility-of-volatility, and measures of jump risk. The evidence suggests that these theories are incomplete descriptions of investors' motives for hedging volatility, with implications I discuss in the conclusion.

1. The VIX premium and low premium-response puzzle

This section provides background on the VIX and its derivatives, before introducing the VIX premium. It then documents that ex-ante premiums tend to fall or stay flat when risk rises, a phenomenon I call the "low premium-response" puzzle.

1.1 Background

Market participants have long used the VIX to track volatility in financial markets. In 2003, CBOE reformulated the VIX in response to research suggesting that it was possible to compute the risk-neutral expectation of realized variance using option prices. In a world with a continuum of liquid strikes and where the S&P 500 evolves without jumps, a static portfolio of out-of-the-money-forward (OMTF) and at-the-money-forward (ATMF) puts and calls plus a dynamic position in an index futures can replicate realized variance over any horizon (Demeterfi, Derman, Kamal, and Zou, 1999; Britten-Jones and Neuberger, 2000). The VIX is the square root of the value of two such option portfolios interpolated to a 30-day horizon and, under the assumption of no jumps, equals:

$$VIX_t = \sqrt{E_t^Q\left[RVar_{t,t+30}\right]}, \tag{1}$$

where $RVar_{t,t+30}$ is the 30-day realized variance in the S&P 500 starting from date *t*.[1]

If the conditions underlying Equation 1 hold, the squared VIX equals the fair strike on a variance swap. Variance swaps are over-the-counter instruments with no up-front premium and whose payoff equals realized variance. By no-arbitrage, the fair strike on a variance swap equals $E_t^Q\left[RVar_{t,t+s}\right]$. Carr and Lee (2009) document a history of the development of the variance swap market, which grew in the late 1990's.

Reformulating the VIX linked it to forward-looking expectations of realized variance and volatility under less restrictive assumptions than its previous version. However, it is useful to distinguish between the VIX *formula*, given in CBOE (2014), as a definition, from the economic relationship in Equation 1, which is model-dependent. Because of jumps, Equation 1 is at best an approximation, and the error can be significant (Aït-Sahalia, Karaman, and Mancini, 2015; Carr and Lee, 2009; Martin, 2017; Andersen, Bondarenko, Gonzalez-Perez, 2015 discuss the effect of jumps and strike truncation in the VIX).

[1] More precisely, Equation 1 should refer to quadratic variation. Realized variance is a consistent estimator of quadratic variation (see, e.g., Andersen and Benzoni, 2009). I replace realized variance in Equation 1 for expositional simplicity (e.g., as do Carr and Wu, 2006, Eqs.8 and 17).

Recent research has nevertheless made extensive use of the modern squared-VIX as a synthetic estimate of risk-neutral conditional variance when estimating the 30-day variance risk premium, which equals $E_t^Q[RVar_{t,t+30}] - E_t^P[RVar_{t,t+30}]$ (e.g., Bekaert and Hoerova, 2014, Bollerslev, Tauchen, and Zhou, 2009, and Drechsler and Yaron, 2011).[2] One reason for this practice despite the approximation error in the VIX is the scarcity of transaction price data in the over-the-counter variance swap market.

These VRP estimates inform leading asset pricing models. In an important paper, Bollerslev, Tauchen, and Zhou (BTZ, 2009) substitute contemporaneous realized variance for $E_t^P[RVar_{t,t+30}]$, and show that the resulting 30-day VRP predicts next month's US equity market return. Along with Drechsler and Yaron (2011), they argue that this is consistent with an asset pricing model featuring long-run risk. Dew-Becker, Giglio, Le, and Rodriguez (2017) use proprietary OTC variance swap quotes to examine the term structure of variance swap prices, as do Aït-Sahalia, Karaman, and Mancini (2015) and Egloff, Leippold, and Wu (2010). They show that only risk on the short end of the term structure is priced, which they argue supports models of disasters with time-varying recovery rates (Gabaix, 2012).[3]

A sensible prediction across models that incorporate a volatility premium is that the premium should increase with risk.[4] The estimated variance risk premiums in Figure 1, however, have often fallen during periods of market turmoil when realized variance spikes, sometimes to even negative levels, a feature that Bekaert and Hoerova (2014, p.186) describe as a "disadvantage of all these models." As they note, the natural explanation is that physical forecast models used to calculate $E_t^P[RVar_{t,t+30}]$ do not adequately capture differing rates of mean-reversion for different components of realized variance. However, even their forecast models that allow for price jumps exhibit this behavior, raising the empirical question of whether this behavior reflects true variation in premiums and risk.

1.2 VIX derivatives

This paper studies the dynamics of volatility premiums in the context of VIX derivatives. CBOE launched futures and options markets linked to the modern VIX formula in March 2004 and February 2006, respectively. If the futures were instead a forward, the dollar payoff and profit of a long position on one dollar of notional equals $VIX_T - F_t^T$, where F_t^T is the forward price on date *t* with expiration date *T*, and

[2] Amengual and Xiu (2014), Kilic and Shaliastovich (2015), and Feunou et al. (2015) study components of variance.
[3] Kelly and Giglio (2016) find that the long-end of the term structure overreacts to shocks relative to the short-end.
[4] A long literature studies this prediction for the equity risk premium (see, e.g., French et al., 1987).

VIX_T is the VIX at date T (computed using a special opening quotation), both expressed as percentage points. Since November 2006, at least five continuous expiration months have been available to trade. Monthly contracts expire near the middle of the month to avoid interpolation in the VIX formula.

Under no-arbitrage, futures prices equal the risk-neutral expectation of the VIX, $F_t^T = E_t^Q[VIX_T]$. Unlike other financial futures, VIX futures prices do not equal the spot VIX adjusted by a cost of carry. Traders cannot statically carry the options underlying today's VIX_t to synthesize VIX_T because the underlying option portfolios on the two dates differ. Convexity, uncertainty about the ATMF strike price at expiration, and strike discretization also present barriers to broader strategies that synthesize VIX_T.

Morgan Stanley (2011) wrote in a note to clients that the VIX derivatives market was "by far the most liquid" for short-dated volatility views, and asset managers such as BlackRock took to advising their clients about VIX strategies (BlackRock, 2013). Variance swaps predate VIX derivatives and are a larger market overall, but much of the trading is in longer maturities. Dew-Becker, Giglio, Le, and Rodriguez (2017) estimate that the bulk of variance swaps traded in 2013 were for maturities between 6 months and 5 years. In contrast, the most active VIX futures contract is often the 1- or 2-month contract. Mixon and Onur (2014) use regulatory data to compare the two markets in 2013-2014, and find that the VIX futures market was twice the size of the variance swap market for contracts with less than 1 year to expiration.

A growing literature studies VIX derivatives. Mencía and Sentana (2013) review several structural pricing models. Park (2015) finds that information in VIX derivatives can lead the S&P 500 options market. Simon and Campasano (2014), Nossman and Wilhelmsson (2009), and Johnson (2017) find evidence supporting time-varying risk premiums by rejecting the expectations hypothesis (Fama, 1984; Mixon, 2007). Dong (2016) studies exchange-traded products linked to VIX futures. My contribution is to construct a direct measure of premiums to study its forecasting power and relate it to anomalous premium behavior.

1.3 The VIX premium

The VIX premium at date *t* with horizon *T-t* equals $VIXP_t^T \equiv E_t^Q[VIX_T] - E_t^P[VIX_T]$. It is the expected dollar loss for a long VIX futures contract position with \$1 notional value held through futures expiration date *T*; conversely, it is the expected dollar gain for a short position. The premium is compensation for uncertainty about future values of the VIX.

I estimate a daily (trading-day) time series of the VIX premium associated with an investment strategy that rolls the 1-month-ahead futures contract each month. I focus on this for several reasons. First, short-horizon premiums are economically interesting: Dew-Becker, Giglio, Le, and Rodriguez (2017) document that volatility premiums are largest on the short end of the term structure. Second, constructing premiums associated with a specific investment strategy facilitates comparing estimated ex-ante and realized ex-post premiums. Third, focusing on the time series of rolling VIX premiums makes the data comparable with other time series. The roll avoids illiquidity as contracts near expiration.

On any given trading date *t*, this strategy holds a position in a futures contract expiring 1-month ahead with expiration date $S^1(t)$. On the last trading day of a month, the strategy liquidates the position at close and re-establishes it in the 2-month-ahead contract expiring at $S^2(t)$ (the "roll"), which becomes the 1-month-ahead contract the following day. Defining $T(t) = S^1(t)$ except on the last day of the month when it is equal to $S^2(t)$, the VIX premium (scaled to one month) equals $\frac{21}{T(t)-t}\left[E_t^Q\left[VIX_{T(t)}\right] - E_t^P\left[VIX_{T(t)}\right]\right]$. A few early months in the sample do not have a contract expiring the next month. For these months, I modify the strategy and premium to reference the nearest available contract. In a typical month, the strategy invests in a new contract when it has 34 trading days to expiration and liquidates it with 13 days to expiration.

To estimate $E_t^Q\left[VIX_{T(t)}\right]$, I use futures prices $F_t^{T(t)}$ under the assumption of no-arbitrage. I estimate $E_t^P\left[VIX_{T(t)}\right]$ using multi-step forecasts of the VIX, $\widehat{VIX}_t^{T(t)}$, generated from a baseline ARMA(2,2) model (e.g., as in Mencía and Sentana, 2013; see Online Appendix for details of lag length selection). I emphasize that I estimate this model out-of-sample using pre-2004 daily data. The estimated process is:

$$VIX_t = \underset{(1.496)}{20.083} + \underset{(0.099)}{1.651}\,(VIX_{t-1} - 20.083) - \underset{(0.098)}{0.654}\,(VIX_{t-2} - 20.083) - \underset{(0.102)}{0.714}\,\varepsilon_{t-1} - \underset{(0.033)}{0.064}\,\varepsilon_{t-2} + \varepsilon_t.$$

ARMA models conveniently produce multi-step forecasts for all forecast horizons. The median forecast horizon at the end of each month is 34 trading days. Below, I show that results are robust to model choice.

Overall, on any trading date *t*, the estimated VIX premium $VIXP_t$ scaled to one month equals:

$$VIXP_t = \frac{21}{T(t)-t}\left[F_t^{T(t)} - \widehat{VIX}_t^{T(t)}\right]. \tag{2}$$

Data on futures settlement prices and the VIX come from Bloomberg. The data span monthly futures contracts with expirations between May 2004 and May 2016. The daily time series features 2,940 trading days between March 2004 and November 2015 when the S&P 500 was published. I aggregate to a time series of 608 trading weeks and 141 months. Weeks follow the Commodity Futures Trading Commission's Traders in Financial Futures (TFF) report, where I obtain data on positions used in Section 3.

Table 1 reports end-of-month summary statistics for the VIX and the estimated VIX premium, while Figure 2 plots the end-of-month estimated risk premium. The average end-of-month premium equals +0.70 points, smaller than average estimates of 30-day volatility risk premiums, a difference I discuss in Section 4. Importantly, however, there is substantial time variation in the premiums, which I turn to now.

1.4 The low premium-response puzzle

Figure 2 suggests visually striking episodes associated with fluctuations in the VIX premium. The most dramatic episode occurs during the financial crisis, when the premium begins falling in early September 2008 just as the crisis enters its most serious phase. Here, I explore whether this "low premium-response" puzzle – the tendency for premiums to fall, or stay flat, as risk rises – is systematic in VIX premiums.

Table 2 reports estimated coefficients from OLS regressions of monthly changes in the VIX premium on changes in risk measures *X*, controlling for three lags of changes of both:

$$\Delta VIXP_t = \alpha + \beta\, \Delta X_t + \sum_{k=1}^{3} (\gamma_k\, \Delta X_{t-k} + \delta_k\, \Delta VIXP_{t-k}) + \varepsilon_t. \tag{3}$$

(Note a slight abuse of notation: t denotes months; variables are as of the last trading day each month.) I test the hypothesis that increases in risk lead to increases in the VIX premium by examining whether $\beta > 0$. Table 2 presents estimates for several risk measures *X*, for which Table 1 reports summary statistics.

The first measure is monthly realized volatility, the square root of the sum of intraday 5-minute squared S&P 500 log price changes from 9:30am to 4:00pm Eastern time, plus close-to-open overnight returns, in a month (see, e.g., Andersen, Bollerslev, Diebold, and Ebens, 2001). I obtain intraday prices from TickData. The motivation is that realized volatility is a measure of market risk that does not mechanically contain information about premiums. Column 1 shows that a one-standard deviation (SD) change in realized volatility (6.4 percentage points) results in a 0.45-point drop in the VIX premium, or 0.43-SDs (a 1-SD change in the premium is 1.04 points). The estimated lag coefficients indicate that premiums subsequently increase, consistent with Todorov (2010). Columns 1a and 1b decompose the effect of realized volatility on premiums into its effect on the futures price, $F_t^{T(t)}$ and the VIX forecast, $\widehat{VIX}_t^{T(t)}$ to show that, contemporaneously, the futures price rises by less than the conditional forecast.

Realized volatility measures overall risk in the market, but not necessarily the risk underlying the variance risk premium. In theoretical models, volatility-of-volatility and jump risk drive the premium. For example, in the long-run risks model of Bollerslev, Tauchen, and Zhou (2009), a representative agent with Epstein-Zin-Weil recursive preferences pays a strictly positive premium to hedge against volatility fluctuations, and the premium is increasing in conditional volatility-of-volatility (their Equation 16). Similarly, the models of Drechsler and Yaron (2011, their Equation 22) and disaster risk models (Dew-Becker, Giglio, Le, and Rodriguez, 2017) feature a premium that increases in vol-of-vol or jump risks.[5] I use the CBOE VIX of VIX (VVIX) index as an indicator of volatility-of-volatility. The VVIX measures the risk-neutral volatility of the 30-day forward VIX.[6] For jump risk, I use the implied-volatility (IV) skew in the S&P 500 (SPX) options market (Bates, 2000; Constantinides and Lian, 2015; Andersen, Fusari, Todorov, 2015). I measure the skew as the difference in implied volatility of out-of-the-money-forward (OMTF) and at-the-money-forward puts in the nearest-expiring set of options. I pick the put option that is OTMF by 1.5 standardized moneyness units ($\frac{\ln(K/F)}{\sigma_{ATM}\sqrt{\tau}}$). Data on the VVIX, from Bloomberg, begins in 2006. Option prices through August 2015 come from OptionMetrics. The VVIX averages 86% (annualized) while the IV skew averages 6 percentage points.

Column 2 reports results for where I measure risk using the VVIX: a 1-SD change (14.0 points) is associated with a 0.36-point VIX premium decrease, or 0.35-SDs. Column 3 shows that, for the SPX IV skew, a 1-SD change is associated with a 0.46-SD decrease in the premium. Column 4 examines changes in the VIX itself, which several studies use to measure overall market stress (Adrian and Shin, 2010, Brunnermeier, Nagel, and Pedersen, 2009). Column 5 examines changes in the CBOE SKEW index, which measures risk-neutral skewness from option prices (Bakshi, Kapadia, and Madan, 2003). For these risk measures, a 1-SD increase is associated with a 0.35 and 0.24-SD premium decrease, respectively. The Online Appendix provides decompositions of these into effects on futures prices and VIX forecasts.

1.5 Further checks

[5]Disaster models include Gabaix (2012) and Wachter (2013). Other models include the intertemporal CAPM, financial intermediary distress (Barras and Malkhozov, 2016; Fournier and Jacobs, 2015), horizon-dependent risk aversion (Andries, Eisenbach, and Schmalz, 2014), Knightian uncertainty (Drechsler, 2013), and cumulative prospect theory (Baele et al., 2015).

[6]CBOE calculates the VVIX by applying the VIX formula to VIX option prices (CBOE, 2012, 2015a, 2015b), which settle in cash on the VIX at expiration and began trading in 2006. They are European-style, and a call option has a payoff equal to $100 \times \max\ (VIX_T - K, 0)$. Bakshi, Madan, and Panayotov (2014) and Huang and Shaliastovich (2014) study VIX option pricing.

These results suggest that the estimated VIX premium initially falls or stay flat before rising later when risk rises, posing a puzzle for standard models of risk and return. Sections 2 and 3 show that ex-post returns, risk, and trader positions are consistent with this anomalous behavior. However, before proceeding, I conduct several checks on the ex-ante relationship in Equation 3 and whether there is evidence of $\beta > 0$.

Is the behavior unique to the financial crisis? No. The crisis is the most prominent illustration of the behavior, but the phenomena exists even in the period from 2010-onward, which excludes the crisis entirely. Table 2, Columns 6-10 report coefficients from estimating Equation 3 in this shortened sample. The point estimates for the contemporaneous term are all negative, and while standard errors are naturally larger, several estimates are statistically reliably negative even with just half the sample. The economic magnitudes are -0.18, -0.28, -0.27, -0.13, and -0.28-SDs for realized volatility, the VVIX, SPX IV skew, VIX, and CBOE SKEW index, respectively. As before, several of these effects reverse over the subsequent months. The Online Appendix reports further results showing that premiums react negatively in the post-2010 sample for risk measures such as realized volatility at the weekly frequency. Figure 4, Panel B also plots the impulse response function of premiums from risk using only post-crisis data (estimated using VARs discussed later in this sub-section) and shows consistent results. Overall, a delayed or negative reaction of premiums to risk has been present in both the full and post-crisis sample.

Is the effect unique to the ARMA VIX forecast model? No. I examine VIX premiums associated with two groups of alternative models. The first group consists of realized variance or volatility models from Corsi (2009), Bekaert and Hoerova (2014, "winning" Models 8 and 11), and Bekaert, Hoerova, and Lo Duca (2013). These models use combinations of realized volatility and its continuous and discontinuous jump components (separated using threshold bi-power variation; see Corsi, Pirino, and Renò, 2010) at daily, weekly, and monthly frequencies, and the VIX itself. The second group augments the first with the average VIX over the past 5-, 10-, 22-, and 66-days. The idea is to adapt the insights of Corsi (2009) and heterogeneous auto-regressive (HAR) models into the VIX setting (Fernandes, Medeiros, and Scharth, 2014). Table 3, Panel A lists the alternative forecast models. I estimate each model using pre-2004 data.[7]

[7]The alternative models produce direct forecasts specific to a given horizon, not multi-step forecasts. I estimate every model for every possible horizon $T(t) - t$, ranging from 9 to 57 trading days, in the pre-2004 data.

Before estimating Equation 3, I first evaluate the (out-of-estimation-sample) post-2004 VIX forecast model performance in Table 3, Panel B. Following Bekaert and Hoerova (2014), I examine model stability using Chow tests, as well as forecast accuracy, measured by the root mean-squared error (RMSE), mean absolute error (MAE), and mean absolute percent error (MAPE). I focus on the 34-trading-day forecast horizon, corresponding to the median horizon for the investment strategy at the end of each month. I compare differences in forecast accuracy using Diebold and Mariano (1995) tests. I also compare the R^2 values of Mincer and Zarnowitz (M-Z) (1969) regressions of actual out-of-sample values on forecasts.

The best models in RMSE, MAE, MAPE, and M-Z R^2 fall in the second group, with values of 6.25, 3.74, 18.1%, and 55.9%, respectively. The values for the ARMA model are 6.31, 3.81, 18.8%, and 54.7%. These differences are economically small and statistically indistinguishable. Consistent with this, the correlation of ARMA forecasts with forecasts from these models is 99%. Part of the reason the ARMA model performs well is that negative MA coefficients reduce the influence of recent innovations to accurately track the overall mean reversion over the 34-day horizon.

Figure 3, Panel A plots the time series of estimated VIX premiums constructed from alternative forecasts of $E_t^P[VIX_{T(t)}]$. Table 3, Panel C reports estimates of Equation 3 for these premiums and for the realized volatility and VVIX risk measures. No model features a positive contemporaneous coefficient: all point estimates are negative, several are statistically reliably different from zero, and magnitudes are comparable with that of Table 2. I report results for the relationship with alternative models and other risk measures in the Online Appendix.

Including futures prices in the forecast should help forecast the VIX. However, including them would use portions of the in-sample period to estimate ex-ante premiums, shortening the already-short sample available to compare with ex-post out-of-sample premiums. Instead, the Online Appendix shows that, even with a forecast model estimated using all available data, futures prices (or another candidate predictor, the VVIX) are typically statistically insignificant in forecast models after conditioning on the above models' predictors. Premiums constructed from these models also exhibit delayed or negative responses to risk.

What about using information through each point in time? All VIX forecast models so far use only pre-2004 data as a stark way of using only out-of-sample information to construct $\widehat{VIX}_t^{T(t)}$. A rolling ARMA forecast model that uses information available up to but excluding date *t* should improve forecast estimates.

The Online Appendix shows that, if anything, the precision and magnitude of estimates change in a way that supports the thesis of the paper, including estimates for reactions of premiums to risk, the ability of premiums to forecast returns, and the relationship with hedging demand.

Is the effect unique to the 1-month premium? No. I compute premiums associated with rolling 2-, 3-, 4-, and 5-month-ahead contracts. To avoid ambiguity in the horizon, I restrict the sample to November 2006-onwards when I do not need to modify each strategy to account for missing months. The VIX premium for rolling *n*-month ahead contracts equals $VIXP_t^n = \frac{21}{T^n(t)-t}\left[F_t^{T^n(t)} - \widehat{VIX}_t^{T^n(t)}\right]$, where $T^n(t) = S^n(t)$, the *n*-month ahead futures expiration date, on every day of the month except the last, when it equals $S^{n+1}(t)$. Figure 3, Panel B plots the time series of estimated premiums. Premiums tend to be smaller in absolute value for larger *n*, consistent with Dew-Becker, Giglio, Le, and Rodriguez (2017). However, their dynamics are highly correlated. Estimating Equation 3 but replacing premiums with $VIXP_t^n$ reveals patterns consistent with the 1-month premium. For brevity, I report these results in the Online Appendix.

Is the effect robust to a vector-autoregression, at different frequencies, or in levels? Yes. The estimates in Table 2 do not allow for the dynamics of premiums to feed back into risk. I allow for this by estimating 4-lag monthly vector autoregressions (VAR) of risk and the VIX premium in levels. I order the risk variable first to assess the contemporaneous impact of risk on the premium. Figure 4 plots the response of the VIX premium to an orthogonalized 1-standard deviation realized volatility shock for the full sample (Panel A) and 2010-onwards sample (Panel B). The figure also plots impulse response functions from a weekly 8-lag VAR of the VIX premium and realized volatility. I use a factor of $\frac{5}{T(t)-t}$ instead of $\frac{21}{T(t)-t}$ in Equation 2 to scale the premium to one week and calculate weekly realized volatility as the sum of 5-minute intraday returns over the past 5 days before annualizing. For both VARs, the premium decreases on impact before rising again in the full sample. In the 2010-onwards sample, the initial decline in the premium reverses over the first month.[8]

[8] The Online Appendix reports the numerical 95% confidence intervals for the impulse response of premiums to risk measures at the finer weekly frequency. They suggest that while the premium falls on impact of a risk shock, point estimates recover by the end of the second month. Premiums then increase beyond zero, and we can reject the null that they equal zero by the end of the third month. Finally, the Online Appendix also reports results when ordering the premium first. By construction, there is no contemporaneous effect of risk on premiums, but a negative lag effect at the weekly frequency.

Is the effect specific to realized volatility? No. As noted in Section 1.4, an important observation is that conditional vol-of-vol and jump risk are closer to notions of risk in theoretical models of the variance risk premium, motivating the inclusion of the VVIX, implied volatility skew, and risk-neutral skewness in Tables 2 and 3. The Online Appendix shows that similar relationships also hold for the Du and Kapadia (2012) "JTIX" measure of jump tail risk. It reports several results for the entire paper when using several of these measures, and these results support the thesis of the paper. The drawback of these measures is that they are price-based, potentially contaminating the estimated relationship with premium dynamics.

2. Ex-post behavior of premiums and risk

This section shows that the low premium-response puzzle is not an artifact of mismeasurement. First, I show that ex-ante premiums predict ex-post price behavior. Second, I show that low premiums tend to forecast high ex-post volatility, and that there have historically been profitable trading strategies that can exploit this behavior.

2.1 Ex-post premiums

True ex-ante premiums should forecast realized premiums with a coefficient equal to one: high (large and positive) estimated ex-ante premiums should forecast high realized ex-post premiums, and vice versa. However, we only estimate true premiums with error, which should bias the predictive ability of estimated premiums away from one and towards zero. For example, one explanation for the low premium-response behavior is that some true premiums are in fact high when estimated premiums are low. If this is the case, some low estimated premiums should be followed by high realized premiums. Other measurement error uncorrelated with premiums also biases predictive coefficients towards zero, via a standard argument.

To test this, I work primarily in return space. To remove the effect of leverage, I examine "fully collateralized" futures excess returns. If t_1 refers to the trading date at the end of month t-1, and t_2 refers to the date at the end of month t, the excess return over month t for the rolling futures strategy defined in Section 1.3 equals $r_t = F_{t_2}^{T(t_1)}/F_{t_1}^{T(t_1)} - 1$.[9] From Table 1, the average monthly return was -3.5% with

[9] See, e.g., Etula (2013), Hong and Yogo (2014), and Singleton (2014, Appendix). More generally, given two dates t_1 and t_2, if a roll date does not fall strictly between two dates t_1 and t_2, the excess return equals between these two dates equals $r_{t_1,t_2} = F_{t_2}^{T(t_1)}/F_{t_1}^{T(t_1)} - 1$. If exactly one roll date t_r does fall strictly between, then $r_{t_1,t_2} = \frac{F_{t_2}^{T(t_r)}}{F_{t_r}^{T(t_r)}}\frac{F_{t_r}^{T(t_1)}}{F_{t_1}^{T(t_1)}} - 1$. I use these to define daily, weekly, and monthly returns. Given that the strategy rolls at the end of the month, the first case applies for monthly returns.

17.5% volatility (61% annualized), or an annualized Sharpe ratio of -0.68. The comparable Sharpe ratio for US equities was 0.51, where I obtain US equity market returns from the website of Kenneth R. French. The Online Appendix describes factor return loadings.[10]

I convert the estimated VIX premium to an estimated expected return. If t_1 refers to the trading date at the end of month *t*-1, the expected return for month *t* estimated at *t*-1 equals:

$$VIXR_{t-1} = \left[\frac{\widehat{VIX}_{t_1}^{T(t_1)}}{F_{t_1}^{T(t_1)}}\right]^{\frac{21}{T(t_1)-t_1}} - 1. \tag{4}$$

True expected returns should forecast r_t with a coefficient of one: large negative expected returns should forecast large negative realized returns. The error-based explanation for the low premium-response puzzle, translated into return space, is that some true expected returns are large and negative when estimated expected returns are less-negative or even positive (above-average). If this is the case, some above-average expected returns should be followed by large-negative realized returns, biasing the predictive relationship towards zero. Uncorrelated measurement error also biases predictive coefficients towards zero.

In practice, the coefficient may deviate from one because I roll contracts before expiration and premiums may not be earned linearly. As I discuss below and in the Online Appendix, this does not appear to affect results. I calculate $VIXR_{t-1}$ using only month *t*-1 data. The following example illustrates the timing. In June (month *t*), the strategy holds the futures contract expiring in the middle of July. As of the end of May (date t_1 in month *t*-1), the expected return $VIXR_{t-1}$ takes the VIX forecast for the July expiration date ($T(t_1)$) and scales it by the July futures price, $F_{t_1}^{T(t_1)}$ using Equation 4. This estimate in May should then forecast the June return of the investment strategy with a coefficient of 1.

Table 4 reports estimates from predictive time series regressions of the form:

$$r_t = \alpha + \beta\, VIXR_{t-1} + \gamma\, Z_{t-1} + \varepsilon_t, \tag{5}$$

where Z_{t-1} denotes control variables. Row 1 begins with the simple univariate regression. The estimated coefficient β equals 0.92 with a Newey and West (1987) standard error of 0.29 when using 3 lags with an

[10] Factor return data are from the website of Kenneth R. French. The CAPM beta equals -3.2 (standard error, or s.e.: 0.46). There are modest but statistically unreliable loadings on HML and SMB (Fama and French, 1992, 1993), momentum (Jegadeesh and Titman, 1993; Carhart, 1997), liquidity innovations (Pastor and Stambaugh, 2003), or time series momentum (Moskowitz, Ooi, and Pedersen, 2012). The R-squared from the CAPM model is 59% and is insensitive to the inclusion of additional factors. Returns load on volatility with statistical and economic significance.

R-squared of 8.8%. Figure 5 plots this predictive relationship. Visually, there is little evidence that the low premium-response is due to measurement error: less-negative (or positive) expected returns are followed by less-negative (or positive) realized returns. Row 2 tests for non-linearities in predictive power by including an interaction of the expected return with its sign. Allowing for a slight abuse of notation, it reports estimates of:

$$r_t = (\alpha + \delta\, \mathbf{1}[VIXR_{t-1} > 0]) + (\beta + \gamma\, \mathbf{1}[VIXR_{t-1} > 0])\, VIXR_{t-1} + \varepsilon_t.$$

If positive expected returns were followed by large-negative realized returns, we should observe negative γ. Instead, the point estimate is positive and statistically indistinguishable from zero.

To interpret these results further, consider again Columns 1a and 1b of Table 2, which suggest that futures prices rise by less than the conditional forecast in response to a risk shock. For a large shock, the forecast increases so much more than the futures price that the premium becomes negative (and expected returns become positive). If this were due to erroneous behavior in the forecast, we should expect futures prices to fall over the next month. Instead, Figure 5 and Table 4 suggest that futures prices tend to rise.

Robustness. Predicting returns is a tricky business; Table 4 includes several robustness checks. Row 3 investigates the role of Stambaugh (1986, 1999) bias. Although the persistence of the premium is modest, accounting for bias using the Kendall (1954) approximation pushes the coefficient to 0.94 with standard error 0.30. Row 4 examines the predictability in the post-2010 period, which uses only half the sample and excludes the financial crisis. The estimated coefficient is 1.20 with a standard error of 0.41. Row 5 shows that the effect is not a one-day microstructure effect and is not due to a shared denominator in both the left- and right-hand side variables, as I omit the first day of the following month for returns.

Rows 6-8 show that the predictive relationship is not subsumed by volatility-related premiums or volatility forecasts. Controlling for the expected VIX change (expressed as a percentage change calculated using Equation 4 but with VIX_t in the denominator), the level of the VIX, or the Bollerslev, Tauchen, and Zhou (2009) VRP yield comparable results.

Rows 9-14 show that the choice of forecast model is largely immaterial among the well-fitting choices in Group 2 of Table 3. Premiums calculated from these models reliably forecast returns: no point estimate is more than one standard error away from 1, and all are almost 3-standard errors away from zero.

Rows 15-16 show that the VIX premium predicts weekly and daily returns with coefficients near one. For these two tests, I re-scale the premium in Equation 4 using a factor of $5/(T(t)-t)$ for the weekly frequency and $1/(T(t)-t)$ for the daily frequency.

Rows 17 and 18 report results in premium space rather than return space. Estimated premiums in Equation 2 predict realized premiums. Given the roll, the monthly realized premium equals the negative futures price change, $F_{t_1}^{T(t_1)} - F_{t_2}^{T(t_1)}$, the realized dollar profit to a short position on one dollar of notional.

Rows 19-23 examine how far out the predictability persists by testing whether the premium predicts returns at *t*+5. At the monthly frequency, there is no reliable predictability 5 months out; in general, the predictability is strongest over the first month. There is reliable predictability for week *t*+5 or day *t*+5 returns, even within the 2010-onwards subsample.

I report three more checks in the Online Appendix. First, I show that predictability occurs through "alpha" and is not subsumed by time-varying market exposures across a wide range of factor models. Second, I show that predictability exists across the term structure. Third, I show that the predictability is not driven by the way the investment strategy rolls contracts each month. Premiums that do not include the scaling factor in Equation 4 predict hold-to-maturity returns for contracts at several horizons with coefficients close to one.

2.2 Ex-post risk

The low premium-response puzzle suggests that when risk rises, premiums increase at best with a delay, often falling initially. However, the estimates in Table 2 rely on ex-ante measures of risk. In this sub-section, I show that falling premiums if anything reflect higher ex-post risk. This provides evidence that the low premium-response puzzle is not due to mismeasurement of ex-ante risk. Combined with the evidence from Table 4, it also shows that timing strategies could have historically profited from low premium-responses.

Table 5 reports estimates from the following OLS regression at the monthly frequency:

$$\Delta X_t = \alpha + \sum_{k=1}^{3} (\beta_k \, \Delta VIXP_{t-k} + \gamma_k \, \Delta X_{t-k}) + \varepsilon_t, \tag{6}$$

for measures of realized risk X_t. Note the difference with Equation 3, which examines how changes in ex-ante risk measures contemporaneously affect premiums. Here, I turn the exercise around and examine whether changes in premiums *predict* future realized risk. I focus on realized market volatility and the realized risk of the investment strategy, calculated as the square root of the sum of daily squared changes in log futures prices.

If a fall in premiums forecasts a fall in risk, we should see $\beta_k > 0$, but the estimates offer very little support for this hypothesis. Point estimates for β_1 are negative for both realized market and investment risk and are reliably different from zero. In terms of economic significance, the estimates in Columns 1 and 2 suggest a one-standard deviation decrease in the VIX premium is predicts a 16-percentage-point rise in the annualized realized risk of the investment strategy, and a 3-point increase in market realized volatility. The unconditional realized volatilities of the two are 61% and 15%, respectively. Columns 3 and 4 repeat this exercise in the 2010-onwards sample. If anything, falling premiums predict higher risk.

This evidence also suggests that the low premium-response is tradable. Premiums and risk do not move together, and if anything, have moved with the opposite sign. A short investor who sees estimated premiums falling can close their position and sidestep ex-post low-profit, high-risk situations. This logic echoes Moreira and Muir (2016), who find that reducing market exposure when volatility is high earns higher returns due to a fall in the price of risk.

To operationalize this logic, I construct trading strategies that time investments in futures using a simple signal: the sign of the VIX premium. These strategies are rudimentary but illustrate the point and do not require any in-sample data to estimate the trading rule, as they simply compare the estimated premium with zero. I monitor the strategy daily and either open, maintain, or close positions at the end of date *t* based on the date *t*-1 VIX premium, $VIXR_{t-1}$. Any newly opened or maintained position is held over date *t*+1 before the decision is repeated. If a position is open at the end of the month, I roll it into the next contract. I assume trading started on March 26, 2004, and that transactions happened at the daily bid/ask prices from Bloomberg. The median spread was 5 cents (32 basis points) of the mid-price.

I consider five timing strategies: long/long (L/L), short/short (S/S), long/cash (L/C), cash/short (C/S), and long/short (L/S). The first term specifies the desired position when $VIXR_{t-1}$ (the futures expected return) is positive, and the second term specifies the desired position when $VIXR_{t-1}$ is negative. I keep any margin invested in a risk-free asset. The L/L and S/S strategies are always-long and always-short, respectively, while the L/C, C/S, and L/S strategies employ timing. I lever each strategy down so that it has approximately the same unconditional return volatility as the S&P 500. The delevering is approximate because exposures may fluctuate between trade dates.

Figure 6 plots the log margin growth for the C/S, S/S, and L/S strategies. Visually, shorting VIX futures (S/S) earns high returns at the expense of large drawdowns around events like the 2008 financial crisis and 2011 European debt crisis, while timing the market with the C/S and L/S strategy mitigates losses or even benefits around these events by keeping the investment parked in cash or in a long position in VIX futures.

Table 6, Panel A, reports summary statistics associated with each strategy. As a benchmark, the total return to the S&P 500 earned a Sharpe ratio of +0.41 during this period (Column 1). Long-only and short-only VIX futures strategies earned annualized Sharpe ratios of -0.78 and +0.57, respectively (Columns 2 and 3). Closing the short when the premium is negative improves Sharpe ratios, consistent with the discussion above—the C/S strategy earns a Sharpe ratio of +0.87 (Column 5). The results from the L/C and L/S strategies (Columns 4 and 6) suggest that the long leg does not improve the Sharpe ratio over the C/S strategy. The logic above explains why: when premiums have fallen far enough so that expected returns are positive (and the strategy goes long), subsequent investment volatility is high.

Rather than examining Sharpe ratios, I also examine alphas. I take the daily returns to the five strategies above and compute their alphas and factor loadings relative to a four-factor model in Table 6, Panel B. The C/S and L/S strategies earn annualized alphas of 11.6% and 14.6%, respectively, twice the magnitude of the always-short S/S strategy, with a lower beta. Table 7 provides an alternative perspective on this by examining how alpha and loadings of the strategies vary with whether the trading signal at date *t*-2 indicates the strategy should hold futures long or short over date *t*. Column 1 shows that, for the L/L strategy, holding long when the signal said short earns -17% annualized alpha, but holding long when the signal said long improves this by 28%. Column 2 (S/S) analogously shows that holding short when the signal said long is costly. Column 3 examines the L/S strategy which trades on the signal and incurs the associated transaction costs. The strategy provides an annualized alpha of 10.9% that is not statistically different whether the strategy is long or short. (The table omits the L/C and C/S strategies as the loadings and alpha when these strategies are in cash are identically zero.) The Online Appendix contains further analysis that breaks down the strategy profitability using time-varying loadings on conditional risk measures such as the VVIX. Overall, the evidence suggests that strategies that use the VIX premium as a trading signal generate alpha.

Returning to Table 6, Panel A also shows the skewness, kurtosis, and maximum drawdowns for each strategy, as Sharpe ratios and alphas do not fully capture performance for nonlinear strategies (Broadie, Chernov, and Johannes, 2009; Constantinides, Jackwerth, and Savov, 2013). The C/S strategy featured less left skew and a lower maximum drawdown than the always-short S/S.

The Online Appendix reports how the strategies fare excluding the financial crisis. Starting in 2010, the C/S and L/S strategies had positive alphas and Sharpe ratios higher than the S&P 500, but the differences are more modest. The C/S and L/S strategies both had Sharpe ratios of +0.96, with annualized four-factor alphas of +9.6% (s.e.: 6.9%) and +17.9% (s.e.: 8.7%), respectively. These strategies outperformed the S/S strategy, which had a Sharpe ratio of +0.71 and four-factor alpha of -0.90% (s.e.: 6.1%).

3. Trader positions and hedging demand

This section provides evidence for an equilibrium explanation of the low premium-response puzzle: a fall in demand from long hedgers when risk rises.

3.1 A conceptual framework

I introduce a simple framework adapted from Cheng, Kirilenko, and Xiong (2015) to provide two intuitions for how data on trader positions inform the low premium-response puzzle. First, if one takes downward-sloping demand curves as given, a positive correlation between changes in premiums and long hedging positions implies that large movements in hedging demand have occurred in the data, even if liquidity supply shifts also occurred. However, this does not isolate the role of the risk shock. Risk shocks could induce premiums to fall through an increase in liquidity supply or fall in hedging demand. The second point is that falling trader exposures indicate that the risk shock acts through a hedging demand channel.

Consider two groups of traders: a group of long hedgers h who pay a hedging premium, and a group of short liquidity suppliers s who earn the premium. In the data, as I show below, the long side is often composed of dealers or asset managers in aggregate post-2010, while the short side is composed of managed money and hedge funds. I consider only one period (out of possibly many) during which shocks generate trade. The demand curves of the two groups are:

$$dx_h = -\beta_h dP - \gamma_h z - u_h,$$

$$dx_s = -\beta_s dP + \gamma_s z + u_s,$$

where dx_h and dx_s are the changes in futures positions of the long hedgers and liquidity suppliers. dP is the change in premium. β_h and β_s are the demand curves' sensitivity to the premium and determine the ability of each group to absorb the other group's trades. This framework is agnostic about the origins of downward-sloping demand curves, for which there are many theories and much evidence (Acharya, Lochstoer, and Ramadorai, 2013; Bollen and Whaley, 2004; Constantinides and Lian, 2015; Gârleanu, Pedersen, Poteshman, 2009), but takes them as given instead by assuming $\beta_h, \beta_s \geq 0$.

I allow for three types of shocks. First, idiosyncratic hedging shocks u_h cause hedgers to reduce their long futures positions. Second, idiosyncratic reductions to liquidity supply u_s cause suppliers to reduce (buy back) their short positions. Finally, a systematic shock z motivates both hedgers and liquidity suppliers to reduce their long and short exposures, respectively (with $\gamma_h, \gamma_s \geq 0$). One can think of z as a shock to the market that leads all groups to want to exit their positions, e.g., during a period of market turmoil.

Market clearing implies that $dx_h + dx_s = 0$. Equilibrium premium and quantity movements are:

$$dP = \frac{1}{\beta_s + \beta_h}[-(\gamma_h - \gamma_s)z - u_h + u_s], \tag{7}$$

$$dx_h = \frac{1}{\beta_s + \beta_h}[-(\gamma_s\beta_h + \gamma_h\beta_s)z - \beta_s u_h - \beta_h u_s], \tag{8}$$

$$dx_s = -dx_h = \frac{1}{\beta_s + \beta_h}[(\gamma_s\beta_h + \gamma_h\beta_s)z + \beta_s u_h + \beta_h u_s]. \tag{9}$$

The covariance between long hedgers' equilibrium positions and premiums equals:

$$Cov(dx_h, dP) = \frac{1}{(\beta_s+\beta_h)^2}[(\gamma_s\beta_h + \gamma_h\beta_s)(\gamma_h - \gamma_s)Var(z) + \beta_s Var(u_h) - \beta_h Var(u_s)]. \tag{10}$$

Equations 7 through 10 suggest two tests. First, Equation 10 suggests that, if $Cov(dx_h, dP) > 0$, premiums moved largely because of either hedging reductions u_h or z shocks that affect long hedgers more than liquidity suppliers ($\gamma_h > \gamma_s$). In other words, a hedging demand shift "*must* have occurred" (Cohen, Diether, Malloy, 2007), even if liquidity supply shifts also occurred. Intuitively, premiums and exposures can fall together only if hedging demand falls, either from u_h or z.

Second, we can use Equations 7 and 8 to tease out whether risk shocks affect premiums through a hedging demand or liquidity supply channel. Since premiums fall when risk rises, Equation 7 tells us that risk shocks effectively act through: 1) positive u_h shocks, 2) positive z shocks with $\gamma_h > \gamma_s$, 3) negative u_s shocks, or 4) negative z shocks with $\gamma_h < \gamma_s$. Cases 1 and 2 relate to hedging demand shocks, while Cases

3 and 4 relate to liquidity supply shocks. Equation 8 sorts this out: If the long side reduces exposures, this excludes the liquidity supply cases 3 and 4. Intuitively, a risk shock that leads premiums to fall should also lead exposures to rise if it acts through a liquidity supply channel.[11]

In this framework, all movements in premiums arise through movements in demand. This is an illustrative simplification. In reality, falling demand may work to suppress or delay increases in premiums associated with risk. The framework and subsequent evidence here is consistent with the thesis that demand and supply shifts affect volatility premiums. Fan, Imerman, and Dai (2016) show that the sign of their synthetic 30-day VRP estimates are related to gains and losses of market-makers' delta-hedged positions, extending logic from Bakshi and Kapadia (2003). Barras and Malkhozov (2016) also find that deteriorations in intermediary health lead to larger differences between two sets of VRPs estimated from options and stocks. More broadly, the option-pricing literature has long recognized that supply and demand and intermediary health influence option prices (Chen, Joslin, and Ni, 2016; Ni, Pan, and Poteshman, 2008; Pan and Poteshman, 2006, in addition to aforementioned papers). I link explicit measures of positions in VIX futures to premiums to offer an equilibrium explanation for the low premium-response puzzle.

3.2 Results

The Commodity Futures Trading Commission (CFTC) publishes a weekly Traders in Financial Futures (TFF) report that summarizes long and short futures positions for aggregate trader groups. The groups are dealers, asset managers (institutional investors, pension funds, or insurance companies), leveraged funds (hedge funds), other reportable traders (e.g., corporate treasuries, small banks, or other financial traders), and non-reportable traders (small traders). The Online Appendix reproduces the exact definitions.

Figure 7 plots the weekly net exposures (long minus short position) for different trader groups. One contract is $1,000 per VIX point, so the vertical axis is also the net notional value in millions. The first key takeaway is that there have been systematic patterns in who is long and who is short, consistent with hedging behavior. Since 2010, dealers and asset managers tend to be net long, while hedge funds tend to short

[11] These tests do not require the assumption that market risk shocks are exogenous in affecting one group but not the other. If risk shocks act through a z shock, the tests identify the sign of $\gamma_h - \gamma_s$ but not the magnitude. Estimating the true structural difference $\gamma_h - \gamma_s$ requires an instrumental variables approach. Heuristically, the first step would be to find an idiosyncratic hedging shock u_h that identifies β_s by estimating $-Cov(dx_s, u_h)/Cov(dP, u_h)$; that is, by using u_h as an instrument in the first stage for endogenous variable dP where the second stage dependent variable is dx_s. The second step would be to find an idiosyncratic liquidity supply shock u_s that identifies β_h by estimating $-Cov(dx_h, u_s)/Cov(dP, u_s)$. One can then estimate $\gamma_h - \gamma_s = -\frac{Cov(dP,z)}{Var(z)}(\beta_s + \beta_h)$. The need for two instrument variables arises because z is a common shock to both trader groups.

volatility (Jurek and Stafford, 2015). I focus on this period as there is more stable trading behavior and because the CFTC did not disclose positions in the TFF between January and May 2009.

The second key takeaway is that positions change significantly through time. Table 8 shows that changes in trading positions are correlated with fluctuations in VIX premiums. It reports estimated coefficients from a regression of weekly changes in net positions for each trader group i, ΔPos_t^i, on weekly changes in the VIX premium, controlling for three lags of each:

$$\Delta Pos_t^i = \alpha + \sum_{k=0}^{3} \beta_k \, \Delta VIXP_{t-k} + \sum_{k=1}^{3} \delta_k \, \Delta Pos_{t-k}^i + \varepsilon_t. \tag{11}$$

To trace out dynamics, I allow for both contemporaneous and lagged effects β_k of the premium on positions. The table shows that dealers and asset managers tend to expand long futures positions as the premium rises ($\beta_k > 0$), while hedge funds and other reportable traders expand short futures positions ($\beta_k < 0$). In terms of the framework above, these results suggest that $Cov(dx_h, dP) > 0$.[12]

Table 9 examines how trader group positions react to risk. For each trader group i, I estimate the relationship between position changes ΔPos_t^i and changes in risk variables ΔX_t, controlling for three lags of changes in risk, changes in positions, and futures price changes ΔF_{t-k}, at the weekly frequency in the following OLS regression:

$$\Delta Pos_t^i = \alpha + \sum_{k=0}^{3} \beta_k \, \Delta X_{t-k} + \sum_{k=1}^{3} (\gamma_k \, \Delta F_{t-k} + \delta_k \, \Delta Pos_{t-k}^i) + \varepsilon_t. \tag{12}$$

I allow for both contemporaneous and lagged effects β_k of risk on positions. I control for futures price changes (the dollar gain/loss to a long position over the week to the rolling investment strategy) because it is well known that hedge funds in futures use trend-following strategies (Fung and Hsieh, 2001; Moskowitz, Ooi, and Pedersen, 2012). For brevity, the table focuses on weekly realized volatility as the measure of risk, as it does not mechanically contain information about premiums; the Online Appendix reports estimates when using the VVIX as a measure of risk.

The table shows that increases in risk tend to lead to reductions in long positions by dealers and asset managers, and reductions in short positions by hedge funds. In terms of economic significance, a 1-SD

[12] From the market-clearing condition, we expect the cross-trader-group sum of coefficients to equal zero, as trader groups' responses "mirror" each other ($dx_h = -dx_s$). Intuitively, if one trader group buys in response to a shock, another group must sell, and estimated coefficients reflect this. In Table 8, cross-trader-group coefficients need not sum to exactly zero because control variables are different for each trader group's regression and because there are more than 2 trader groups. Specifically, each group's regression contains lags of that group's own position changes as controls. This comment applies to Table 9 as well.

move in weekly annualized realized volatility (5.3%) is associated with a -0.25-SD position change for dealers and +0.17-SD position change for hedge funds contemporaneously. Per the framework above, this is consistent with risk shocks acting to reduce hedging demand.

Prior to 2010, long hedgers and short liquidity suppliers also reduced their positions in response to risk shocks. The main difference with the post-2010 sample is that prior to 2010, dealers were short VIX futures while hedge funds, asset managers, other reportable traders, and non-reportable traders were net long on average, as Figure 7 illustrates. The Online Appendix shows that non-reportable traders reduced their long positions and dealers reduced their short positions in response to risk shocks, consistent with risk shocks leading to falls in hedging demand, albeit with a different group of hedgers, in this pre-2010 sample. Ideally, one could use (CFTC-restricted) micro-level data underlying the aggregate TFF report to explore the reasons for this change in positioning, as well as other motives for hedging and speculation.

Figure 8 traces out the 13-week impulse responses of trader positions to realized volatility shocks. I estimate these from two-variable, eight-lag weekly VARs of 5-day realized volatility and net futures positions for each trader group. I order realized volatility first and the net position second to allow for the contemporaneous effect of risk on positions. Dealers and asset managers tend to reduce long positions before re-building them, resulting in a hump-shaped response mirrored by hedge funds on the short side. As the Online Appendix reports, traders respond similarly to VVIX shocks: an increase leads to a hump-shaped reduction in exposures. It also reports results when reversing the order of these VARs.

3.3 Potential mechanisms

Why do dealers reduce their hedges when risk rises? The conceptual framework shows how to use price-quantity relationships to identify hedging demand effects from liquidity supply effects but is largely agnostic about motives to hedge. The main challenge in answering this question is that, other than volatility risk defined broadly, we do not observe what specific underlying asset or volatility risk dealers hedge with VIX futures. Here, I provide exploratory evidence for potential mechanisms. To add intuition, the Online Appendix develops a model of hedging a generic underlying risk. It begins with the observation that, under basic assumptions, hedging demand should increase if risk increases, making the results in Table 9 potentially a puzzle. The model then highlights three non-exclusive potential reasons for why hedging demand might decrease instead.

First, dealers may be hedging customer positions, and customer demand for VIX futures may fall when risk rises. In this view, dealers go long-futures to hedge the "underlying risk" of long-volatility exposure they sell to customers, and reduce hedges when risk rises because customers reduce demand. Table 10 explores this hypothesis. Panel A shows that dealers' futures positions track two natural sources of customer demand for long-VIX exposure: flows for the popular iPath S&P 500 VIX Short-Term Futures exchange-traded note (VXX) issued by Barclays (Column 1), as well the net notional position of VIX options held by the public (Column 2; the public has been net-long on average in the VIX option market).[13] Panel B shows that both sources of customer demand decline when market volatility increases. Together, this evidence lends credence to this hypothesis.

Second, dealers may reduce hedges when risk rises if the effectiveness of VIX futures as a hedge declines. This occurs if futures price risk increases by more than the underlying risk. The Online Appendix shows that this a less-likely explanation for the results in Table 9: the ability of VIX futures to hedge candidate risks such as the VXX or the stock market does not significantly weaken with realized volatility.

Third, dealers may scale back all risky positions—both in underlying risks and their hedges—when risk rises. The idea is that large increases in risk decrease dealer risk appetite, for example by shifting value-at-risk constraints (Adrian and Shin 2010, 2014; Danielsson, Shin, and Zigrand, 2012), leading dealers to withdraw from all markets. The Online Appendix model formalizes this "withdrawal" effect and shows that this view differs from the first in that it views dealer exposure to underlying risk as endogenous. To test this intuition, I correlate measures of systemic risk with dealer position changes on the idea that these proxy for financial sector risk aversion (the inverse of risk appetite).[14] Columns 3-4 of Table 10 Panels A and B show that increases in systemic risk measures are associated with dealers closing positions and that these

[13] As an ETN, issuance and redemption keeps the market price of VXX close to the daily indicative value. I obtain this data from Bloomberg. I define the net notional VIX option position as [# calls long - # calls short] – [# puts long - # puts short] held by public and proprietary traders. I calculate this using the CBOE Open-Close daily trade data, which provides daily option-level data on the number of open/close, buy/sell orders from these groups. Chen, Joslin, and Ni (2016); Gârleanu, Pedersen, Poteshman (2009); Ni, Pan, and Poteshman (2008); and Pan and Poteshman (2006) describe these data. I compute the stock of the position by summing the public and proprietary flows (all buys minus sell orders) for each option through time before summing across options. See Fournier and Jacobs (2015) for a similar calculation. The public tends to be net long-VIX in the options market, meaning dealers would want to long VIX futures to hedge the negative delta from having sold these options.

[14] I examine financial sector equity volatility and the SRISK measure of Brownlees and Engle (2017). Giglio, Kelly, and Pruitt (2016) find that financial sector equity volatility is a particularly informative measure of systemic risk for downside macroeconomic risk. I measure this quantity using the 21-day price volatility of the State Street Financial Select Sector SPDR ETF (ticker: XLF), which provides exposure to the financial sector of the S&P 500 index. Brownlees and Engle (2017) show that SRISK, a measure of capital shortfall conditional on a severe market decline, tracks the health of the financial system.

measures also increase with market volatility, supporting this hypothesis. However, one important question is whether dealer risk aversion truly changes at a weekly frequency, an unresolved question in the broader literature on financial intermediary asset pricing (e.g., Danielsson, Shin, and Zigrand, 2012, He and Krishnamurthy 2013).

This evidence suggests that declines in customer demand and dealer risk appetite help explain why dealer hedging declines when risk rises. This evidence is exploratory due to the challenges of not observing dealers' activities in the unknown underlying risk as well as their constraints. It leaves open several questions about why customer demand declines and about the relationship with pre-2010 trading behavior. I comment on potential avenues for future research in the conclusion.

4. Relationship with variance risk premiums

What is the relationship between the VIX premium and the traditionally-studied 30-day VRP? Heuristically, suppose there are three dates (0, 1, and 2), with 30 calendar days separating dates-1 and 2. The risk in a VIX futures position, formed at date-0 and expiring at date-1, is driven by uncertainty in date-1 risk-neutral conditional volatility, per Equation 1. The risk underlying the 30-day VRP studied by several papers discussed in Section 1 is driven by uncertainty about 30-day realized variance from date 0.

To make this more precise, we need two conditions for discussion purposes: 1) Equation 1 holds, and 2) VIX futures settle on the squared VIX rather than the VIX itself. Such a hypothetical "VIX-squared" futures contract would pay the fair strike of a 30-day variance swap at expiration. The premium on this hypothetical contract is $E_0^Q[VIX_1^2] - E_0^P[VIX_1^2]$. Using Equation 1, defining $VRP_1 = E_1^Q[RVar_{1,2}] - E_1^P[RVar_{1,2}]$ as the 30-day VRP at time 1, and re-arranging results in the following:

$$E_0^Q[VIX_1^2] - E_0^P[VIX_1^2] = \left(E_0^Q[E_1^P[RVar_{1,2}]] - E_0^P[E_1^P[RVar_{1,2}]]\right) + \left(E_0^Q[VRP_1] - E_0^P[VRP_1]\right). \quad (13)$$

The first term equals the premium on date-1 30-day physical conditional variance, while the second term equals the premium on the date-1 30-day variance risk premium.

A *forward variance* strategy that combines a long 2-period variance swap position with a short 1-period swap and liquidates at date 1 embeds the same premium as this hypothetical contract. VIX futures have returns consistent with forward variance strategies. For an investor standing at the end of each month who rolls short-term monthly VIX futures as per Section 1.3, dates-1 and 2 are typically 1.5 and 2.5 months away. Using proprietary data on quoted over-the-counter variance swap prices, Dew-Becker, Giglio, Le and Rodriguez (2017) document that the average monthly return for a forward variance swap from month 1 to month 2 was -5.8%, and the return for month 2 to month 3 was +0.7%. Consistent with these numbers, the average return on short-term monthly VIX futures was -3.5% per month. Furthermore, I show in the Online Appendix that option strategies that mimic forward variance can span up to 90% of monthly VIX futures return variance.

Further progress is made more complicated by the fact that the two conditions do not hold. First, price jumps induce significant approximation error in Equation 1. This error contaminates estimates of the 30-day VRP which use the squared VIX as an approximation for risk-neutral expected variance (Aït-Sahalia, Karman, Mancini, 2015; Martin, 2017).[15] The error also affects the interpretation of the VIX premium, although VIX premiums remain well-defined because they take the VIX formula as given. Second, because VIX futures do not settle on the squared VIX, convexity terms appear when directly relating the VIX premium to VRPs.[16]

To make progress, I take a pragmatic approach and ask: How much common variation do the two premiums share? First, I examine how much uncertainty in future physical conditional variance (underlying much of the VIX premium) is due to uncertainty in future 30-day realized variance (underlying the 30-day VRP). I take the standpoint of an investor standing at the end of each month who has just rolled into a futures contract expiring 1.5 months in the future. Ex-ante, future conditional variance in 1.5 months should depend significantly on future 30-day realized variance. To gauge this, I estimate OLS regressions relating conditional variance at each futures expiration date $T(t)$ to realized variance beginning as of the end-of-month investment date t of the rolling strategy:

$$E^{P}_{T(t)}\left[RVar_{T(t)+21}\right] = \alpha + \beta\, RVar_{t,t+21} + \varepsilon_t, \tag{14}$$

using Bekaert and Hoerova (2014) Models 8 and 11 (their "winning" models) to calculate $E^{P}_{T(t)}\left[RVar_{T(t)+21}\right]$. The estimated β for Model 8 (11) equals 0.57 (0.59) with a robust standard error of

[15] On jumps, see Bates (2000); Broadie, Chernov, and Johannes (2007); Pan (2002); and Eraker (2004). Bollerslev and Todorov (2011) and Bollerslev, Todorov, and Xu (2015) also discuss the role of tail risk in the VIX.

[16] Write $VIXP_0 = E^Q_0[VIX_1] - E^P_0[VIX_1]$ as $VIXP_0 = \sqrt{E^Q_0[VIX_1^2] - var^Q_0[VIX_1]} - \sqrt{E^P_0[VIX_1^2] - var^P_0[VIX_1]}$. Even if Equation 1 held, the convexity terms complicate the relationship with $E^Q_0[VIX_1^2] - E^P_0[VIX_1^2]$ or even $\sqrt{E^Q_0[VIX_1^2]} - \sqrt{E^P_0[VIX_1^2]}$. See also the discussion in Carr and Wu (2006) and Dupire (2006).

0.07 (0.06). The R^2 values for both models are 73%, suggesting that there is overlapping uncertainty. Furthermore, VIX futures returns also have an economically and statistically significant loading on realized volatility, as the Online Appendix reports.

Second, I examine correlations of estimated VIX premiums and several 30-day VRP estimates from the literature in Table 11. I report these for both levels (Panel A) and changes (Panel B) to shed light on whether the two share common dynamics. I convert VRPs to volatility premiums by taking the square root of both risk-neutral and physical expected variance. Rows 2 and 3 show that VIX premiums are correlated with the two leading VRPs from Bekaert and Hoerova (2014), with correlations of +0.79 and +0.70 for the VIX premium in levels and +0.44 and +0.45 in changes. Row 4 shows that the correlations with the Bollerslev, Tauchen, and Zhou (2009) VRP are +0.44 in levels and +0.25 in changes.

Rows 5 and 6 show that the VIX premium is less correlated with VRPs from Zhou (2010) (-0.23 in levels, -0.53 in changes) and with those computed from a GARCH-based model of volatility (also negative). However, these VRPs are also only weakly correlated with the BTZ and Bekaert and Hoerova (BH, 2014) VRPs, particularly in changes. The low intra-VRP correlations stem largely from differences in variance forecast models. Given the reliability of the BH premiums that they document, the correlation of estimated VIX premiums with their estimated variance premiums suggests that true premiums are correlated.

Third, I examine whether the VIX premium provides explanatory power for asset prices in several settings where the literature identifies the 30-day VRP or VIX as important. I provide a brief overview of findings with full results in the Online Appendix.

Stock market returns. Table 12, Panel A examines to what extent variance and VIX premiums predict monthly non-overlapping U.S. stock market excess returns (from Ken French's website). Columns 1 through 6 extend existing findings from Bollerslev, Tauchen, and Zhou (2009, BTZ) and Bekaert and Hoerova (2014, BH) through November 2015. BTZ find that a VRP calculated as $VIX_t^2 - RVar_{t-1,t}$ statistically reliably predicts market returns. BH document that substituting $E_t^P[RVar_{t,t+1}]$ for $RVar_{t-1,t}$ weakens the VRP's statistical reliability as a predictor, but that adding $E_t^P[RVar_{t,t+1}]$ as an additional explanatory variable recovers the VRP's predictive power; Columns 3-6 support this conclusion.

Columns 7 and 8 show that the VIX premium has some predictive power for market returns over the shorter sample starting in March 2004. One must exercise great care in interpreting stock market predictability regressions over short samples. My goal here is more modest and is to show that, to the extent that the 30-day VRP predicts market returns, the VIX premium shares some of that variation. In the Online Appendix, I corroborate this point by showing that, when including both the 30-day VRP and VIX premiums together to predict stock market returns, the statistical reliability of both premiums is diminished.

Corporate credit spreads. Collin-Dufresne, Goldstein, and Martin (2001; CGM) document the importance of the VIX in explaining changes in the US corporate credit spread (over Treasuries) during the period July 1988 through December 1997. Rather than examine a panel of individual credit spreads, I examine the time series of credit spreads and relate them to the 10-year Treasury yield (and its square), the 10Y-1Y Treasury spread, the S&P 500 implied volatility skew, the VIX, and S&P 500 total return, following their Equation 1 and Table 3. All variables (except for the market return) are in changes.[17]

Table 12, Panel B examines the relationship between changes in the BBB spread and changes in the VIX and VIX premium. The BBB spread averages 2.3% with a standard deviation of 1.3% in my sample; changes average 1 basis point and have a standard deviation of 34 basis points. Column 1 replicates the finding that the VIX helps explain the spread. Column 2 shows that a one-standard deviation increase in the VIX premium is associated with a +0.23-standard deviation increase in the spread, although with only modest statistical reliability. Columns 3 and 4 break up the VIX into realized volatility plus the VIX minus realized volatility, and the VIX premium adds explanatory power with more statistical reliability.

Sovereign CDS spreads. Pan and Singleton (2008) and Longstaff, Pan, Pedersen, and Singleton (2011; LPPS) find-that the VIX and volatility risk premiums help explain monthly movements in 5-year sovereign CDS spreads, particularly their risk premiums. I examine the 25 of the 26 countries that LPPS examine except for Pakistan, for which I was unable to obtain reliable data.[18] LPPS find that global financial variables have explanatory power for CDS spreads incremental to local financial market variables.

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[17]I use the Bank of America–Merrill Lynch (BAML) option-adjusted spreads over Treasuries, and Treasury yield data from the Federal Reserve Board's H.15 data series. The BAML credit indices differ from the bonds analyzed in the CGM. CGM examine only noncallable, nonputtable debt, while the BAML indices are a market-capitalization weighted index of constituent option-adjusted spreads over Treasuries. CGM include firm-specific stock returns. I omit this in the analysis of the aggregate time series. CGM find that the VIX has an economically and statistically significant relationship with credit spreads in several ratings groups.

[18]Pan and Singleton (2008) extract risk premiums from CDS spreads of Mexico, Turkey, and Korea, and relate these in levels to the VIX. I focus on the LPPS specification, as their analysis spans a wider group of countries. I obtain data on sovereign CDS spreads, local stock market performance from the MSCI local-currency stock market indices, as well as spot exchange rates (tickers in the Online Appendix) from Bloomberg, and the value of foreign reserves reported monthly to the IMF from Datastream.

In the spirit of LPPS, I focus on whether the VIX, volatility premiums, and VIX premiums contain information above and beyond local financial market variables. Table 12, Panel C reports estimates of the relationship between monthly CDS changes and changes in these variables for the 25 countries in a panel, with country fixed effects, adapting LPPS Table 3 to a panel setting. An increase in the VIX premium is associated with higher CDS spreads. The VIX premium also strengthens or "de-noises" the relationship between the 30-day VRP and CDS spreads. In country-by-country regressions, the average economic significance is a +0.17–SD change in CDS spread per 1–SD change in the premium.

Foreign currency carry trades. Brunnermeier, Nagel, and Pedersen (2009; BNP) argue that the VIX helps explain foreign currency carry trade crashes through sudden changes in speculator risk appetite. One key result is that the VIX helps explain returns to a long/short equal-weight portfolio that goes long the *k* currencies with the highest interest rates and short the *k* currencies with the lowest interest rates for *k* up to 3 (BNP Table 7) when examining eight major currency markets.[19]

Table 12, Panel D reports the results for *k*=3. Column 1 replicates BNP's basic finding that the VIX is contemporaneously correlated with the portfolio returns. As in the case with the credit spreads, including the VIX premium increases the economic significance of the VIX while also containing explanatory power itself (Column 2). When breaking up the VIX into realized volatility and the VIX minus realized volatility, the VIX premium has modest explanatory power (Columns 3 and 4).

Summary. VIX futures returns are consistent with those of short-term forward variance strategies. They are correlated with measures of spot 30-day variance risk premiums and share common variation that helps explain other asset prices, consistent with Bakshi, Panayotov, and Skoulakis (2011).[20]

5. Conclusion

[19]The currencies are: Australia (AUD), Canada (CAD), Japan (JPY), New Zealand (NZD), Norway (NOK), Switzerland (CHF), Great Britain (GBP), and the euro (EUR). I follow BNP in data construction and obtain interbank and FX rates from Bloomberg.

[20] I examine four other settings in which price dislocations or liquidity provision have been associated with the VIX. For brevity, I omit these tables. The first is the daily return to reversal strategies in US equity markets. Nagel (2012) finds that the level of the VIX predict these returns with a five-day lag. I replicate this original finding and find that, save for the bid-ask bounce component of returns (see Section 2.5 of Nagel, 2012), the VIX premium contains little explanatory power beyond the VIX or the 30-day VRP. Second, I also find that the VIX premium does not have incremental explanatory power for Treasury market liquidity (Hu, Pan, and Wang, 2013). Third, I also find little incremental explanatory power for corporate bond market liquidity (Bao, Pan, and Wang, 2011). Fourth, in commodity futures markets, the estimated relationship between changes in the VIX premium and futures returns is negative, but not reliably different from zero, controlling for the VRP (Cheng, Kirilenko, and Xiong, 2015).

This paper shows that estimated premiums in the VIX futures market often fall or stay flat when risk rises, and that this "low premium-response" reflects true variation in premiums and risk. Estimated premiums tend to reliably predict realized premiums, and falling estimated premiums also tend to predict rising ex-post risk. This behavior poses a puzzle for standard theories of volatility premiums.

The paper also shows that market participants have tended to reduce their futures exposures as risk rises, consistent with a fall in demand for volatility insurance. The exploratory evidence in Section 3.3 suggests two potential explanations for why—declining customer demand and dealer risk appetite—although more are possible. For example, the government may provide free insurance to the financial sector in particularly bad states of the world, reducing the motive to hedge or provide private insurance (Kelly, Lustig, and Van Nieuwerburgh, 2016). This is a particularly interesting hypothesis because it suggests that dealers might decrease hedges but not decrease underlying volatility risk given that the government is providing free insurance, potentially resulting in a net increase in risk for dealers (i.e., risk-shifting). An important key to disentangling these explanations is further identifying what underlying risks dealers hedge with VIX futures as well as what risks their customers are hedging. Models of volatility premiums should include interactions between heterogeneous agents in a way that allows for the price of volatility risk to fall when risk rises to account for premium and trader position dynamics in the data. Exploring these questions and their connections with time-varying premiums is a fruitful area for future work.

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Figure 1. Estimated variance risk premiums. This figure plots estimated monthly variance risk premiums from Bollerslev, Tauchen, and Zhou (2009) through December 2014 and daily VRPs from Bekaert and Hoerova (2014) Model 11 through August 2010. Data are from Hao Zhou's website and Maria Hoerova.

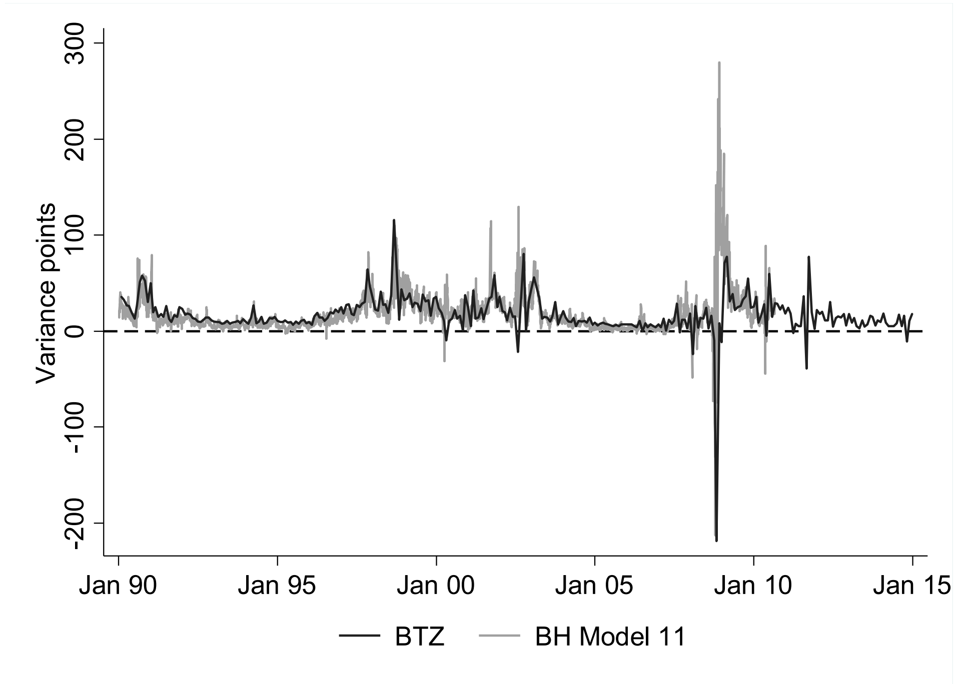


Figure 2. The VIX premium. This figure plots monthly VIX premiums estimated from Equation (2) using the baseline ARMA(2,2) VIX forecast model.

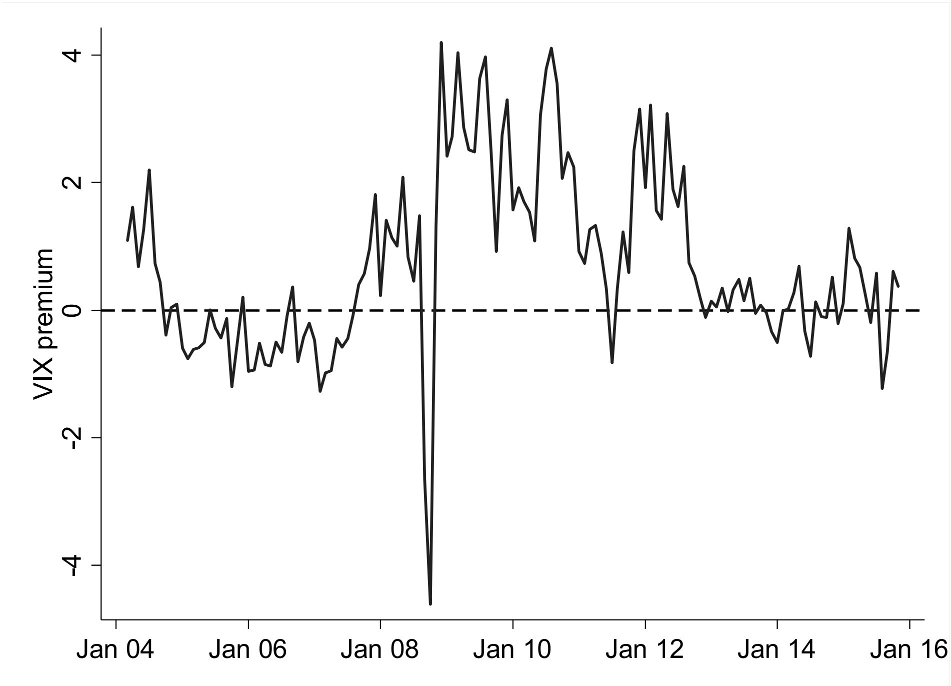
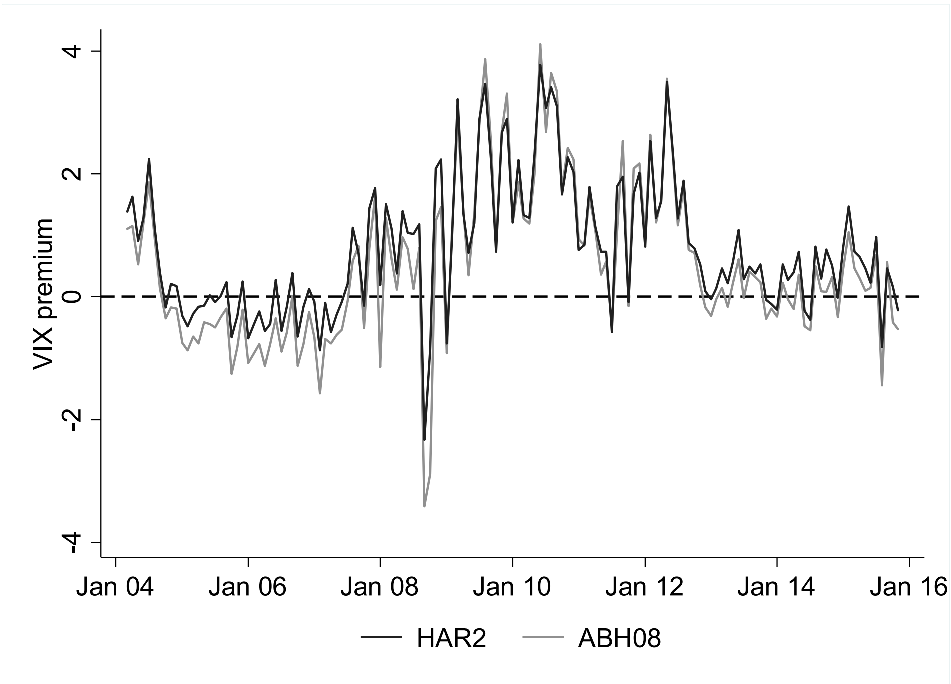


Figure 3. Alternative estimates of the VIX premium. Panel A plots the monthly time series of estimated VIX premiums using selected alternative forecast models from Table 3. Panel B plots the monthly time series of estimated VIX premiums for strategies that roll the 2-, 3-, 4-, and 5-month ahead futures contracts. This sample starts in November 2006 when there is a continuous term structure for those months each day.

Panel A: Alternative forecast models



Panel B: Term structure

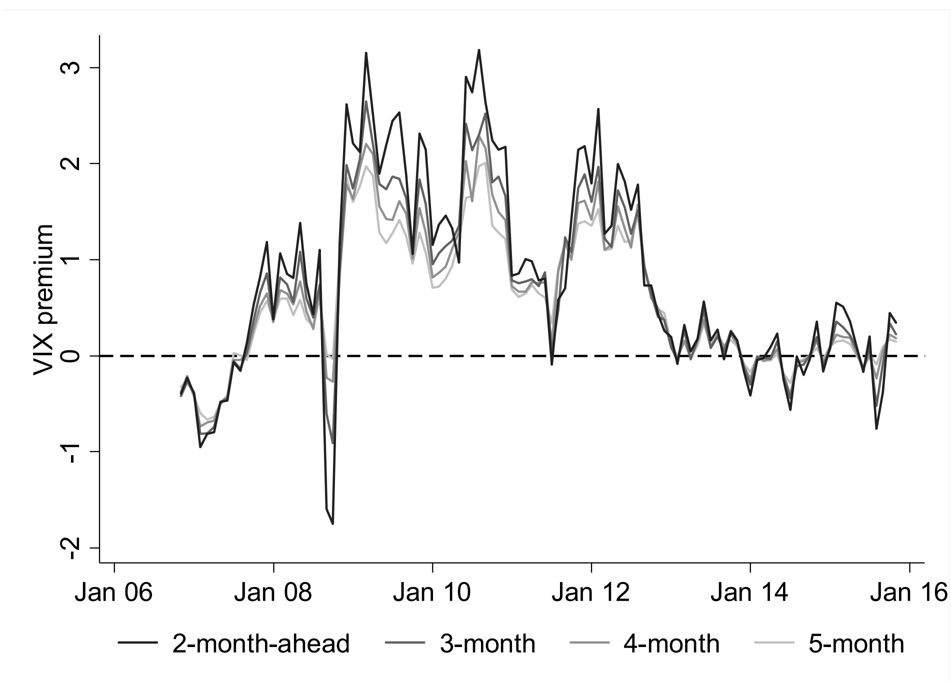
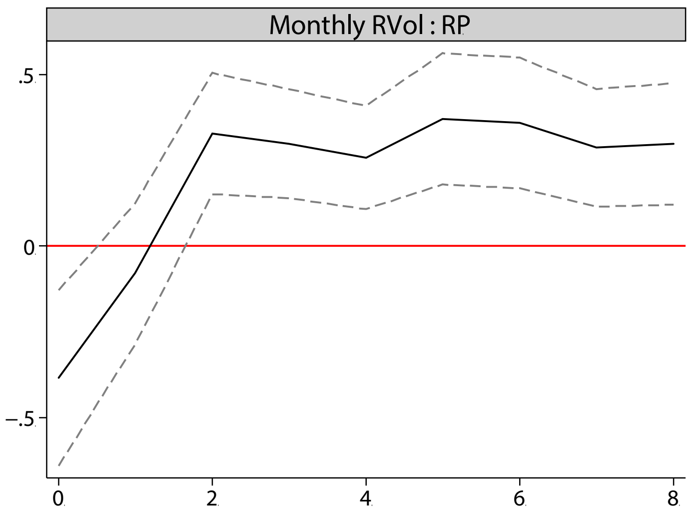


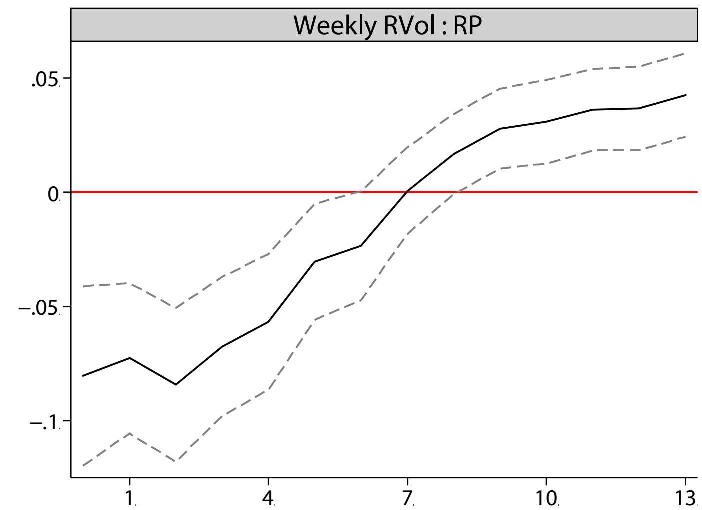
Figure 4. Response of the VIX premium to realized volatility shocks. This figure plots the response of the VIX premium to a 1-standard deviation realized volatility shock estimated from orthogonalized impulse response functions of 4-lag monthly VARs and 8-lag weekly two-variable VARs, with realized volatility ordered first. Panel A plots all responses for the full sample and Panel B plots responses for the 2010-onwards sample. The dashed lines mark 95% confidence intervals based on bootstrapped standard errors.

Panel A: Full sample

Monthly (*T*=137)

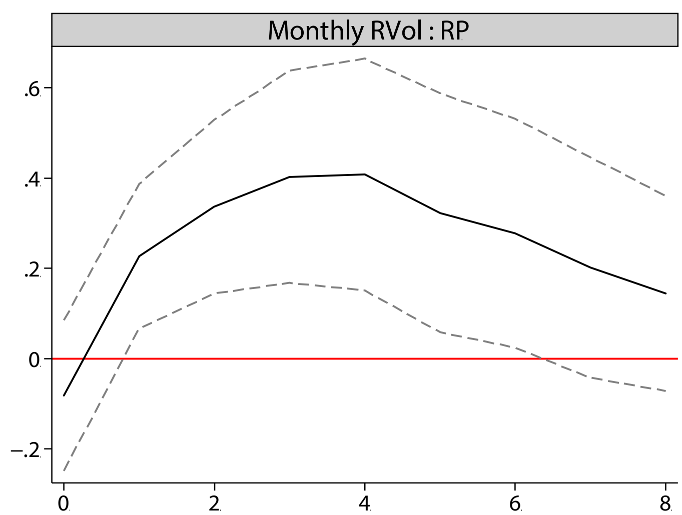


Weekly (*T*=600)



Panel B: 2010-onwards sample

Monthly (*T*=67)



Weekly (*T*=299)

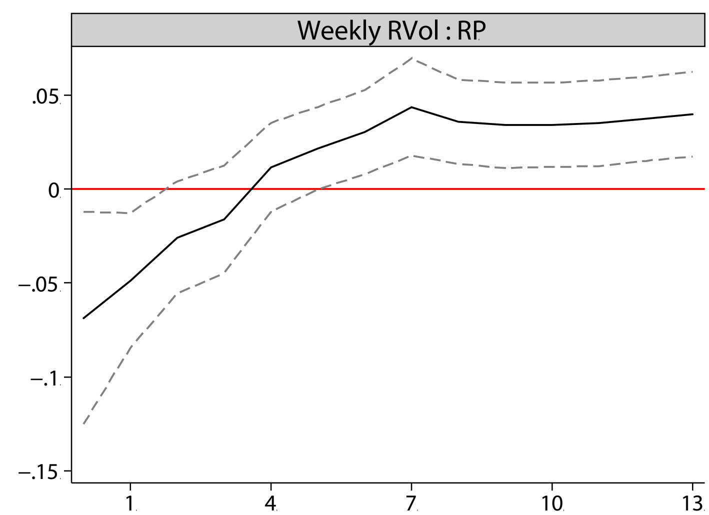


Figure 5. Monthly return predictability. This figure plots the ex-post excess return to the rolling futures investment strategy in month t+1 against the ex-ante estimated VIX premium expressed as an expected return in month t found in Equation 4. The fitted line reflects the estimated coefficients from Equation 5.

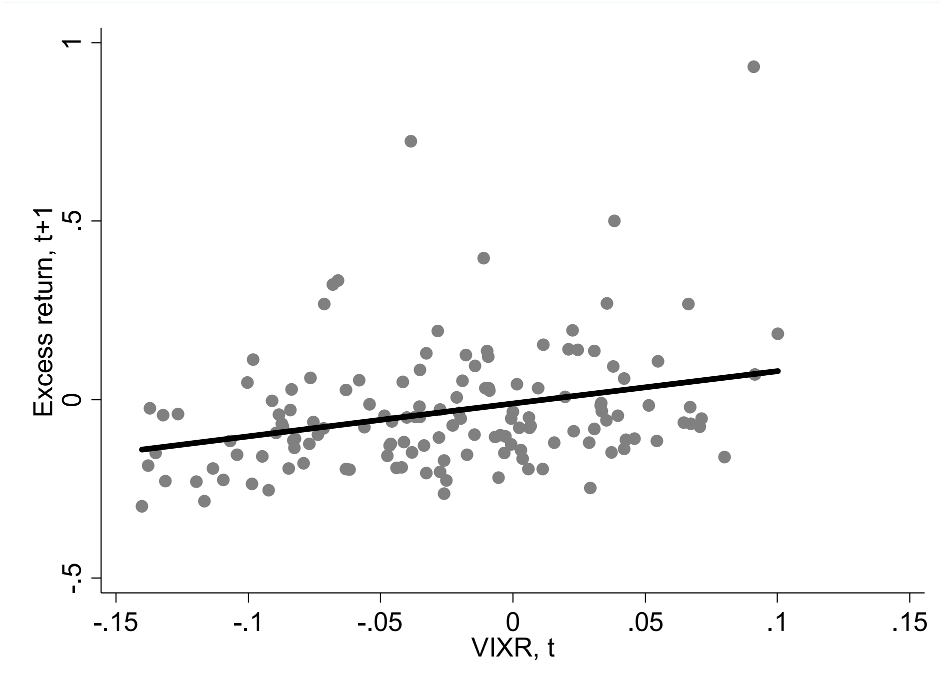


Figure 6. Trading profits. This figure plots the log margin account growth for the S/S, C/S, and L/S trading strategies.

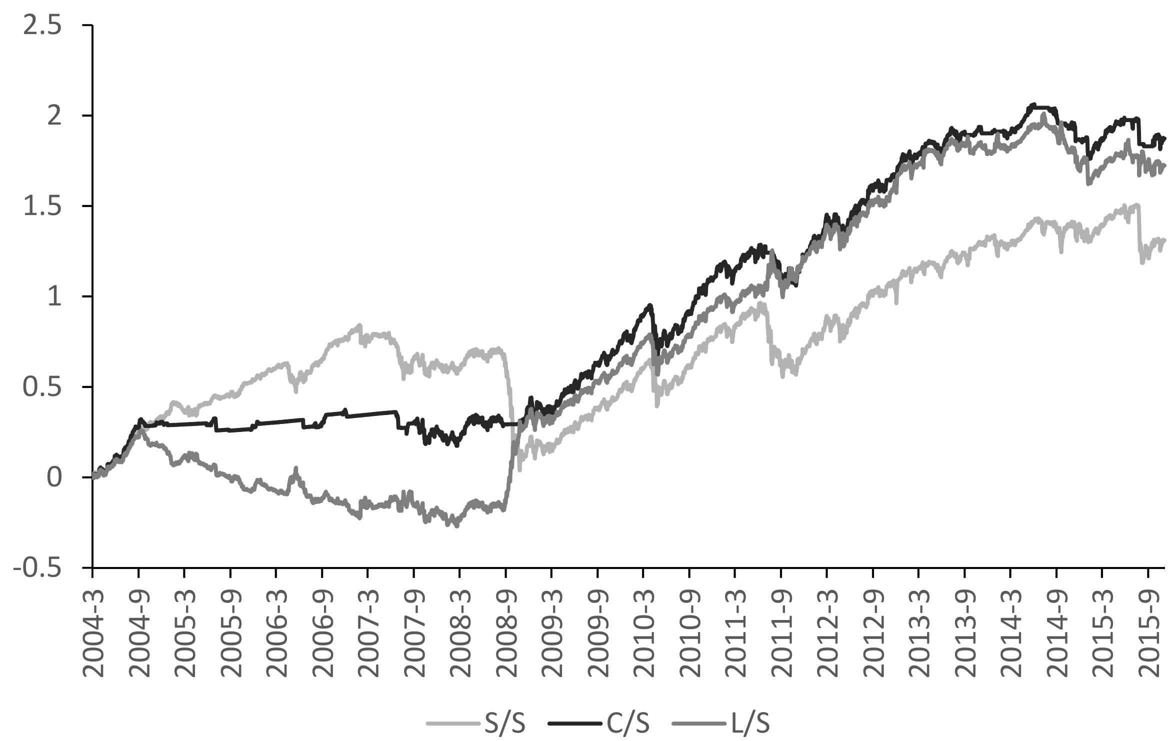


Figure 7. Net positions of trader groups. This figure plots the weekly aggregate net position (long minus short) of the four trader groups in the CFTC Traders in Financial Futures (TFF) report. Units are in thousands of contracts, which are also the net notional position in $ millions.

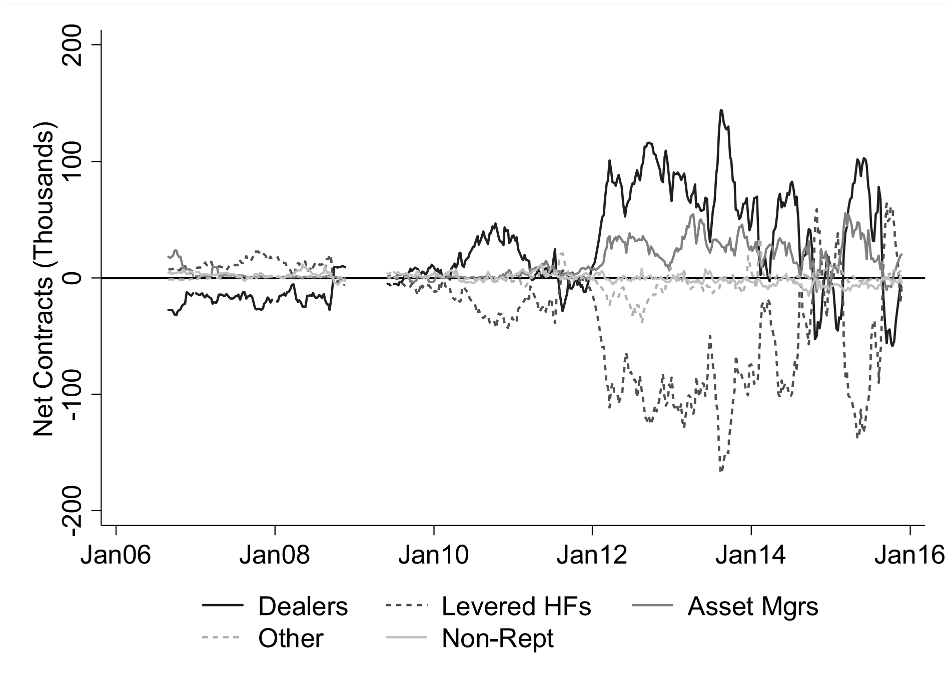


Figure 8. Responses of net positions to realized volatility shocks. This figure plots responses of positions to realized volatility shocks calculated from orthogonalized impulse response functions of four different eight-lag weekly VARs with two variables. Each VAR orders realized volatility first and the net position of the trader group position second. Units are in thousands of contracts, which are also the net notional position in $ millions. The sample begins in 2010 with 299 observations. The dashed lines mark 95% confidence intervals based on bootstrapped standard errors.

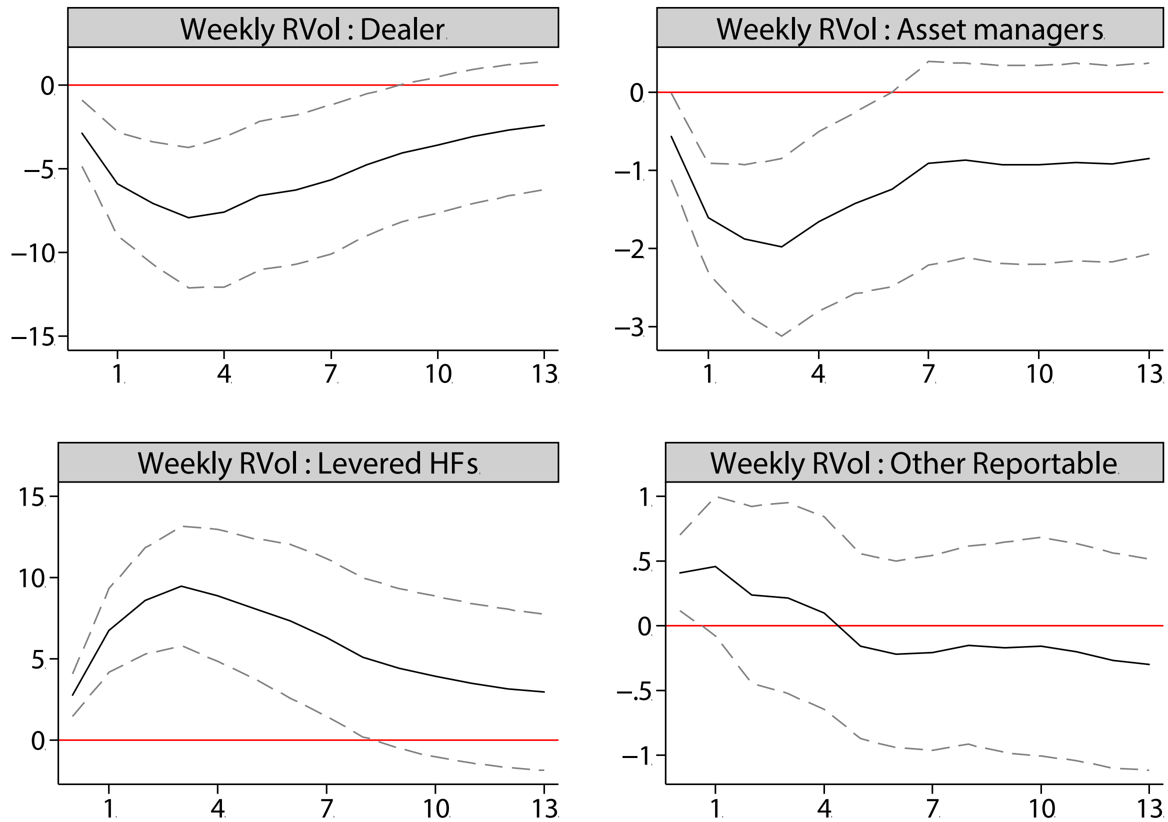


Table 1. Summary statistics. This table reports summary statistics in the monthly time series. VIX futures prices are for the contracts newly held at the end of each month by the 1-month rolling investment strategy, after liquidating the existing position and rolling into the new contract to be held over the following month. The average return is for the same investment strategy. The VIX premium equals the estimated premium from Equation 2 as of the end of each month, when it references the contract newly held by the investment strategy. The expected return VIXR re-expresses this premium from Equation 4. Other variables are defined in the text. The units from the CBOE SKEW index are 100 – 10**S*, where *S* is the risk-neutral skewness in the S&P 500 price index calculated from option prices. Net futures positions are from the Traders in Financial Futures reports published each week by the CFTC, as of the last report each month, and equal the long position minus the short position of each trader group.

VIX, VIX futures, and risk	T	First	Last	Mean	SD	Min	Max	Median	Units
CBOE Volatility Index (VIX)	141	Mar-04	Nov-15	19.57	8.76	10.42	59.89	16.74	Percent Ann.
VIX futures									
…average price	141	Mar-04	Nov-15	20.01	8.20	11.31	54.57	17.50	Dollars
…average monthly return	140	Apr-04	Nov-15	-3.46	17.50	-30.00	93.37	-6.65	Percent
VIX premium									
…average dollar premium (VIXP)	141	Mar-04	Nov-15	0.70	1.41	-4.62	4.20	0.44	Dollars
…as monthly expected return (VIXR)	141	Mar-04	Nov-15	-2.51	5.65	-14.03	10.01	-2.27	Percent
Realized volatility	141	Mar-04	Nov-15	14.64	9.51	5.82	74.55	11.47	Percent Ann.
CBOE VIX of VIX index (VVIX)	117	Mar-06	Nov-15	85.78	13.32	37.35	127.28	85.33	Percent Ann.
SPX IV skew	138	Mar-04	Aug-15	5.77	2.78	2.45	21.04	4.96	Percent
CBOE SKEW Index	141	Mar-04	Nov-15	120.20	5.85	106.43	139.35	120.13	See caption
VIX call option IV skew	100	Jun-06	Aug-15	31.28	9.58	6.22	50.91	32.42	Percent
Market excess return	140	Apr-04	Nov-15	0.62	4.23	-17.23	11.35	1.18	Percent

VIX futures positions (end of month)	T	First	Last	Mean	SD	Min	Max	Median	Units
Open interest, all contracts	141	Mar-04	Nov-15	155.41	149.20	1.01	438.17	69.39	000's Contracts
Net positions									
…dealers	107	Aug-06	Nov-15	22.20	42.99	-50.07	133.44	9.05	000's Contracts
…asset managers	107	Aug-06	Nov-15	12.25	14.48	-12.11	52.11	7.01	000's Contracts
…leveraged funds	107	Aug-06	Nov-15	-32.60	48.77	-158.07	58.77	-16.12	000's Contracts
…other reportable	107	Aug-06	Nov-15	-1.53	6.61	-26.22	11.32	0.13	000's Contracts
…non-reportable	107	Aug-06	Nov-15	-0.32	4.30	-11.26	9.86	0.11	000's Contracts

Table 2. VIX premiums and risk. Columns 1-5 estimate Equation 3 in the full monthly time series. Columns 1a and 1b decompose the effect of realized volatility on premiums into the effect on futures prices $F_t^{T(t)}$ and the effect on the VIX forecast $\widehat{VIX}_t^{T(t)}$ by replacing the dependent variable in Equation 3 with the change in futures price and change in VIX forecast, respectively. Columns 7-12 estimate Equation 3 for the sample starting in January 2010. The table organizes columns by risk variable *X* and reports Newey and West (1987) standard errors with three lags. Bold coefficients indicate those that are statistically reliably different from zero at the 5% level.

Dependent variable: ΔRP, *t*

	Full sample							2010-onwards				
X:	R.Vol.	Dep.Var: Futures	Dep.Var: Forecast	VVIX	SPX Skew	VIX	SKEW	R.Vol.	VVIX	SPX Skew	VIX	SKEW
	(1)	(1a)	(1b)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
ΔX, *t*	**-0.070**	**0.201**	**0.271**	**-0.026**	**-0.230**	**-0.075**	**-0.047**	-0.026	**-0.016**	**-0.120**	-0.022	**-0.041**
	(0.020)	(0.021)	(0.030)	(0.009)	(0.052)	(0.029)	(0.015)	(0.020)	(0.007)	(0.049)	(0.024)	(0.016)
ΔX, *t*-1	**0.024**	**0.116**	**0.092**	-0.001	-0.015	0.023	-0.032	**0.047**	0.003	0.052	0.027	**-0.049**
	(0.010)	(0.036)	(0.036)	(0.007)	(0.044)	(0.018)	(0.017)	(0.019)	(0.007)	(0.063)	(0.021)	(0.017)
ΔX, *t*-2	**0.040**	-0.011	-0.051	**0.018**	**0.217**	**0.064**	-0.007	**0.046**	**0.024**	**0.230**	**0.070**	-0.024
	(0.015)	(0.041)	(0.035)	(0.008)	(0.053)	(0.023)	(0.017)	(0.017)	(0.010)	(0.049)	(0.019)	(0.019)
ΔX, *t*-3	**0.051**	**0.094**	0.043	**0.018**	**0.160**	**0.065**	-0.004	**0.070**	**0.024**	**0.204**	**0.082**	-0.008
	(0.017)	(0.038)	(0.029)	(0.006)	(0.049)	(0.022)	(0.013)	(0.011)	(0.008)	(0.048)	(0.016)	(0.016)
ΔRP, *t*-1	**-0.227**	-0.261	-0.034	-0.136	**-0.290**	**-0.244**	-0.099	**-0.270**	**-0.278**	**-0.342**	**-0.351**	-0.229
	(0.089)	(0.230)	(0.219)	(0.140)	(0.091)	(0.092)	(0.141)	(0.109)	(0.108)	(0.110)	(0.095)	(0.130)
ΔRP, *t*-2	**-0.341**	-0.261	0.080	**-0.337**	**-0.165**	**-0.321**	**-0.435**	**-0.241**	-0.110	-0.077	-0.211	**-0.213**
	(0.077)	(0.261)	(0.227)	(0.100)	(0.082)	(0.082)	(0.123)	(0.102)	(0.106)	(0.125)	(0.131)	(0.079)
ΔRP, *t*-3	**0.294**	0.083	-0.212	**0.178**	**0.356**	**0.259**	0.116	**0.373**	**0.393**	**0.511**	**0.363**	0.220
	(0.108)	(0.251)	(0.202)	(0.072)	(0.092)	(0.097)	(0.075)	(0.086)	(0.129)	(0.096)	(0.090)	(0.159)
Constant	-0.016	-0.017	-0.001	-0.010	-0.012	-0.015	-0.007	-0.037	-0.037	-0.031	-0.027	-0.018
	(0.053)	(0.106)	(0.088)	(0.078)	(0.051)	(0.056)	(0.075)	(0.074)	(0.074)	(0.065)	(0.075)	(0.094)
T	137	137	137	113	134	137	137	67	67	64	67	67
R^2	0.547	0.412	0.537	0.398	0.613	0.507	0.282	0.468	0.409	0.558	0.481	0.284

Table 3. Alternative VIX premium estimates. Panel A describes alternative VIX forecast models. BH (2014) and BHL (2013) reference Bekaert and Hoerova (2014) and Bekaert, Hoerova, and Lo Duca (2013), respectively. In the columns, RVol(s) indicates s-day realized volatility, the square root of s-day realized variance $RVar(s)$. J(s) indicates the jump component of realized volatility, calculated as the square root of $\max[RVar(s) - TBPV(s), 0]$ where $TBPV(s)$ is the threshold bi-power variation of Corsi et al. (2010), following Bekaert and Hoerova and their Appendix. C(s) is the continuous component of realized volatility, calculated as the square root of $RVar(s) - J^2(s)$. VIX(s) indicates the s-day trailing average of the VIX. VIX(u,v) indicates both the u- and v-day trailing average VIX are included; analogous comments apply to C, J, and RVol. Panel B reports results of comparing out-of-sample (post-2004) forecast accuracy at the 34-day horizon. In the first column, italics indicate models that fail the Chow stability test. In the RMSE, MAE, and MAPE columns, underlined indicates the "winning" model in that category. Bold indicates that Diebold and Mariano (1995) tests reject a given model as worse than the best model in that category at the 5% statistical level. Panel C repeats the analysis of Table 2 for realized volatility and VVIX risk measures. I report Newey and West (1987) standard errors with three lags. In this panel, bold coefficients indicate those that are statistically reliably different from zero at the 5% level.

Panel A: Forecast models

	RVol (22)	RVol (5,1)	C (1,5,22)	J (1,5,22)	VIX (1)	VIX (5,22)	VIX (10,66)
Group 1 (Realized vol. models)							
Corsi (2009)	x	x					
BH (2014) Model 8			x		x		
BH (2014) Model 11			x	x			
BHL (2013)	x				x		
Group 2 (Augmented)							
HAR1					x	x	
HAR2					x	x	x
AC (Corsi, 2009)	x	x			x	x	x
ABH8 (BH 2014 Model 8)			x		x	x	x
ABH11 (BH 2014 Model 11)			x	x	x	x	x
ABHL (BHL 2013)	x				x	x	x

Panel B: Out-of-sample forecast accuracy

	RMSE	MAE	MAPE	M-Z R2
ARMA(2,2)	6.308	3.806	18.784	0.547
Group 1				
Corsi (2009)	**6.810**	**4.877**	**27.283**	0.518
BH (2014) Model 8	6.343	**4.010**	**20.467**	0.545
BH (2014) Model 11	**6.844**	**4.931**	**27.593**	0.520
BHL (2013)	6.366	**4.060**	**20.712**	0.544
Group 2				
HAR 1	6.320	3.793	18.553	0.545
HAR 2	6.292	<u>3.742</u>	<u>18.149</u>	0.549
AC	6.275	**3.960**	**20.016**	0.557
ABH8	<u>6.246</u>	**3.906**	**19.706**	<u>0.559</u>
ABH11	6.273	3.833	**19.128**	0.553
ABHL	6.268	**3.955**	**19.994**	0.558

Table 3, continued.

Panel C: Relationship to risk

X:	Realized volatility						VVIX					
Forecast model:	HAR1	HAR2	AC	ABH8	ABH11	ABHL	HAR1	HAR2	AC	ABH8	ABH11	ABHL
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
ΔX, *t*	**-0.064**	-0.019	**-0.072**	**-0.048**	-0.021	**-0.074**	**-0.022**	**-0.016**	**-0.025**	**-0.019**	-0.012	**-0.026**
	(0.019)	(0.022)	(0.025)	(0.023)	(0.023)	(0.026)	(0.009)	(0.007)	(0.011)	(0.009)	(0.008)	(0.011)
ΔX, *t*-1	0.017	**0.032**	**0.046**	**0.045**	**0.047**	**0.039**	-0.006	0.010	0.006	0.009	**0.014**	0.005
	(0.011)	(0.009)	(0.012)	(0.011)	(0.012)	(0.012)	(0.006)	(0.007)	(0.006)	(0.007)	(0.007)	(0.007)
ΔX, *t*-2	**0.031**	0.009	-0.018	-0.013	-0.011	-0.016	**0.018**	0.013	0.013	0.016	**0.019**	0.012
	(0.014)	(0.015)	(0.017)	(0.017)	(0.015)	(0.018)	(0.007)	(0.008)	(0.009)	(0.008)	(0.008)	(0.009)
ΔX, *t*-3	**0.049**	0.002	0.017	0.017	0.010	0.017	**0.015**	**0.012**	0.014	0.012	0.010	0.014
	(0.017)	(0.014)	(0.015)	(0.016)	(0.017)	(0.016)	(0.006)	(0.006)	(0.007)	(0.006)	(0.006)	(0.007)
ΔRP, *t*-1	**-0.233**	**-0.484**	**-0.422**	**-0.401**	**-0.393**	**-0.448**	-0.156	**-0.503**	**-0.512**	**-0.507**	**-0.499**	**-0.509**
	(0.092)	(0.092)	(0.088)	(0.092)	(0.086)	(0.094)	(0.122)	(0.075)	(0.097)	(0.099)	(0.092)	(0.095)
ΔRP, *t*-2	**-0.334**	**-0.516**	**-0.489**	**-0.462**	**-0.431**	**-0.483**	**-0.310**	**-0.557**	**-0.492**	**-0.477**	**-0.463**	**-0.479**
	(0.086)	(0.098)	(0.080)	(0.086)	(0.091)	(0.081)	(0.106)	(0.082)	(0.066)	(0.071)	(0.082)	(0.066)
ΔRP, *t*-3	**0.300**	-0.028	-0.048	0.026	0.038	-0.044	**0.193**	-0.020	-0.028	0.042	0.051	-0.017
	(0.102)	(0.103)	(0.085)	(0.088)	(0.096)	(0.092)	(0.076)	(0.101)	(0.065)	(0.074)	(0.092)	(0.076)
Constant	-0.016	-0.019	-0.021	-0.018	-0.017	-0.020	-0.007	-0.013	-0.012	-0.010	-0.010	-0.011
	(0.052)	(0.062)	(0.068)	(0.066)	(0.067)	(0.069)	(0.076)	(0.071)	(0.091)	(0.084)	(0.081)	(0.091)
T	137	137	137	137	137	137	113	113	113	113	113	113
R^2	0.512	0.431	0.541	0.496	0.433	0.524	0.368	0.482	0.432	0.445	0.426	0.426

Table 4. Return predictability. This table reports estimates from predicting ex-post returns to the futures investment strategy using ex-ante estimated VIX premiums in Equation 5 or variations of it. β denotes the coefficient on the main predictor while γ denotes the coefficient on any additional variable. I report standard errors in parentheses. NW denotes Newey and West (1987) standard errors with the indicated number of lags. Bold coefficients indicate those that are statistically reliably different from zero at the 5% level.

	Forecast regression dependent variable	Predictor	β	s.e.(β)	γ	s.e.(γ)	R^2	T	SE
(1)	Futures return, *t*+1	*VIXR*	**0.917**	(0.289)			0.088	140	N-W (3)
(2)	…with positive/negative interaction (γ)	*VIXR*	**0.971**	(0.333)	1.612	(1.668)	0.112	140	N-W (3)
(3)	…Stambaugh bias-adjustment	*VIXR*	**0.942**	(0.299)					Bootstrap
(4)	…only 2010-onwards	*VIXR*	**1.198**	(0.412)			0.096	70	N-W (3)
(5)	…excluding first day of next month	*VIXR*	**0.803**	(0.285)			0.070	140	N-W (3)
(6)	…controlling for expected VIX change	*VIXR*	**0.967**	(0.329)	0.189	(0.356)	0.104	140	N-W (3)
(7)	…controlling for VIX level	*VIXR*	**1.021**	(0.312)	0.003	(0.002)	0.105	140	N-W (3)
(8)	…controlling for VRP (BTZ)	*VIXR*	**0.762**	(0.295)	-0.006	(0.004)	0.104	140	N-W (3)
(9)	…VIX forecast model: HAR1	*VIXR*	**0.985**	(0.305)			0.091	140	N-W (3)
(10)	…VIX forecast model: HAR2	*VIXR*	**1.262**	(0.429)			0.102	140	N-W (3)
(11)	…VIX forecast model: AC	*VIXR*	**1.179**	(0.388)			0.131	140	N-W (3)
(12)	…VIX forecast model: ABH8	*VIXR*	**1.030**	(0.337)			0.104	140	N-W (3)
(13)	…VIX forecast model: ABH11	*VIXR*	**0.884**	(0.293)			0.079	140	N-W (3)
(14)	…VIX forecast model: ABHL	*VIXR*	**1.171**	(0.384)			0.130	140	N-W (3)
(15)	…weekly frequency	*VIXR*	**0.832**	(0.215)			0.030	607	N-W (6)
(16)	…daily frequency	*VIXR*	**1.066**	(0.231)			0.009	2939	N-W (20)
(17)	Realized dollar premium	*VIXP*	**1.260**	(0.334)			0.183	140	N-W (3)
(18)	…only 2010-onwards	*VIXP*	**1.484**	(0.348)			0.190	70	N-W (3)
(19)	Futures return, *t*+5	*VIXR*	0.068	(0.298)			0.000	136	N-W (3)
(20)	…weekly frequency	*VIXR*	**0.524**	(0.180)			0.012	603	N-W (6)
(21)	…only 2010-onwards	*VIXR*	**0.647**	(0.261)			0.011	302	N-W (6)
(22)	…daily frequency	*VIXR*	**0.952**	(0.224)			0.007	2935	N-W (20)
(23)	…only 2010-onwards	*VIXR*	**1.342**	(0.328)			0.009	1483	N-W (20)

Table 5. VIX premiums and ex-post volatility. This table reports estimates from predicting monthly changes in ex-post volatility using changes in estimated premiums and lagged volatility in Equation 6. Column 1 reports estimates for the volatility of daily returns to the investment strategy, calculated as the square root of the sum of squared log daily returns in a month. Column 2 reports estimates for market realized volatility calculated as the sum of squared 5-minute returns in a month, including overnight returns. Units for volatility are annualized percentage points. Columns 3 and 4 repeat this exercise for the 2010-onwards sample. I report Newey and West (1987) standard errors with three lags. Bold coefficients indicate those that are statistically reliably different from zero at the 5% level.

	Full sample		2010-onwards	
$\Delta\sigma$:	Strategy	Market	Strategy	Market
	(1)	(2)	(3)	(4)
ΔRP, *t*-1	**-15.141**	**-2.769**	**-29.303**	-2.204
	(4.555)	(1.070)	(10.204)	(1.147)
ΔRP, *t*-2	-2.897	-0.825	**-19.885**	-2.054
	(3.619)	(0.499)	(8.793)	(1.072)
ΔRP, *t*-3	**-9.969**	-1.187	**-21.920**	-1.699
	(3.171)	(0.730)	(7.619)	(0.859)
$\Delta\sigma$, *t*-1	**-0.689**	**-0.321**	**-0.830**	**-0.402**
	(0.092)	(0.097)	(0.099)	(0.082)
$\Delta\sigma$, *t*-2	**-0.281**	**-0.203**	**-0.351**	-0.224
	(0.085)	(0.097)	(0.135)	(0.133)
$\Delta\sigma$, *t*-3	-0.136	-0.005	-0.128	0.061
	(0.082)	(0.086)	(0.109)	(0.138)
Constant	0.826	-0.018	-0.182	-0.209
	(3.045)	(0.494)	(5.435)	(0.586)
T	136	137	67	67
R^2	0.344	0.165	0.455	0.209

Table 6. Trading strategies. Panel A reports summary statistics for excess returns for the S&P 500 total return index, as well as excess returns for trading strategies which are either long (L) or in cash (C) when the expected return (*VIXR*) is positive, and short (S) or in cash (C) when the expected return is negative. The first letter of each strategy denotes the action when *VIXR* is positive and the second denotes the action when it is negative. Positions are opened, closed, or maintained on date *t* based on information from date *t*-1, with open or maintained positions held over date *t*+1. At position formation, the number of contracts opened equals is set so that the magnitude of the exposure (futures price x # contracts) divided by the margin balance equals the row "|Weight| at rebalance." This weight is fixed so that the ex-post volatility of the strategy is similar to that of holding the S&P500. If a position is open at the end of the month, it is rolled and re-formed in the next contract. Means, standard deviations, and Sharpe ratios are annualized. The magnitude of the mean return (and alpha) of the S/S strategy differs from L/L because S/S does not rebalance each day. The maximum drawdown equals the maximum running loss from the previous peak over the sample, in percent/100. Panel B reports four-factor regressions of daily excess returns of each strategy on the market, HML, SMB, and momentum. All strategies trade at bid and ask prices. Units for alpha are annualized in percent/100. Newey and West (1987) standard errors with 20 lags are in parentheses. Bold coefficients and means indicate those that are statistically reliably different from zero at the 5% level.

Panel A: Summary statistics

Strategy:	SPXT (1)	L/L (2)	S/S (3)	L/C (4)	C/S (5)	L/S (6)
Mean excess return	0.081	**-0.155**	**0.123**	0.034	**0.166**	**0.154**
…standard error	(0.046)	(0.058)	(0.062)	(0.062)	(0.049)	(0.054)
Standard deviation	0.196	0.200	0.215	0.202	0.190	0.195
Daily skew	-0.081	0.923	-0.825	2.256	-0.403	0.285
Daily kurtosis	14.657	9.565	13.714	30.653	12.505	9.194
Sharpe ratio	0.413	-0.775	0.572	0.168	0.874	0.790
Max drawdown	-0.553	-0.867	-0.553	-0.555	-0.264	-0.412
|Weight| at rebalance		0.33	0.33	0.54	0.40	0.32

Panel B: Factor loadings

Strategy:	L/L (1)	S/S (2)	L/C (3)	C/S (4)	L/S (5)
Excess market	**-0.820**	**0.898**	**-0.586**	**0.532**	0.063
	(0.067)	(0.060)	(0.072)	(0.096)	(0.106)
HML	-0.011	-0.013	**0.151**	0.106	0.178
	(0.064)	(0.065)	(0.069)	(0.084)	(0.092)
SMB	-0.056	-0.006	**0.167**	**0.201**	**0.269**
	(0.070)	(0.064)	(0.056)	(0.080)	(0.076)
Momentum	**-0.205**	**0.229**	**-0.221**	0.067	-0.083
	(0.031)	(0.037)	(0.063)	(0.056)	(0.078)
Constant	**-0.080**	0.041	0.086	**0.116**	**0.146**
	(0.040)	(0.044)	(0.058)	(0.045)	(0.060)
T	2940	2940	2940	2940	2940
R^2	0.595	0.599	0.259	0.337	0.046

Table 7. Trading strategies and time-varying loadings. This table breaks down the profitability of trading strategy using time-varying loadings that vary with whether the strategy is long or short by reporting OLS estimates of:

$$r_t^{strategy} = (\alpha_0 + \alpha_1\ \mathbf{1}[LONG_{t-2}]) + (\beta_0 + \beta_1\ \mathbf{1}[LONG_{t-2}])r_t^{MKT},$$

where $r_t^{strategy}$ is the excess return to each strategy across the columns, r_t^{MKT} is the excess return to the market, and where this equation has been appropriately expanded for the four-factor model including SMB, HML and Momentum. The variable $\mathbf{1}[LONG_{t-2}]$ is an indicator that is 1 if the trading signal $VIXR$ dated *t*-2 was positive (i.e., indicated the strategy should open or maintain a long futures position on date *t*-1 to be held over date *t*). Units for alpha are annualized in percent/100. Newey and West (1987) standard errors with 20 lags are in parentheses. Bold coefficients indicate those that are statistically reliably different from zero at the 5% level.

Strategy:	L/L	S/S	L/S
	(1)	(2)	(3)
Excess market	**-0.864**	**0.890**	**0.838**
	(0.049)	(0.051)	(0.051)
SMB	0.010	-0.029	-0.019
	(0.049)	(0.048)	(0.050)
HML	0.028	-0.039	-0.045
	(0.053)	(0.062)	(0.057)
Momentum	**-0.159**	**0.167**	**0.144**
	(0.034)	(0.042)	(0.036)
Long signal	**0.282**	**-0.322**	0.011
	(0.087)	(0.099)	(0.088)
Interaction terms:			
Long signal x…			
Excess market	0.075	0.028	**-1.585**
	(0.098)	(0.095)	(0.110)
SMB	-0.088	0.029	-0.057
	(0.096)	(0.101)	(0.098)
HML	-0.083	0.087	0.013
	(0.127)	(0.140)	(0.128)
Momentum	**-0.222**	**0.259**	**-0.514**
	(0.066)	(0.083)	(0.068)
Constant	**-0.169**	**0.145**	**0.109**
	(0.044)	(0.044)	(0.043)
T	2940	2940	2940
R^2	0.603	0.605	0.580

Table 8. Position changes and premium changes. This table reports a regression of weekly changes in net positions (ΔY) on contemporaneous and three lags of the VIX premium as well as three lags of net position changes (Equation 11). The trader categories are dealers (Dealers), asset managers (A Mgr), leveraged hedge funds (HF), other reportable traders (Other), and nonreportable traders (NR). Units are in thousands of futures contracts, which are also the net notional position in $ millions. The sample runs from 2010 onwards. I report Newey and West (1987) standard errors with 6 lags in parentheses. Bold coefficients indicate those that are statistically reliably different from zero at the 5% level.

Dep. Var.: ΔGroup Y net positions, *t*	Dealers (1)	A Mgr (2)	HF (3)	Other (4)	NR (5)
ΔVIXP, *t*	**9.145**	4.460	**-9.841**	-1.479	**-1.570**
	(4.391)	(2.329)	(2.967)	(1.145)	(0.786)
ΔVIXP, *t*-1	**8.236**	**6.619**	**-11.266**	**-3.673**	**-1.404**
	(3.457)	(2.073)	(5.141)	(1.649)	(0.635)
ΔVIXP, *t*-2	5.187	**4.918**	**-9.452**	**-1.968**	0.191
	(2.970)	(1.863)	(3.617)	(0.918)	(0.674)
ΔVIXP, *t*-3	**10.818**	1.524	**-10.966**	-1.658	0.570
	(2.485)	(1.877)	(3.484)	(0.990)	(0.606)
ΔY, *t*-1	**0.318**	-0.104	**0.303**	0.108	**-0.267**
	(0.060)	(0.078)	(0.061)	(0.065)	(0.068)
ΔY, *t*-2	0.024	-0.075	-0.073	**-0.322**	-0.068
	(0.068)	(0.072)	(0.071)	(0.146)	(0.056)
ΔY, *t*-3	-0.073	-0.002	0.040	-0.076	-0.029
	(0.058)	(0.060)	(0.071)	(0.042)	(0.050)
Constant	0.028	0.110	-0.081	-0.010	-0.031
	(0.569)	(0.296)	(0.658)	(0.183)	(0.121)
T	303	303	303	303	303
R^2	0.183	0.060	0.161	0.137	0.090

Table 9. Position changes and risk. This table reports a regression of weekly changes in net positions (ΔY) on changes in realized variance and futures price changes (Equation 12). The trader categories are dealers (Dealers), asset managers (A Mgr), leveraged hedge funds (HF), other reportable traders (Other), and nonreportable traders (NR). Units are in thousands of futures contracts, which are also the net notional position in $ millions. The sample runs from 2010 onwards. I report Newey and West (1987) standard errors with 6 lags in parentheses. Bold coefficients indicate those that are statistically reliably different from zero at the 5% level.

Dep. Var.: ΔGroup Y net positions, *t*	Dealers	A Mgr	HF	Other	NR
	(1)	(2)	(3)	(4)	(5)
ΔRVol, *t*	**-0.525**	-0.076	**0.425**	**0.111**	0.041
	(0.186)	(0.077)	(0.118)	(0.042)	(0.044)
ΔRVol, *t*-1	**-0.400**	**-0.193**	**0.525**	0.103	0.039
	(0.128)	(0.092)	(0.157)	(0.059)	(0.033)
ΔRVol, *t*-2	-0.154	-0.128	**0.315**	0.059	-0.003
	(0.119)	(0.068)	(0.145)	(0.038)	(0.027)
ΔRVol, *t*-3	**-0.338**	-0.126	**0.404**	**0.093**	-0.001
	(0.152)	(0.072)	(0.178)	(0.038)	(0.021)
ΔF, *t*-1	**-1.021**	-0.273	**1.535**	**-0.289**	-0.045
	(0.390)	(0.197)	(0.454)	(0.090)	(0.071)
ΔF, *t*-2	-0.494	-0.135	0.408	-0.033	0.105
	(0.336)	(0.160)	(0.394)	(0.124)	(0.083)
ΔF, *t*-3	0.296	0.004	-0.007	-0.175	0.000
	(0.314)	(0.135)	(0.322)	(0.128)	(0.085)
ΔY, *t*-1	**0.275**	-0.089	**0.274**	**0.138**	**-0.268**
	(0.048)	(0.080)	(0.053)	(0.063)	(0.069)
ΔY, *t*-2	0.057	-0.069	-0.070	**-0.309**	-0.072
	(0.064)	(0.068)	(0.066)	(0.144)	(0.063)
ΔY, *t*-3	-0.061	-0.004	0.046	-0.055	-0.032
	(0.063)	(0.062)	(0.063)	(0.042)	(0.048)
Constant	-0.347	-0.029	0.490	-0.116	-0.011
	(0.632)	(0.328)	(0.722)	(0.201)	(0.131)
T	303	303	303	303	303
R^2	0.256	0.067	0.263	0.141	0.080

Table 10. Why do dealers reduce positions when volatility rises? Panel A reports the results of estimating Equation 12 but replacing ΔX_t with weekly flows for the VXX ETN (Column 1), changes in the signed net notional position of VIX options held by the public (Column 2), changes in the 21-trading-day total return volatility of the XLF Financial Select Sector SPDR ETF (Column 3), and the 4-week log change in the US Aggregate SRISK systemic risk measure of Brownlees and Engle (2017; Column 4). I thank the NYU V-Lab for providing data on SRISK. Panel B reports the results of placing these variables on the left-hand side and estimating their relationship with changes in weekly volatility, controlling for three lags of changes in the left-hand side variable. For brevity, I do not report the control variables in Equation 12 for Panel A and lagged changes in Y for Panel B. The sample runs from 2010-onwards. I report Newey and West (1987) standard errors with 6 lags in parentheses. Bold coefficients indicate those that are statistically reliably different from zero at the 5% level.

Panel A

Dep. Var.: ΔDealer net positions, *t*	Customer demand hypothesis		Risk appetite hypothesis	
ΔX=	VXX flow	ΔVIX Option	ΔFin Vol	SRISK Growth
	(1)	(2)	(3)	(4)
ΔX, *t*	**3.219**	**4.804**	**-4.941**	**-2.939**
	(0.690)	(1.932)	(2.172)	(1.354)
ΔX, *t*-1	0.805	**3.591**	-0.546	0.042
	(0.654)	(1.538)	(1.707)	(1.185)
ΔX, *t*-2	-0.493	2.441	0.546	1.791
	(0.745)	(1.311)	(1.686)	(1.042)
ΔX, *t*-3	-0.554	**2.701**	-1.093	0.390
	(0.514)	(1.286)	(1.579)	(0.885)
T	303	290	303	303
Controls?	Y	Y	Y	Y
R^2	0.264	0.216	0.214	0.246

Panel B

Dep. Var.: ΔY, *t*	Customer demand hypothesis		Risk appetite hypothesis	
ΔY=	VXX flow	ΔVIX Option	ΔFin Vol	SRISK Growth
	(1)	(2)	(3)	(4)
ΔRVol, *t*	-0.292	**-0.220**	**0.268**	**0.187**
	(0.188)	(0.044)	(0.054)	(0.093)
ΔRVol, *t*-1	**-0.506**	**-0.142**	**0.177**	**0.157**
	(0.094)	(0.067)	(0.042)	(0.057)
ΔRVol, *t*-2	**-0.384**	-0.055	**0.201**	0.088
	(0.103)	(0.041)	(0.035)	(0.055)
ΔRVol, *t*-3	**-0.334**	-0.022	**0.175**	**0.120**
	(0.064)	(0.034)	(0.033)	(0.060)
T	303	290	303	303
Controls?	Y	Y	Y	Y
R^2	0.169	0.140	0.508	0.564

Table 11. Correlations with variance risk premiums. This table reports monthly correlations of VIX premiums (VIXP) in levels and changes with volatility risk premiums, computed from variance risk premiums. Because sample sizes differ slightly for different variables, I report pairwise correlations. The BH VRP variables are from Maria Hoerova and are available through August 2010 (T=78). BTZ and Zhou VRPs end in December 2014 (T=130). I obtained these from the website of Hao Zhou.

Panel A: Levels

		(1)	(2)	(3)	(4)	(5)	(6)
(1)	VIX Premium	1.00					
(2)	BH Model 8 VRP	0.79	1.00				
(3)	BH Model 11 VRP	0.70	0.89	1.00			
(4)	BTZ VRP	0.44	0.66	0.62	1.00		
(5)	Zhou VRP	-0.23	0.31	0.25	0.27	1.00	
(6)	GARCH VRP	-0.06	0.45	0.39	-0.09	0.61	1.00

Panel B: Changes

		(1)	(2)	(3)	(4)	(5)	(6)
(1)	VIX Premium	1.00					
(2)	BH Model 8 VRP	0.44	1.00				
(3)	BH Model 11 VRP	0.45	0.78	1.00			
(4)	BTZ VRP	0.25	0.67	0.70	1.00		
(5)	Zhou VRP	-0.53	0.15	0.07	0.20	1.00	
(6)	GARCH VRP	-0.33	0.18	0.19	0.25	0.69	1.00

Table 12. VIX premiums and other asset prices. Panel A, Columns 1-6 reports monthly regressions of stock returns on lagged VRPs ("Premium"), controlling for the 30-day conditional variance forecast ("Forecast"). BTZ references the variance risk premium from Bollerslev, Tauchen, and Zhou (2009), while BH Model 8 and Model 11 reference the "winning" conditional variance models from Bekaert and Hoerova (2014), both of which I update through November 2015. Columns 7 and 8 report regressions of stock returns on the lagged VIX premium as well as the conditional VIX forecast. I report Newey and West (1987) standard errors with three lags in parentheses. Panel B reports the results of a regression of monthly changes in the Bank of America-Merrill Lynch corporate BBB spread on explanatory variables, following Collin-Dufresne, Goldstein, and Martin (2001) Equation 1. Variables are contemporaneous and in changes. Newey and West (1987) standard errors with two lags are in parentheses. Panel C reports the results of a regression of monthly changes in sovereign CDS spreads on explanatory variables in a panel of 25 countries, adapting Longstaff, Pan, Pedersen, and Singleton (2011) Table 3. Variables are contemporaneous and in changes. Standard errors clustered by month are in parentheses. Panel D reports a regression of monthly returns to the k=3 currency carry trade strategy on explanatory variables, following Brunnermeier, Nagel, and Pedersen (2009) Table 7. Variables are in changes and contemporaneous. Newey and West (1987) standard errors with three lags are denoted in parentheses. For Panels B and C, the Online Appendix reports full results. For all panels, bold coefficients indicate those that are statistically reliably different from zero at the 5% level.

Panel A. Stock market predictability

	BTZ		BH Model 8		BH Model 11		VIXP	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Premium	**0.640**	**0.601**	0.385	**0.930**	0.384	**0.646**	**7.960**	**8.578**
	(0.144)	(0.181)	(0.279)	(0.331)	(0.235)	(0.246)	(3.726)	(4.321)
Forecast		-0.062		**-0.576**		**-0.416**		2.005
		(0.069)		(0.167)		(0.117)		(5.624)
Constant	-3.212	-1.268	0.251	0.325	0.378	3.167	1.813	1.286
	(3.220)	(4.085)	(4.959)	(4.493)	(4.268)	(3.935)	(5.588)	(6.221)
N	310	310	310	310	310	310	140	140
R^2	0.054	0.056	0.013	0.047	0.016	0.042	0.049	0.052

Panel B. US corporate credit spreads

Dependent variable: BAML BBB Spread	(1)	(2)	(3)	(4)
VIX	0.019	**0.028**		
	(0.010)	(0.014)		
VIX premium		0.064		**0.113**
		(0.038)		(0.040)
Realized volatility			**0.070**	**0.128**
			(0.031)	(0.043)
VIX - Realized			-0.001	0.009
			(0.009)	(0.009)
Controls	Y	Y	Y	Y
T	136	136	136	136
R^2	0.452	0.476	0.538	0.607

Table 12, continued.

Panel C. Sovereign CDS spreads

Dependent variable: CDS spread	(1)	(2)	(3)	(4)
VIX	**2.330**	**3.057**		
	(0.809)	(0.728)		
VIX premium		**7.033**		**7.733**
		(2.491)		(2.459)
Realized volatility			**8.149**	**11.148**
			(3.005)	(2.910)
VIX-Realized			**2.225**	**2.699**
			(0.727)	(0.657)
Local financial variables	Y	Y	Y	Y
Country FE	Y	Y	Y	Y
Observations	3198	3198	3198	3198
R^2	0.155	0.165	0.156	0.166
T	140	140	140	140

Panel D. Foreign currency carry trades

Dependent variable: Returns for k=3	(1)	(2)	(3)	(4)
VIX	**-0.275**	**-0.312**		
	(0.043)	(0.048)		
VIX premium		**-0.419**		**-0.482**
		(0.182)		(0.231)
Realized volatility			**-0.962**	**-1.121**
			(0.151)	(0.183)
VIX - Realized			**-0.255**	**-0.276**
			(0.050)	(0.044)
Constant	0.218	0.216	0.218	0.214
	(0.183)	(0.173)	(0.184)	(0.172)
T	140	140	140	140
R^2	0.292	0.318	0.294	0.326