Early Birds Get the Vol: Morning Volatility Uncertainty and Variance Risk Premium

Mattia Bevilacqua[a] and Rodrigo Hizmeri[a]

[a]University of Liverpool

This Draft: December 14, 2025
First Draft: January 18, 2025

Abstract

We document that morning volatility-of-volatility (VVIX), measured at 10:00 EST during the U.S.–European market overlap, strongly predicts next-day variance asset returns. Predictive power peaks with t-statistics reaching 5.6 and adjusted R^2 of 2.6%, but diminishes after 11:00 EST. Trading strategies exploiting this pattern generate Sharpe ratios exceeding 2.0, remaining economically meaningful even after transaction costs. Crucially, intraday returns display a flat relationship with morning VVIX on high volatility uncertainty days, while close-to-close returns exhibit strong predictability. These findings are difficult to reconcile with standard risk premium theories but are consistent with limited attention and slow-moving beliefs about volatility.

Keywords: Volatility uncertainty; variance risk premium; VVIX; Limited attention; Slow-moving beliefs.
JEL Codes: G11, G12, G13, G14.

[⋄]We are grateful for insightful discussions with Kevin Aretz, Yannick Dillschneider, Gustavo Freire, Pedro Garcia-Ares, Elise Gourier, Anastasios Kagkadis, Alex Kostakis, Felix Matthys (discussant), Chay Ornthanalai, Ser-Huang Poon (discussant), Lucio Sarno, Philipp Schuster, Aurelio Vasquez, and Chardin Wese Simen. We also thank the conference participants at the Cancun Derivatives and Asset Pricing Conference 2025, the 2nd Liverpool Workshop in Option Markets, and seminar participants at Erasmus University Rotterdam, the University of Birmingham, and the University of Manchester for their helpful comments.
E-mail addresses: m.bevilacqua@liverpool.ac.uk (M. Bevilacqua), r.hizmeri@liverpool.ac.uk (R. Hizmeri). Correspondence to: University of Liverpool Management School, Accounting and Finance Group, Chatham Street, Liverpool, L69 7ZH, United Kingdom.

1 Introduction

The pricing of volatility risk is central to asset pricing and investment theory,[1] manifesting most prominently through the Variance Risk Premium (VRP). The VRP, which represents the compensation investors demand for bearing future volatility uncertainty, is consistently documented as a negative quantity, reflecting a collective willingness to pay for essential volatility protection. However, this premium exhibits considerable temporal variation, particularly during periods of heightened market anxiety or financial stress. Despite its fundamental role in derivative markets, the precise mechanism and timing by which investors' real-time perceptions of uncertainty become incorporated into variance asset prices remain an ongoing challenge in empirical finance.

This challenge is amplified by a persistent puzzle concerning the pricing of volatility claims (e.g., Cheng, 2019; Lochstoer and Muir, 2022). These instruments, which provide insurance against future volatility uncertainty and are thus unconditionally expensive, appear initially *too cheap* during periods of heightened volatility uncertainty, but are priced higher later on. This finding is difficult to rationalize because these claims are typically riskier after uncertainty rises, suggesting that risk premium should increase rather than decline or flatten. This paper contributes to resolving this puzzle by identifying when the volatility uncertainty signal arrives and documenting the market's delayed response to this information. While existing rational risk premium theories struggle to explain this finding, limited attention and slow-moving beliefs are largely consistent with it: investors either fail to monitor morning volatility uncertainty signals due to limited attention (Hong and Stein, 1999; Hirshleifer et al., 2009) or update their beliefs too conservatively when they do observe them (Cheng, 2019; Lochstoer and Muir, 2022). Such delayed incorporation generates initial underreaction to morning VVIX signals, leading to predictable next-day returns as prices gradually adjust to reflect the elevated uncertainty.

[1] Volatility risk is a fundamental factor influencing asset prices and investment decisions, therefore receiving extensive attention in the literature (e.g., Bansal and Yaron, 2004; Bansal et al., 2014; Andrei and Hasler, 2015; Campbell et al., 2018, among others).

We investigate when volatility uncertainty signals arrive and whether they are promptly incorporated into variance asset prices. We show that morning volatility-of-volatility (VVIX) index serves as a real-time proxy for investor uncertainty. The VVIX is derived directly from the prices of VIX options, capturing the market's expectation regarding future VIX levels, thus, the risk embedded in variance claims,[2] making it intrinsically linked to the VRP (e.g., Bardgett et al., 2019; Huang et al., 2019). Central to our findings, we employ an innovative intraday analysis, moving beyond the standard daily closing prices used in prior literature. By partitioning the trading day into segments, we are able to isolate precisely when uncertainty signals emerge and, crucially, whether markets respond efficiently. To measure the VRP, we examine returns on variance-sensitive assets: synthetic variance swaps, VIX futures, S&P 500 straddles, and VIX straddles. This approach relies on tradable assets and is therefore preferred over the traditional VRP measure ($\mathbb{E}_t[RV_{t+h}] - IV^2$), as it permits clean tests of economic significance through implementable trading strategies while eliminating model dependence and estimation error inherent in forecasting realized variance (Johnson, 2017).

Our empirical analysis yields several key findings. First, we document that morning VVIX ($VVIX^M$), measured at 10:00 EST during the U.S.–European market overlap period, exhibits strong predictive power for next-day close-to-close variance asset returns across all instruments considered. The coefficients are both economically and statistically highly significant; a one-standard-deviation increase in $VVIX^M$, for instance, raises VIX futures returns by 0.71% and variance swap returns by 2.98%. This robust predictability is reflected in R^2 values of up to 2.6%, and it holds out-of-sample. Crucially, this predictive power diminishes rapidly after 11:00 EST, becoming insignificant by midday, indicating that morning information carries unique content that dissipates as the trading day progresses.

We argue that the timing of this effect is not coincidental. The U.S.–European overlap window represents a critical juncture when overnight developments are first incorporated into

[2] The volatility-of-volatility has been shown to be fundamental state variable of theoretical models of variance risk premia (Bollerslev et al., 2009; Drechsler and Yaron, 2011; Dew-Becker et al., 2017).

U.S. option prices, making VVIX at 10:00 EST the market's initial comprehensive assessment of volatility uncertainty. Rather than all investors responding immediately to this signal, we observe heterogeneous information processing: attentive investors react quickly to morning VVIX, while inattentive investors incorporate the information with delay. This heterogeneity is evident in trading volume patterns around high-morning VVIX days (Figure 3). When VVIX is elevated at 10:00 EST, volume increases slightly on day 0 relative to pre-event days, then rises gradually and remains for several days, indicating delayed trading. In contrast, when VVIX is elevated at midday or close, volume peaks on the event day but quickly reverts thereafter. This pattern provides direct evidence that morning volatility uncertainty is incorporated with delay, consistent with limited attention, slow information diffusion, and slow-moving beliefs about volatility (Hirshleifer et al., 2009; Hong and Stein, 1999; Cheng, 2019; Lochstoer and Muir, 2022).

Second, and most compellingly, we compute intraday returns across all four instruments, from 10:00 to 16:00 EST. We find a flat, insignificant relationship between intraday returns and $VVIX^M$ on high VVIX days (i.e., days on which VVIX exceeds its 75th percentile), whereas the same relationship using close-to-close returns is strongly significant.

Third, we examine the economic value of $VVIX^M$ through trading strategies that buy (sell) variance assets on days when morning VVIX exceeds (falls below) a given threshold. Using the 75th percentile as a threshold, these strategies generate annualized Sharpe ratios of 1.73 for SPX straddles, 1.51 for VIX straddles, 2.09 for VIX futures, and 2.87 for variance swaps –substantially outperforming the benchmark that consistently sells the variance asset. Notably, the profitability stems from both legs of the strategy: buying variance assets during high-uncertainty days and selling during low-uncertainty days. Importantly, the same strategy, implemented using VVIX measured outside the morning overlap window, yields no economically significant returns.

To provide further support for the delayed information incorporation, we test the relationship between $VVIX^M$ and intraday variance asset returns, i.e., returns between 10:00

and 16:00 EST. The intuition is as follows: if investors display, on average, limited attention or slow responses to morning volatility uncertainty, we should expect a weaker relationship between intraday returns and $VVIX^M$ on days with high volatility uncertainty. Additionally, we should also expect that our trading strategy, implemented immediately following elevated morning VVIX, yields economically insignificant returns. Our results strongly support the slow response bias in that the relationship between morning VVIX and intraday returns on days with high morning volatility uncertainty (i.e., $VVIX^M$ exceeding its 75th percentile) is flat and generally insignificant. Furthermore, the returns accrued from buying intraday variance assets on days when $VVIX^M$ exceeds its 75th percentile are insignificantly different from zero, supporting our limited attention and slow information processing hypotheses.

Fourth, we subject our findings to an extensive battery of robustness tests to rule out alternative explanations. We first control for established risk measures that have been shown to predict variance asset returns, such as jumps, VIX_t^2, VIX slope, VRP, and implied volatility skew constructed from morning and end-of-day data (e.g., Todorov, 2010; Johnson, 2017; Cheng, 2019). Across all specifications, $VVIX^M$ retains its predictive power, indicating that morning volatility uncertainty captures unique information not subsumed by these established predictors. We next examine whether overnight information or market microstructure effects explain our findings. Overnight returns and realized variance computed from E-mini S&P 500 futures during the European market opening capture news arriving before U.S. market open; controlling for these measures ensures that $VVIX^M$ is not simply proxying for overnight price movements. Order imbalances in both S&P 500 E-mini futures and VIX options markets address the concern that predictability arises from an inventory effect or temporary price pressure rather than fundamental uncertainty pricing. The predictive power of $VVIX^M$ remains intact after including these controls.

Finally, we verify that our results are not driven by calendar effects or anticipated macroeconomic news. Day-of-the-week dummies account for well-documented return seasonalities, particularly the tendency for variance assets to exhibit distinct patterns on Mondays and

Fridays. Excluding FOMC and ECB announcement days ensures that predictability does not arise mechanically from scheduled monetary policy releases, which are known to affect volatility dynamics. The exclusion of daylight saving time transition days rules out any spurious effects from the temporary misalignment of U.S. and European trading hours. Our findings remain robust across all these specifications, reinforcing the conclusion that morning VVIX captures a genuine signal about volatility uncertainty that investors incorporate with delay due to limited attention and slow information processing.

The rest of the paper is organized as follows. Section 1.1 reviews the literature, positioning our contribution within the existing research. Section 2 details the construction of the VVIX, the calculation of the variance asset returns, and presents our data. Section 3 presents our main empirical findings. Section 4 subjects our findings to a comprehensive battery of robustness tests and alternative explanations. Finally, Section 5 concludes. Additional material and results are presented in the paper Appendix.

1.1 Related Literature

This paper contributes to the literature studying variance risk premia and their determinants. A large body of research documents that the unconditional variance risk premium is negative, reflecting investors' willingness to pay for protection against volatility uncertainty (e.g., Coval and Shumway, 2001; Bakshi and Kapadia, 2003; Carr and Wu, 2009), with shorter maturities commanding the most pronounced risk premia (e.g., Eraker and Wu, 2017; Dew-Becker et al., 2017). While the existence of this premium is well established, its dynamics remain an active area of inquiry. Todorov (2010) and Aït-Sahalia et al. (2020) document that variance risk premia amplify following downward equity price jumps. However, Cheng (2019) uncovers a puzzling pattern: the VIX premium falls or remains flat precisely when future volatility uncertainty rises,[3] which is the opposite of what standard risk-based explanations would

[3] Jacobs et al. (2025) complement this evidence from a market microstructure perspective, showing that volatility demand falls during market turmoil as market makers reduce their willingness to absorb order flow, further contributing to the delayed price adjustment.

predict.

Our paper builds on behavioral explanations for this puzzle. Two mechanisms can generate delayed price responses to volatility information. First, limited attention: investors with finite information-processing capacity cannot continuously monitor all relevant signals (Sims, 2003; Hirshleifer et al., 2009; DellaVigna and Pollet, 2009), generating delayed responses to information they fail to observe in real time.[4] Second, slow-moving beliefs: Lochstoer and Muir (2022) show that investors who do observe volatility signals may nonetheless update their expectations too conservatively, underestimating volatility persistence. These mechanisms are complementary rather than competing, as investors may both fail to monitor morning volatility uncertainty and, conditional on eventually observing it, underweight its implications. We contribute by identifying precisely *when* volatility uncertainty signals arrive and documenting their delayed incorporation into prices, consistent with both channels operating in volatility markets.

We also connect to the strand of the literature examining the information content of volatility-of-volatility measures. Park (2015) shows that VVIX successfully predicts tail risk hedging returns. Bardgett et al. (2019) and Huang et al. (2019) document that market volatility of volatility is a significant risk factor affecting index and volatility index option returns, beyond volatility itself. Kaeck (2018) shows that exploiting the variance-of-variance risk premium leads to profitable strategies. Hollstein and Prokopczuk (2018) and Baltussen et al. (2018) document that the volatility-of-volatility can also predict the cross-section of stocks. Our study departs from this literature by revealing that VVIX's predictive content is not uniformly distributed across trading hours but instead concentrates during the U.S.–European market overlap window. This finding highlights the importance of temporal disaggregation in understanding how uncertainty is priced in variance markets –a dimension that prior work, relying exclusively on daily closing values, has overlooked.

[4] Cohen and Frazzini (2008) document that information requiring cognitive effort to connect to asset values is incorporated with delay—in their setting, stock prices of supplier firms adjust slowly to news about their major customers.

Finally, we contribute to the growing literature examining the information content of equity, futures, and option markets at more granular times. Extant literature has been devoted to examining intraday price continuation, documenting predictable patterns over half-hour intervals, and between first half-hour and last half-hour returns (e.g., Heston et al., 2010; Gao et al., 2018).[5] Bogousslavsky (2016) provides a theoretical justification based on infrequent portfolio rebalancing. In future markets, Boyarchenko et al. (2023) and Bondarenko and Muravyev (2023) identify substantial positive U.S. equity returns coinciding with European market openings. Research on option market remains sparse. Muravyev and Ni (2020) document distinct patterns in S&P 500 option returns, finding negative variance risk premia overnight but mildly positive premia during trading hours, while Da et al. (2024) show that half-hour straddle returns predict in the same interval the following day. We contribute by documenting that morning VVIX serves as a real-time proxy for investors' uncertainty, and trading strategies exploiting this signal generate Sharpe ratios substantially exceeding the benchmark strategy that consistently short the variance assets.

2 Data and methodology

2.1 Data

We obtain high-frequency VIX and S&P 500 (SPX) options data from CBOE LiveVol, sampled at 1-minute intervals from 09:31 to 16:15. The dataset comprises quote prices, trade prices, option volume, open interest, and underlying asset quotes. VIX options span September 2006 to June 2022, while SPX options cover January 2012 to June 2022. From Refinitiv Tick History, we collect high-frequency E-mini S&P 500 futures (September 2006–June 2022) and VIX futures (January 2014–June 2022) data. After standard cleaning procedures, we sample futures data at 1-minute intervals using previous tick interpolation. Both futures

[5] For early work examining intraday patterns in financial markets, please see, among others, Wood et al. (1985); Smirlock and Starks (1986); Admati and Pfleiderer (1988).

series use front-month contracts with expiry rollovers. End-of-day option data and daily zero-coupon interest rates come from OptionMetrics, with rates assumed constant intraday.

2.2 VVIX index

The CBOE volatility-of-volatility (VVIX) index, proposed by the Chicago Board Options Exchange (CBOE), is derived directly from the prices of VIX options, capturing the market's expectation regarding future VIX levels over the next 30-day horizon, directly capturing the risk embedded in variance claims. Following the VIX methodology, we compute the implied volatility-of-volatility using intraday VIX options as:

$$\mathbb{VVIX}_t^2 = \frac{2e^{r_f T}}{T}\left[\int_0^{F_t} \frac{1}{K^2} P_t(K) dK + \int_{F_t}^{\infty} \frac{1}{K^2} C_t(K) dK\right] \tag{1}$$

where F_t denotes the VIX forward price, $C(\cdot)$, and $P(\cdot)$ represent VIX call and put option prices at time t with maturity T (in minutes) and strike price K. The squared VVIX is derived from a portfolio of out-of-the-money (OTM) VIX options at each timestamp.[6] This approach builds on Britten-Jones and Neuberger (2000) and Jiang and Tian (2005), who show that VIX^2 can be computed model-free from a portfolio of OTM options with a continuous, infinite strike range. The forward price represents a theoretical 30-day VIX futures contract, reflecting market expectations of future VIX levels. This measure captures investors' evolving expectations of VIX forward volatility throughout the trading day.

To determine the optimal times for measuring VVIX throughout the trading, we first examine the intraday patterns of trading activity and market liquidity in VIX options. Figure 1 presents the average intraday relative bid-ask spread and trading volume for VIX options from September 2006 to June 2022. Trading begins with low volume and wide spreads. Volume peaks at 10:00, coinciding with narrower spreads, both gradually declining before rising again around closing time. Trading volume and relative bid-ask spread display the

[6]For detailed VIX methodology, see the CBOE white paper at http://www.cboe.com/micro/vix.

usual U-shaped pattern documented in the literature, and align with prior findings about sparse quotes and wide spreads immediately following market opening times (e.g., Chan et al., 1995).

Based on these patterns, we construct VVIX measures at hourly intervals from 10:00 to 16:00 EST. Proxying the opening time at 10:00 ensures that VVIX calculations are not contaminated by opening illiquidity (e.g., Muravyev and Ni, 2020; Almeida et al., 2024). The hourly frequency balances the need to track intraday dynamics with practical considerations of data granularity and the gradual nature of information diffusion needed to investigate whether volatility uncertainty is promptly incorporated into variance assets.

Table B1 in the Appendix presents the correlations and AR(1) coefficients for the VVIX measures computed at different intraday intervals. Correlations range from 0.78 to 0.99, with the 10:00 VVIX exhibiting the weakest correlation with other sampling times. This pattern suggests that the volatility-of-volatility information captured at 10:00 contains distinct components relative to other intraday periods, likely reflecting the unique market dynamics following the opening period. Furthermore, this time displays the lowest persistence among all sampling intervals, indicating stronger mean-reversion properties, which is consistent with a higher prevalence of volatility jumps during the post-opening period.

Finally, Figure 2 plots the time series of the VVIX and VIX measured at 10:00, 12:00, 14:00, and 16:00. The two series show a weak correlation overall, with the 10:00 measurement exhibiting the lowest correlation –approximately 10% lower than at other times of the day. Measures at 12:00, 14:00, and 16:00 display similar correlation levels. These findings suggest that VVIX follows distinct dynamics from traditional volatility risk factors, with this difference being most pronounced in the morning.

2.3 Variance Assets

Volatility-of-volatility reflects market expectations regarding future VIX levels, capturing the risk embedded in variance claims and making VVIX intrinsically linked to the variance risk premium. To examine how this uncertainty signal is incorporated into prices, we focus on close-to-close excess returns of four variance-sensitive assets: SPX straddles, variance swaps, VIX futures, and VIX straddles. As Johnson (2017) notes, these variance asset returns offer advantages over traditional variance risk premium measures calculated from option-implied and realized variances.[7] First, they capture maturity-specific variance premia more effectively than risk-neutral and physical variance differences. Second, they directly connect to asset pricing models examining tradable risk premia. Third, they are model-free, operating independently of statistical assumptions used for realized variance estimation.

We proxy variance swap returns using synthetic variance swaps replicated by S&P 500 option portfolios, priced at $VIX^2_{t,T}$ (Carr and Madan, 1998). Daily synthetic variance swap returns thus reflect the replicating option portfolio's daily returns. We also examine at-the-money S&P 500 straddle returns, which primarily expose investors to volatility risks while offering lower transaction costs due to higher liquidity. Additionally, we analyze VIX futures and VIX straddle returns. VIX futures contracts have traded since 2004, with historical end-of-day data publicly available on the CBOE Website. VIX straddles provide exposure to volatility-of-volatility risk, offering a natural instrument to examine how VVIX signals are priced on the VVIX itself. To examine maturity-dependent variation in risk premia associated with these assets, we implement a constant maturity strategy across horizons $T = 1, 2, 3, 6$ months (Johnson, 2017; Eraker and Wu, 2017). Appendix A details the variance asset computations.

Table B2 presents summary statistics for variance assets excess returns, including annualized Sharpe ratios. We test the null hypothesis of zero mean against a negative mean using bootstrapped standard errors (2,500 replications) and report p-values. Consistent with Co-

[7] Computing conditional variance risk premium as the difference between risk-neutral and physical measure conditional variances requires daily estimation for each day t and maturity T (Bollerslev et al., 2009; Todorov, 2010; Bekaert and Hoerova, 2014), or comparing future realized variance with option-implied variance (Carr and Wu, 2009; Feunou et al., 2014). These methods present challenges for analyzing maturity-specific variance risk premia at fixed forecast horizons. While both approaches accommodate different maturities T, they estimate risk premia over entire maturity periods, complicating the distinction between maturity-based and horizon-based risk premia differences.

val and Shumway (2001) and Dew-Becker et al. (2017), all variance assets exhibit negative average excess returns that decrease with maturity, indicating investors pay higher insurance premiums for shorter maturities. Variance swaps generate the largest negative returns, significant across all maturities, with absolute Sharpe ratios exceeding 1.0. SPX straddles show significant negative returns at the 10% level for the first three maturities, while VIX straddles command lower but still negative premiums. As is typical for hedging instruments, these assets exhibit right skewness and leptokurtosis. Table B3 shows correlations across 1-, 3-, and 6-month maturities. Assets correlate positively, with same-maturity correlations generally exceeding 50% and cross-maturity correlations above 36%, suggesting exposure to common but not identical risk factors.

3 Empirical Results

3.1 When Does Volatility Uncertainty Predict?

This section examines when volatility uncertainty signals arrive and whether they are promptly incorporated into variance asset prices. We estimate univariate predictive regressions of close-to-close excess returns on VVIX measured hourly from 10:00 to 16:00 EST:

$$r_{t+1} - r_{f,t+1} = \alpha + \beta VVIX_t^h + \epsilon_{t+1}, \tag{2}$$

where $r_{t+1} - r_{f,t+1}$ represents next-day close-to-close excess returns for one of the variance assets: S&P 500 straddles, variance swaps, VIX straddles, and VIX futures. $VVIX_t^h$ denotes the VVIX measured at hour h on day t.

Table 1 presents in-sample regression results across four panels. Panels A through D display coefficients, HAC-robust t-statistics using 12 lags,[8] and adjusted R-squared values for S&P 500 straddles, variance swaps, VIX straddles, and VIX futures, all with constant

[8]The optimal number of lags equals $\lceil 0.75 \times T^{1/3} \rceil$, where T is the number of observations.

maturity of one month. Our analysis reveals a striking pattern: morning VVIX, particularly during the U.S.–European market overlap, proves especially valuable for predicting next-day variance asset returns. Predictive performance peaks at 10:00, with t-statistics ranging from 4.5 to 6.1 and adjusted R^2 values between 1.99% and 2.63%. This predictive power sharply attenuates after 11:00, as the market overlap concludes, with coefficients becoming both statistically and economically insignificant. While VVIX measures calculated after the overlap period show a negative but statistically insignificant relationship with next-day returns, during the overlap period, VVIX exhibits a strong positive relationship: a one-standard-deviation increase in VVIX corresponds to gains of 0.71 and 2.98 percentage points in VIX futures and variance swap returns, respectively. These findings suggest that morning volatility uncertainty contains richer predictive content than afternoon measurements, likely reflecting a cleaner uncertainty signal before intraday noise accumulates.

However, as Welch and Goyal (2008) and Campbell and Thompson (2008) emphasize, many predictors that perform strongly in-sample fail out-of-sample. We therefore assess whether this morning predictive advantage persists in real-time forecasting. For every VVIX measure throughout the trading day, we estimate predictive regressions (Equation (2)) using an expanding window with an initial window size of one year, re-estimating the model daily. We evaluate predictive power using the out-of-sample R^2:

$$R^2_{oos} = 1 - \frac{\sum_{t=1}^{T} \left(r^e_{t+1} - \widehat{r}_{t+1|t}\right)^2}{\sum_{t=1}^{T} \left(r^e_{t+1} - \mu_{t+1|t}\right)^2}, \tag{3}$$

where $r^e_{t+1} = r_{t+1} - r_{f,t+1}$ denotes the excess return, and $\widehat{r}_{t+1|t}$ is the forecast computed using information available up to time t. The term $\mu_{t+1|t}$ represents the benchmark model. Following Campbell and Thompson (2008), we consider the historical mean through t, defined as $\mu_{t+1|t} = \dfrac{1}{t} \sum_{s=1}^{t} r^e_s$. Since the historical mean may be a poor predictor over short horizons, potentially inflating R^2_{oos}, we also consider the full-sample mean ($\mu_{t+1|t} = \mu$), which provides a more demanding benchmark by incorporating future information. We assess statistical significance using the Clark and West (2007) statistic, where the null hypothesis is that the regressor has no predictive power. Table 2 reports the out-of-sample results.

A positive R^2_{oos} indicates that the predictor outperforms the benchmark. As can be seen, models considering the VVIX computed during the overlap period exhibit significant predictive power across all variance assets, surpassing both benchmarks and reinforcing our in-sample findings. In contrast, models using VVIX measured outside this morning window show consistently inferior performance. Both in-sample and out-of-sample results indicate that predictive power peaks at 10:00 and declines thereafter, with statistical significance dissipating after 11:00. This temporal decay in VVIX's predictive capacity suggests that morning volatility uncertainty, measured during the overlap window, provides fundamental information about variance risk premia that is not immediately incorporated into prices.

The striking concentration of predictive power in the morning hours reflects the critical U.S.–European market overlap, serving as the first comprehensive opportunity for global investors to incorporate overnight information into VIX option prices. Therefore, VVIX measured at 10:00 EST captures the market's initial comprehensive assessment of volatility uncertainty, synthesizing information that accumulated while the U.S. markets were closed. However, rather than observing uniform, immediate price incorporation, our results reveal heterogeneous information processing among investors: attentive investors react to the morning signal, while inattentive investors incorporate this critical information with a delay.

To distinguish between immediate and delayed incorporation, we examine trading volume patterns around days with elevated morning VVIX. The logic is straightforward: if all investors respond immediately to the morning uncertainty signal, we should observe elevated volume on day t followed by normal volume on subsequent days. However, if some investors are inattentive or slow to update their beliefs, volume should remain elevated as these investors belatedly adjust their positions. Figure 3 presents event study results for trading volume in SPX options, VIX futures, and VIX options around high-VVIX days. Panel A conditions on VVIX measured at 10:00 EST, while Panels B and C condition on VVIX at

12:00 and 16:00 EST, respectively. High VVIX days are defined as days when VVIX exceeds its 75th percentile.[9] The results reveal a clear divergence across conditioning times. When morning VVIX is elevated, trading volume increases modesty on day 0, then rises gradually and remains persistently elevated for several days thereafter. This pattern is consistent across SPX options, VIX futures, and VIX options. In contrast, when we condition on elevated VVIX at midday or market close, volume peaks on day 0 but shows no persistence, reverting quickly by day $T + 1$. The stark contrast between morning and afternoon VVIX days provides direct evidence that morning volatility uncertainty information is incorporated gradually rather than instantaneously, consistent with models of limited attention (Hirshleifer et al., 2009), slow information diffusion (Hong and Stein, 1999), and slow-moving beliefs about volatility (Cheng, 2019; Lochstoer and Muir, 2022).

In summary, both in-sample and out-of-sample evidence demonstrate that VVIX's predictive power for variance asset returns is concentrated during the U.S.–European market overlap, peaking at 10:00 EST and dissipating by midday. Trading volume dynamics confirm that this morning signal is incorporated gradually rather than immediately, consistent with limited attention and slow-moving beliefs. Given the unique predictive content of morning volatility uncertainty, the remainder of our empirical analysis focuses exclusively on VVIX measured at 10:00 EST, which we denote $VVIX^M$.

3.2 Trading on Morning Volatility Uncertainty

If morning VVIX captures volatility uncertainty that investors incorporate with delay, a natural implication is that variance asset prices temporarily deviate from fundamentals. Elevated morning VVIX signals heightened uncertainty, yet prices do not fully adjust until the following day, rendering variance assets "too cheap" relative to their expected returns. Conversely, low morning VVIX indicates subdued uncertainty, making the typical negative variance risk premium more pronounced. A trading strategy that buys variance assets fol-

[9] Results are qualitatively similar when using the median as the threshold.

lowing high morning VVIX and sells following low morning VVIX exploits both sides of this mispricing.

Table 3 tests this implication directly, reporting annualized Sharpe ratios for strategies conditioned on morning VVIX. The benchmark represents the unconditional strategy of systematically selling variance assets, capturing the well-documented negative variance risk premium. Panel A presents the long-short strategy, which buys variance assets when morning VVIX exceeds the threshold ϖ and sells otherwise. Panels B and C decompose this strategy into its long-only and short-only components to isolate the source of profitability. The results confirm substantial economic value from the morning VVIX signal. The long-short strategy achieves Sharpe ratios ranging from 1.51 to 2.87 using the 75th percentile threshold, substantially outperforming the benchmark across all variance assets. For VIX futures, the strategy generates a Sharpe ratio of 2.09, nearly four times the benchmark of 0.54. SPX straddles yield 1.73 compared to 0.64, while variance swaps achieve 2.87 versus 2.74.

Decomposing the strategy reveals that both legs contribute to profitability, consistent with our two-sided mispricing hypothesis. The long-only strategy (Panel B) generates particularly strong performance at the 75th percentile threshold, with Sharpe ratios of 2.52 for SPX straddles, 2.41 for VIX straddles, and 3.24 for VIX futures. These results confirm that buying variance assets following elevated morning VVIX –precisely when underreaction renders them “too cheap”– yields substantial positive returns. The short-only strategy (Panel C) also delivers consistent profits, with Sharpe ratios ranging from 1.46 to 2.37 at the 75th percentile threshold. This indicates that selling variance assets when morning uncertainty is subdued, thereby harvesting the more pronounced negative variance risk premium, remains profitable.

Notably, the long-only leg exhibits greater sensitivity to the threshold choice. At the 75th percentile, long-only Sharpe ratios increase markedly relative to the median threshold for SPX straddles (0.76 to 2.52), VIX straddles (1.14 to 2.41), and VIX futures (0.98 to 3.24), suggesting that more extreme morning VVIX realizations contain stronger signals of underreaction. In contrast, short-only performance remains relatively stable across thresholds, reflecting the persistent nature of the unconditional variance risk premium during periods of low uncertainty.

3.2.1 Is the Predictability Unique to Morning VVIX?

Our trading strategy conditions on VVIX measured at 10:00 EST, exploiting the predictability documented during the U.S.–European market overlap. A natural question is whether similar strategies based on VVIX measured later in the day generate comparable returns. If the morning signal reflects unique information about volatility uncertainty that investors incorporate with delay, we should expect the predictive content, and thus profitability, to dissipate as the trading day progresses.

Figure 4 confirms that the profitability of our strategy is unique to morning VVIX. The top row displays average next-day returns on high-VVIX days (above the 75th percentile), while the bottom row displays returns on low-VVIX days (below the 75th percentile). When conditioning on VVIX at 10:00 EST, the long-only strategy generates substantial positive returns across all variance assets, and the short-only strategy captures negative returns consistent with the variance risk premium. Crucially, this return differential collapses when conditioning on VVIX later in the day. By midday, average returns on high-VVIX days are statistically indistinguishable from zero and, for some assets, turn negative. Similarly, returns on low-VVIX days become less reliably negative as the conditioning time moves toward market close. The stark contrast between morning and afternoon underscores that the predictive content of VVIX is concentrated in the early trading hours, precisely when our mechanism predicts that uncertainty information arrives but has not yet been fully incorporated into prices.

3.2.2 Robustness to Transaction Costs

We now assess the practical feasibility of trading strategies based on the morning $VVIX$ signal, focusing on the two most liquid instruments in our sample: SPX straddles and VIX futures. Table 4 reports annualized Sharpe ratios under varying levels of round-trip transaction costs. We consider daily round-trip costs of 0.40% and 0.65%, benchmarked against median round-trip costs observed over the most recent three and five years of SPX options data, respectively.[10] An important distinction in implementation is that SPX straddles require daily rebalancing to maintain at-the-money positions. In contrast, our VIX futures strategy holds positions until the signal triggers a change in direction, substantially reducing transaction frequency.

The results demonstrate that the morning VVIX signal retains economic value after accounting for realistic transaction costs. The benchmark strategy of consistently selling SPX straddles, which is profitable in gross terms (Sharpe ratio of 0.64), delivers a negative Sharpe ratio once transaction costs are incorporated, indicating that its profitability disappears under realistic implementation. In contrast, the morning VVIX strategy remains profitable: using the 75th percentile as a threshold, it generates Sharpe ratios of 0.89 and 0.36 under transaction costs of 0.40% and 0.65%, respectively. VIX futures exhibit even stronger resilience. The strategy produces Sharpe ratios of 1.99 and 1.93 at cost levels of 0.40% and 0.65%, respectively –only modestly below the gross Sharpe ratio of 2.09. This robustness reflects both the strength of the underlying signal and the lower rebalancing frequency inherent in the futures implementation. Overall, the economic value of morning VVIX is preserved after accounting for transaction costs, particularly in the more liquid VIX futures market.

[10] VIX futures typically incur substantially lower transaction costs than SPX options. We apply the same conservative cost estimates across both assets to ensure a robust, comparable analysis.

3.2.3 Testing the Underreaction Mechanism: Intraday Evidence

Our findings are consistent with models of limited attention (Hirshleifer et al., 2009), slow information diffusion (Hong and Stein, 1999), and slow-moving beliefs about volatility (Cheng, 2019; Lochstoer and Muir, 2022). These frameworks share a common prediction: prices should not fully adjust immediately following the arrival of volatility uncertainty information. We test this prediction directly by examining returns from 10:00 EST to market close on the same day.[11] If investors incorporate morning volatility uncertainty with delay, intraday returns should be largely unrelated to the morning VVIX signal –the predictable returns should instead materialize from day t close to day $t+1$ close, as documented in our main results. Conversely, if prices adjust rapidly within the trading day, intraday returns should capture much of the predictable variation, diminishing the next-day predictability we document. This test provides direct evidence on the speed of information incorporation in variance markets. The sample period for this intraday analysis spans January 2013 to June 2022.[12]

The scatter plots reveal a striking contrast that strongly supports the delayed incorporation of volatility uncertainty into variance asset prices, consistent with models of limited attention, slow information diffusion, and slow-moving beliefs about volatility. For intraday returns (10:00–16:00), Figure 5, the relationship with standardized $VVIX^M$ is essentially flat and statistically insignificant across all variance assets. For instance, SPX straddles show a coefficient of -0.313 (t-stat: -0.980) with an R^2 of just 0.24%, whereas VIX futures show a coefficient of 0.384 (t-stat: 0.793) with R^2 of 0.38%. In contrast, close-to-close returns, Figure 6, display strongly significant positive slopes. For instance, SPX straddles and VIX futures obtain slope coefficients of 1.42 and 0.91, significant at the 1% and 5% levels, and R^2 values of 1.96% and 2.12%, respectively.

[11] Results remain qualitatively unchanged if price formation is set to 10:01, 10:05, or 10:05 EST.

[12] The descriptive statistics for the subsample, reported in Table B4, reveal well-documented different stylized facts between intraday and close-to-close return dynamics. Intraday returns (10:00–16:00 EST) exhibit smaller mean losses compared to close-to-close dynamics, consistent with Muravyev and Ni (2020), yielding negative Sharpe ratios an order of magnitude smaller than those of close-to-close returns.

Figure 7 reinforces these findings by presenting average returns on high and low $VVIX^M$ days, equivalent to the returns from long-only and short-only strategies, respectively. The top panels display average intraday returns (10:00–16:00 EST), while the bottom panels display average close-to-close returns. On high $VVIX^M$ days (left panels), intraday returns are economically small and statistically indistinguishable from zero across all variance assets, with 95% confidence bands comfortably spanning zero. In contrast, close-to-close returns on high $VVIX^M$ days are substantially positive and statistically significant, particularly for VIX straddles and SPX straddles. On low $VVIX^M$ days (right panels), both intraday and close-to-close returns are negative, consistent with the unconditional variance risk premium. However, the magnitude is considerably larger for close-to-close returns, especially for variance swaps, which exhibit average losses exceeding 5%. This asymmetry between intraday and close-to-close returns conditional on morning volatility uncertainty provides further evidence supporting our hypotheses about limited attention and slow-moving beliefs about volatility.

4 Alternative Explanations

Our interpretation attributes the predictability of variance asset returns to limited attention and slow-moving beliefs about volatility. However, alternative mechanisms could generate similar patterns. We now examine whether our findings are driven by known risk factors, overnight price discovery, inventory effects captured by order imbalances, calendar anomalies, scheduled macroeconomic announcements, earnings releases, daylight saving time disruptions, or structural changes in market access following the CFE's 2014 extension of VIX futures trading hours.

4.1 Alternative Risk Measures

We begin by evaluating whether the VVIX measured at 10:00 (hereafter denoted as $VVIX^M$) provides incremental predictive power beyond established predictors. Our analysis incorporates several control variables identified as significant in prior literature. These include the lagged variance asset return (r_t), and the variance risk premium (VRP_t), which is calculated as the difference between the squared VIX and the expected realized variance ($VRP_t = VIX_t^2 - \mathbb{E}_t[RV_{t+1}]$) following Bollerslev et al. (2009), the VIX term structure slope ($SLOPE_{VIX}$) as documented by Johnson (2017), the VIX implied volatility skew ($IVSKEW^C$) computed at 10:00 (Xing et al., 2010),[13] the squared VIX level estimated at 10:00 (VIX_t^2).[14]

We run the following regression model:

$$r_{t+1} - r_{f,t+1} = \alpha + \beta VVIX_t^M + \boldsymbol{\lambda}' \boldsymbol{X}_t + \epsilon_{t+1}, \tag{4}$$

where $r_{t+1} - r_{f,t+1}$ represents next-day close-to-close excess returns for one of the variance assets: S&P 500 straddles, variance swaps, VIX straddles, and VIX futures. All these assets have a constant maturity of 1-month. $\boldsymbol{X}$ is a matrix including all the control variables. We report these results in Table 5.

The results indicate that the ability of the $VVIX^M$ to predict future variance asset returns is incremental to that of other known predictors. The statistical significance and economic magnitude of $VVIX^M$ remain intact when adding one variable at a time and several controls together. This finding holds across all variance assets. In contrast, aside from the lag in the variance asset return, none of the controls remains consistently significant across all variance assets. This finding highlights the crucial importance of the morning VVIX

[13] We define $IVSKEW^C$ as the difference between the 10:00 OTM call implied volatility (with moneyness of 1.10) and the 10:00 at-the-money (ATM) call implied volatility (with moneyness of 1.0). Given the nature of the VIX index implied volatility, we select a measure based on call options in our analysis. However, results remain qualitatively and quantitatively similar if we consider the $IVSKEW^P$, computed as OTM put implied volatility (with moneyness of 0.9) minus ATM put implied volatility (with moneyness of 1.0).

[14] Results remain unchanged if we consider the VIX_t^2 estimated at 16:00.

in predicting variance asset returns. To illustrate, the VIX^2 computed at 10:00 renders insignificant for predicting SPX straddles and VIX futures, while $VVIX^M$ gets a t-statistic of 6.5 and 7.5, respectively, when the two variables are considered jointly. These results are also economically significant as one standard deviation in the morning VVIX increases the SPX straddle and VIX futures returns by 1.15 and 0.76 percentage points.

The explanatory power of our models, as measured by the adjusted-R^2, reveals a remarkable pattern. Comparing the univariate models that include $VVIX^M$ (first column of each panel) with the multivariate specifications that incorporate all controls, we find that the addition of control variables yields only modest improvements in model performance. For instance, in predicting next-day S&P 500 straddle returns (Panel A), the univariate model with $VVIX^M$ achieves an adjusted-R^2 of 1.99%. When we include the full set of control variables, it only increases marginally to 3.03%. Table C1, in the Appendix, repeats this exercise, replacing the VIX_t^2 with either the left-tail variation (LTV) of Bollerslev et al. (2015) or the NOISE measure of Hu et al. (2013); results are qualitatively similar. This pattern demonstrates that $VVIX^M$ accounts for approximately 60% to 65% of the model's explanatory power, with the comprehensive models incorporating all control variables exhibiting only about a 1 percentage point improvement over the univariate specification.[15]

Overall, the robust predictive capacity of $VVIX^M$ and the absence of consistent predictability among established volatility and risk predictors indicate that morning VVIX dynamics capture fundamentally distinct information content. Our findings suggest that higher morning VVIX signals heightened uncertainty that materially impacts variance asset pricing, whereas increases in traditional control variables fail to generate comparable market responses.

[15]A crash indicator ($CRASH$) that equals one if the S&P 500 experienced a crash during the previous 21 trading days is also adopted as an additional control. $CRASH$ is defined as the first percentile and proxies for downward jumps in the S&P 500 index (Todorov, 2010). In untabulated results, we observe that $CRASH$ is not statistically significant across the predicted variance assets, nor does it affect the predictive power of $VVIX^M$.

4.2 Overnight Information

Our $VVIX^M$ measure has emerged as a significant predictor of variance asset returns, with information content that is incremental to established predictors from both end-of-day and morning information. To ensure that our findings reflect the unique information processing during the U.S.-European overlap period rather than overnight information persistence, which is already contained in assets trading nearly round the clock such as the E-mini S&P 500 futures,[16] we control for various measures computed during the overnight period.

In our analysis of overnight market behavior, we examine two distinct metrics: overnight returns and overnight realized variance, measured across selected time windows. Our analysis centers on four key market timestamps: The European market opening (EUO) at 3:00 EST, the U.S. market opening (USO) at 09:30 EST, the U.S. market at 10:00 EST (US10), and the U.S. market close (USC) at 16:00 EST. Figure 8 illustrates the E-mini trading volume across the different times of the day, where volume spikes are clearly observable at these specific four times.[17] Using these timestamps, we compute overnight returns across four distinct windows: EUO to USO, EUO to US10, USC to USO, and USC to US10. We also calculate the overnight realized variance as the sum of squared overnight returns during the EUO to USO period.

Results from Table 6 strongly support our hypothesis that morning VVIX captures incremental information beyond overnight developments. $VVIX^M$ exhibits robust predictive power across all four variance assets, with t-statistics ranging from 4.6 to 7.2 and economically significant coefficients. In contrast, overnight returns from E-mini futures demonstrate limited predictive ability, with most coefficients statistically insignificant. Where overnight measures do exhibit significance –notably for VIX futures and variance swap returns– the ef-

[16] E-mini S&P 500 index futures have traded approximately 24 hours a day since the late 1990s. Trading outside regular hours allows investors to respond to: i) global macroeconomic news when international markets move; ii) economic reports and announcements occurring outside regular trading hours; and iii) geopolitical risks from events happening worldwide.

[17] Trading volume also spikes around 08:30 and 16:15, although considering overnight returns based on these times does not alter the results.

fects are economically modest and do not diminish the predictive strength of morning VVIX. These results confirm that $VVIX^M$ contains valuable information for variance asset pricing that extends beyond what overnight price movements reveal, consistent with our hypothesis that morning volatility uncertainty, captured during the U.S.-European market overlap, contains crucial information about future variance asset prices that is not reflected purely by assets trading around the clock.

4.3 Order Imbalances

Institutional hedging demand consistently drives net buying of protective instruments such as S&P 500 index put options, VIX call options, and VIX futures. Market makers absorb these order imbalances and demand a premium for bearing the resulting inventory risk (Boyarchenko et al., 2023). This mechanism explains well-known features like implied volatility skew and variance risk premium (e.g. Bollen and Whaley, 2004; Garleanu et al., 2008).[18] However, recent evidence by Cheng (2019) documents a decline in net long volatility exposure by end users during periods of volatility uncertainty, reflecting increased constraints under stress. Jacobs et al. (2025) corroborate that end users reduce their net volatility positions in periods of high volatility uncertainty due to the interaction between their demand for volatility and that of market makers, as well as changes in the slope and position of these demand curves during times of elevated risk.

Given the importance of order imbalance and price pressure for future asset returns and volatility, we investigate whether such imbalances underlie the predictive power of our $VVIX^M$. Order imbalances could conceivably drive dynamics through temporary inventory imbalances. Therefore, if $VVIX^M$ predictive signal is embedded in the pressure of order flows, then including an order imbalance proxy should attenuate, or potentially eliminate its significance. We compute order imbalances using the Lee and Ready (1991) algorithm,

[18] Risk-averse dealers raise option prices, especially for downside protection, to compensate for the inventory risk, producing a steep implied volatility curve and systematic option-selling profits for liquidity providers (i.e. the variance risk premium) (e.g., Bollen and Whaley, 2004).

defining the $OI_t^i = \#\text{buy orders} - \#\text{sell orders}$.[19] We compute order imbalance measures at every hour, either overnight or within the intraday day.[20] We focus on three specific overnight and intraday order imbalances computed within one-hour windows at times most relevant for our analysis, preceding or occurring simultaneously with our $VVIX^M$: European market open (OI_{EUO}^i), U.S. 10:00 (OI_{US10}^i), and the closing of the U.S. market (OI_{USC}^i). i denotes the asset class: S&P 500 E-Mini Futures (ES) or VIX options (VIX).

Table 7 shows that $VVIX^M$ maintains robust predictive power even after controlling for order imbalances, with only modest improvements in adjusted R^2 when adding order flow controls. Interestingly, the results indicate that $VVIX^M$ captures forward-looking institutional decision-making rather than mechanical trading effects. By contrast, order imbalances, while occasionally significant, capture only the backward-looking evidence of reduced hedging activity –the mechanical implementation of decisions already reflected in prices through the VVIX signal.[21]

4.4 Subsample Analysis: CFE Rule expanding VIX Futures Trading Hours

On June 6, 2014, the CFE expanded VIX futures trading hours to operate nearly 24 hours a day, five days a week.[22] This extension enables investors to trade both E-mini and VIX futures almost continuously in all time zones during weekdays, facilitating immediate responses to emerging market information.[23] The continuous trading environment may diminish the

[19] Following the Lee and Ready (1991) algorithm, we sign trades as follows: if a transaction occurs above the previous quote mid-point, it is regarded as a purchase and vice versa. If a transaction occurs exactly at the quote mid-point, it is signed using the previous transaction price, which is called the tick test (i.e., buys if the sign of the last non-zero price change is positive and vice versa).

[20] We follow previous literature by applying standard filtering procedures in the computation of the order imbalance measures (e.g., Chordia and Subrahmanyam, 2004).

[21] It is also important to note that no trading or trading less does not show up as strongly in order imbalance measures as active trading does, explaining why the predictive power of order imbalances is relatively weak.

[22] For more information, please see CBOE Futures Exchanges, LLC Rule Certification.

[23] In March, 2015, the CBOE introduced extended hours for S&P 500 and VIX options, allowing trading from 3:00 to 09:15 EST. However, the launch of 24-hour S&P 500 and VIX options trading took place only in 2021. For more information, please see https://www.cboe.com/insights/posts/

predictive power of our $VVIX^M$ measure, as investors can now adjust their VIX futures positions throughout the extended trading hours rather than concentrating their trading activity around the 10:00 measurement window. Furthermore, the transition to around-the-clock trading suggests that volatility information, which was historically concentrated at market open, may now diffuse across the entire trading day, potentially reducing the unique informational content captured by $VVIX^M$'s morning volatility measurements.

We evaluate $VVIX^M$'s performance during this reduced sample period, namely from June 2014 to June 2022, by replicating the analyses conducted in the previous Sections. We discuss these results in turn. Table 8 presents the results from both univariate and multivariate regressions controlling for the risk measures specified in Section 4.1, with one modification: given the availability of SPX options for this subsample, we replace the end-of-day $SLOPE_{VIX}$ measure with its 10:00 counterpart. The results suggest that $VVIX^M$ maintains its predictive power in this shorter sample period, indicating that the transition to around-the-clock trading does not explain away the strong predictive ability of our morning-based measure.[24] Furthermore, both the coefficient magnitudes and adjusted-R^2 values remain either comparable to or larger than those in our main analysis, reinforcing $VVIX^M$'s fundamental role in explaining future variance asset returns.

Next, we test whether the predictive power of the $VVIX^M$ remains robust when controlling for overnight trading information from E-mini and VIX futures. Using overnight measures constructed using the European market open (EUO) and U.S. market open (USO), we construct overnight returns for the E-mini and VIX futures, as outlined in Section 4.2.[25] We also include the VIX futures price at EUO (VXF^{EUO}).[26] Table 9 shows that the pre-

`cboe-global-trading-hours`.

[24] Results remain both quantitatively and qualitatively similar after replacing VIX^2 with either LTV or Noise, as reported in Table C2 in the Appendix.

[25] We adopt the subscripts ES and VXF to denote variables calculated from E-mini and VIX futures returns, respectively.

[26] The opening of European markets is considered an important time leading, for instance, to the largest positive U.S. S&P 500 index futures returns (between 2:00 and 3:00, EST) (see, e.g. Boyarchenko et al., 2023). The opening of the European stock market also coincides with the VIX and SPX options trading opening time (3:00 EST). Moreover, it also overlaps with the Asian markets. For instance, 3:00 EST is typically around the closing time of the Hong Kong stock market.

dictive power of $VVIX^M$ remains largely unchanged after including overnight information, even after controlling for VIX futures observed at EUO or US10 times. This result indicates that the VVIX information is fundamentally different from that captured by risk measures computed around the clock.

Finally, Table 10 reports the results controlling for order imbalances computed across various times during the subsample period. For this analysis, we also compute order imbalances for VIX Futures at the European Market Open (EUO). The $VVIX^M$ maintains strong statistical significance across all variance assets, with coefficients and adjusted R^2 values comparable to the full sample period. Importantly, the extended trading hours do not diminish the unique informational content of morning VVIX relative to order flow effects. Even when institutional investors can adjust VIX futures positions nearly continuously, the 10:00 EST measurement during the U.S.-European overlap period continues to capture critical uncertainty signals that order imbalances cannot fully explain.

Overall, while investors could manage their risk and trade volatility nearly 24 hours, during the subsample period analyzed, $VVIX^M$ retains crucial information for predicting future variance assets. Thus, the strong $VVIX^M$ predictive ability we detect cannot entirely be attributed to the inception of the nearly 24-hour CME Rule expanding VIX futures trading hours, and it is not subsumed by any other variables capturing overnight or morning investors' beliefs and reflecting financial markets' updates.

4.5 Day-of-the-Week Effects

To ensure our findings are not driven by specific calendar or announcement effects, we conduct several robustness tests. First, we examine the day-of-the-week effects (Birru, 2018), as institutional trading patterns vary systematically across weekdays. Monday effects may reflect amplified uncertainty processing due to weekend information accumulation, while Friday effects could capture position unwinding behaviors. Additionally, Wednesday is the standard expiration day of VIX options.Thus, we include Monday, Wednesday, and Friday dummy variables to control for these patterns. Table C3 shows that while some of these dummy variables are significant, $VVIX^M$ retains its magnitude and significance, indicating that calendar effects do not drive the information content of morning VVIX.[27]

4.6 Macroeconomic Announcements and Daylight Saving Time

Second, we examine major monetary policy announcements. Federal Open Market Committee (FOMC) meetings typically announce decisions around 14:00, while additional economic announcements occur during morning hours, making FOMC days particularly noteworthy for our analysis. In addition, Amengual and Xiu (2018) show that sudden downward jumps in implied volatility are closely associated with the resolution of monetary policy uncertainty, especially following FOMC statements and speeches by the Federal Reserve chair. Such days may influence our predictions and inflate the outcomes of the trading strategy, as the volatility entry points on these days could be biased downward due to the resolution of uncertainty.

Moreover, European Central Bank monetary policy decisions are announced around 8:00, potentially creating spillover effects during market opening. Finally, we remove the daylight saving time discrepancies between the U.S. and Europe. When regions change clocks on different dates, the overlap window shifts by one hour for 2-3 weeks twice yearly, providing exogenous variation in institutional interaction time. Table C4 shows that excluding FOMC and ECB announcements days, as well as daylight saving discrepancy periods, has no material impact on our results. Across all specifications, $VVIX^M$ maintains its statistical and economic significance. In untabulated results, we also control for the European implied volatility index, VSTOXX, collected from https://stoxx.com/index/v2tx/. The VSTOXX index is based on EURO STOXX 50 options prices and computed similarly to the VIX for the S&P 500 in the U.S., reflecting the European market uncertainty expectations. The predictive power of the morning VVIX remains significant. Overall, these

[27] We also consider adding the day-of-the-week dummies as well as their interactions with the morning VVIX in the same regression. The results and overall conclusion remain unchanged.

findings reinforce the morning VVIX's role in capturing unique market volatility uncertainty information to predict variance asset returns that are not driven by specific macroeconomic announcements, and the resolution of the monetary policy uncertainty effect.

4.7 Earnings Announcements

Next, we check whether specific days associated with earnings announcements by large U.S. firms could affect our results. Chan and Marsh (2022) document unique days, defined as leading earnings announcement days (LEADs), as times when an aggregate of influential S&P 500 large firms disclose quarterly earnings news early in the earnings season. The waves of such corporate earnings announcements, when aggregated, have the potential to move the market.

We collect quarterly earnings announcements for all the constituents of the S&P 500 index within our sample period from the Institutional Brokers' Estimate System (I/B/E/S) summary file. We follow the filtering procedures and methodology in Chan and Marsh (2022), and select the LEADs being the days when leading news is reported, specifically on Tuesday through Thursday in the first week of the reporting quarter that has a minimum of 50 announcers. We repeat our regression analysis after removing the LEADs from our sample. The (untabulated) results remain unchanged, suggesting that our findings are not driven by corporate activities, even those related to large firms' announcements.

4.8 Longer Maturities

Finally, to investigate whether the predictive power of $VVIX^M$ extends beyond short-term horizons, we estimate Equation (4) for variance assets with constant maturities of 2, 3, and 6 months. This analysis addresses several important questions. First, if high levels of morning VVIX trigger investors' underreaction and sluggish response to volatility news, its predictive power should diminish at longer horizons where such short-term frictions are less influential. Second, longer-maturity variance assets may be less sensitive to intraday volatility uncertainty fluctuations, as they aggregate volatility expectations over extended periods. The results, presented in Tables D1–D3 in Appendix D, demonstrate that $VVIX^M$ maintains its strong predictive capacity across these longer horizons, though with systematically declining magnitude.[28] The coefficients decrease monotonically with maturity. Importantly, none of the controls exhibits consistent significance across all variance assets and maturities, confirming the unique informational content of $VVIX^M$.[29]

5 Conclusion

This paper documents that morning volatility-of-volatility, measured at 10:00 EST during the U.S.–European market overlap, strongly predicts next-day variance asset returns. Predictive power peaks during this window with t-statistics reaching 6.1 and adjusted R^2 of 2.6%, but diminishes rapidly after 11:00 EST. Trading strategies exploiting this pattern generate annualized Sharpe ratios exceeding 2.0, remaining economically significant after accounting for transaction costs.

Our findings contribute to the literature in three ways. First, we identify precisely *when* volatility uncertainty signals arrive –a dimension that prior work relying on closing prices has overlooked. The U.S.–European overlap window represents the market's first comprehensive assessment of volatility uncertainty, synthesizing information accumulated overnight. Second, we document that this information is incorporated into prices gradually rather than immediately. The flat relationship between morning VVIX and intraday returns on high volatility uncertainty days, contrasted with the strong relationship for close-to-close returns, provides direct evidence of delayed price adjustment. Third, our results are consistent with limited attention and slow-moving beliefs about volatility, and we rule out alternative explanations. Morning VVIX retains its predictive power after controlling for established risk measures, including the variance risk premium, VIX level, and implied volatility skew. The

[28] Results for the subsample period (Tables D4–D6) provide similar conclusions.

[29] In untabulated results, we also control for overnight information and order imbalance for longer-maturity assets. The conclusions remain unchanged, with $VVIX^M$ retaining its predictive ability across all maturities.

predictability does not arise from overnight information embedded in assets trading around the clock, nor from inventory effects captured by order imbalances in futures and options markets. Calendar effects, macroeconomic announcements, and the extension of VIX futures trading hours similarly fail to explain our findings.

References

Admati, A. R. and Pfleiderer, P. (1988). A theory of intraday patterns: Volume and price variability. *The Review of Financial Studies*, 1(1):3–40.

Aït-Sahalia, Y., Karaman, M., and Mancini, L. (2020). The term structure of equity and variance risk premia. *Journal of Econometrics*, 219(2):204–230.

Almeida, C., Freire, G., and Hizmeri, R. (2024). 0dte asset pricing. *Available at SSRN*.

Amengual, D. and Xiu, D. (2018). Resolution of policy uncertainty and sudden declines in volatility. *Journal of Econometrics*, 203(2):297–315.

Andrei, D. and Hasler, M. (2015). Investor attention and stock market volatility. *The Review of Financial Studies*, 28(1):33–72.

Bakshi, G. and Kapadia, N. (2003). Delta-hedged gains and the negative market volatility risk premium. *The Review of Financial Studies*, 16(2):527–566.

Baltussen, G., Van Bekkum, S., and Van Der Grient, B. (2018). Unknown unknowns: Uncertainty about risk and stock returns. *Journal of Financial and Quantitative Analysis*, 53(4):1615–1651.

Bansal, R., Kiku, D., Shaliastovich, I., and Yaron, A. (2014). Volatility, the macroeconomy, and asset prices. *The Journal of Finance*, 69(6):2471–2511.

Bansal, R. and Yaron, A. (2004). Risks for the long run: A potential resolution of asset pricing puzzles. *The journal of Finance*, 59(4):1481–1509.

Bardgett, C., Gourier, E., and Leippold, M. (2019). Inferring volatility dynamics and risk premia from the *s&p* 500 and *vix* markets. *Journal of Financial Economics*, 131(3):593–618.

Bekaert, G. and Hoerova, M. (2014). The VIX, the variance premium and stock market volatility. *Journal of Econometrics*, 183(2):181–192.

Birru, J. (2018). Day of the week and the cross-section of returns. *Journal of Financial Economics*, 130(1):182–214.

Bogousslavsky, V. (2016). Infrequent rebalancing, return autocorrelation, and seasonality. *The Journal of Finance*, 71(6):2967–3006.

Bollen, N. P. and Whaley, R. E. (2004). Does net buying pressure affect the shape of implied volatility functions? *The Journal of Finance*, 59(2):711–753.

Bollerslev, T., Tauchen, G., and Zhou, H. (2009). Expected stock returns and variance risk premia. *The Review of Financial Studies*, 22(11):4463–4492.

Bollerslev, T., Todorov, V., and Xu, L. (2015). Tail risk premia and return predictability. *Journal of Financial Economics*, 118(1):113–134.

Bondarenko, O. and Muravyev, D. (2023). Market return around the clock: A puzzle. *Journal of Financial and Quantitative Analysis*, 58(3):939–967.

Boyarchenko, N., Larsen, L. C., and Whelan, P. (2023). The overnight drift. *The Review of Financial Studies*, 36(9):3502–3547.

Britten-Jones, M. and Neuberger, A. (2000). Option prices, implied price processes, and stochastic volatility. *The Journal of Finance*, 55(2):839–866.

Campbell, J. Y., Giglio, S., Polk, C., and Turley, R. (2018). An intertemporal capm with stochastic volatility. *Journal of Financial Economics*, 128(2):207–233.

Campbell, J. Y. and Thompson, S. B. (2008). Predicting excess stock returns out of sample: Can anything beat the historical average? *The Review of Financial Studies*, 21(4):1509–1531.

Carr, P. and Madan, D. (1998). Towards a theory of volatility trading. *Volatility: New estimation techniques for pricing derivatives*, 29:417–427.

Carr, P. and Wu, L. (2009). Variance risk premiums. *The Review of Financial Studies*, 22(3):1311–1341.

Chan, K., Chung, Y. P., and Johnson, H. (1995). The intraday behavior of bid-ask spreads for nyse stocks and cboe options. *Journal of Financial and Quantitative Analysis*, 30(3):329–346.

Chan, K. F. and Marsh, T. (2022). Asset pricing on earnings announcement days. *Journal of Financial Economics*, 144(3):1022–1042.

Cheng, I.-H. (2019). The VIX premium. *The Review of Financial Studies*, 32(1):180–227.

Chordia, T. and Subrahmanyam, A. (2004). Order imbalance and individual stock returns: Theory and evidence. *Journal of Financial Economics*, 72(3):485–518.

Clark, T. E. and West, K. D. (2007). Approximately normal tests for equal predictive accuracy in nested models. *Journal of Econometrics*, 138(1):291–311.

Cohen, L. and Frazzini, A. (2008). Economic links and predictable returns. *The Journal of Finance*, 63(4):1977–2011.

Coval, J. D. and Shumway, T. (2001). Expected option returns. *The Journal of Finance*, 56(3):983–1009.

Da, Z., Goyenko, R., and Zhang, C. (2024). Intraday option return: A tale of two momentum. *Available at SSRN 5018430*.

DellaVigna, S. and Pollet, J. M. (2009). Investor inattention and friday earnings announcements. *The Journal of Finance*, 64(2):709–749.

Dew-Becker, I., Giglio, S., Le, A., and Rodriguez, M. (2017). The price of variance risk. *Journal of Financial Economics*, 123(2):225–250.

Drechsler, I. and Yaron, A. (2011). What's vol got to do with it. *The Review of Financial Studies*, 24(1):1–45.

Eraker, B. and Wu, Y. (2017). Explaining the negative returns to volatility claims: An equilibrium approach. *Journal of Financial Economics*, 125(1):72–98.

Feunou, B., Fontaine, J.-S., Taamouti, A., and Tédongap, R. (2014). Risk premium, variance premium, and the maturity structure of uncertainty. *Review of Finance*, 18(1):219–269.

Gao, L., Han, Y., Li, S. Z., and Zhou, G. (2018). Market intraday momentum. *Journal of Financial Economics*, 129(2):394–414.

Garleanu, N., Pedersen, L. H., and Poteshman, A. M. (2008). Demand-based option pricing. *The Review of Financial Studies*, 22(10):4259–4299.

Heston, S. L., Korajczyk, R. A., and Sadka, R. (2010). Intraday patterns in the cross-section of stock returns. *The Journal of Finance*, 65(4):1369–1407.

Hirshleifer, D., Lim, S. S., and Teoh, S. H. (2009). Driven to distraction: Extraneous events and underreaction to earnings news. *The Journal of Finance*, 64(5):2289–2325.

Hollstein, F. and Prokopczuk, M. (2018). How aggregate volatility-of-volatility affects stock returns. *The Review of Asset Pricing Studies*, 8(2):253–292.

Hong, H. and Stein, J. C. (1999). A unified theory of underreaction, momentum trading, and overreaction in asset markets. *The Journal of Finance*, 54(6):2143–2184.

Hu, G. X., Pan, J., and Wang, J. (2013). Noise as information for illiquidity. *The Journal of Finance*, 68(6):2341–2382.

Huang, D., Schlag, C., Shaliastovich, I., and Thimme, J. (2019). Volatility-of-volatility risk. *Journal of Financial and Quantitative Analysis*, 54(6):2423–2452.

Jacobs, K., Mai, A. T., and Pederzoli, P. (2025). Why does volatility demand fall during market turmoil? a market maker perspective. *Working Paper*.

Jiang, G. J. and Tian, Y. S. (2005). The model-free implied volatility and its information content. *The Review of Financial Studies*, 18(4):1305–1342.

Johnson, T. L. (2017). Risk premia and the VIX term structure. *Journal of Financial and Quantitative Analysis*, 52(6):2461–2490.

Kaeck, A. (2018). Variance-of-variance risk premium. *Review of Finance*, 22(4):1549–1579.

Lee, C. M. and Ready, M. J. (1991). Inferring trade direction from intraday data. *The Journal of Finance*, 46(2):733–746.

Lochstoer, L. A. and Muir, T. (2022). Volatility expectations and returns. *The Journal of Finance*, 77(2):1055–1096.

Muravyev, D. and Ni, X. C. (2020). Why do option returns change sign from day to night? *Journal of Financial Economics*, 136(1):219–238.

Park, Y.-H. (2015). Volatility-of-volatility and tail risk hedging returns. *Journal of Financial Markets*, 26:38–63.

Sims, C. A. (2003). Implications of rational inattention. *Journal of Monetary Economics*, 50(3):665–690.

Smirlock, M. and Starks, L. (1986). Day-of-the-week and intraday effects in stock returns. *Journal of Financial Economics*, 17(1):197–210.

Todorov, V. (2010). Variance risk-premium dynamics: The role of jumps. *The Review of Financial Studies*, 23(1):345–383.

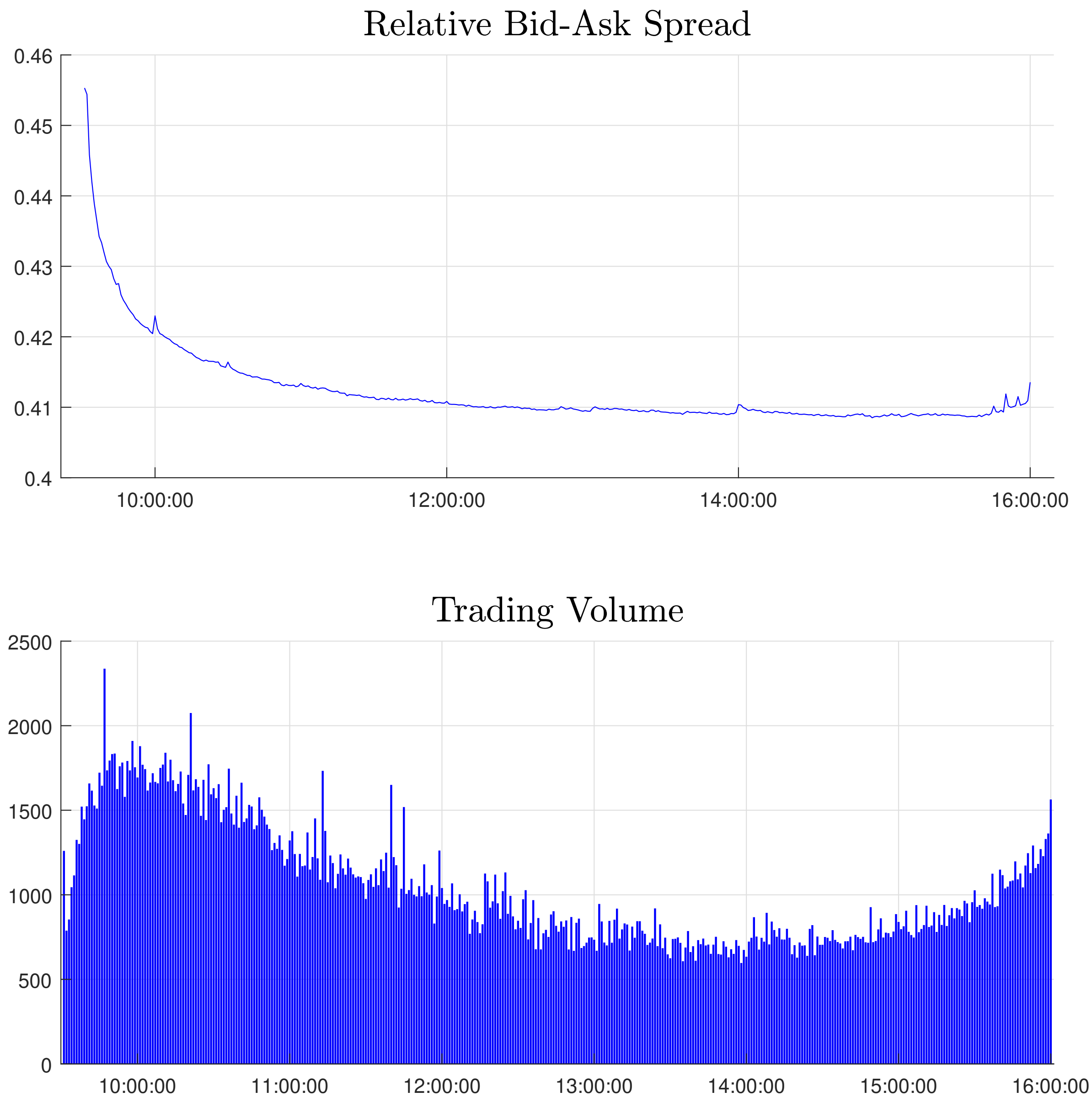
Welch, I. and Goyal, A. (2008). A comprehensive look at the empirical performance of equity premium prediction. *The Review of Financial Studies*, 21(4):1455–1508.

Wood, R. A., McInish, T. H., and Ord, J. K. (1985). An investigation of transactions data for NYSE stocks. *The Journal of Finance*, 40(3):723–739.

Xing, Y., Zhang, X., and Zhao, R. (2010). What does the individual option volatility smirk tell us about future equity returns? *Journal of Financial and Quantitative Analysis*, 45(3):641–662.

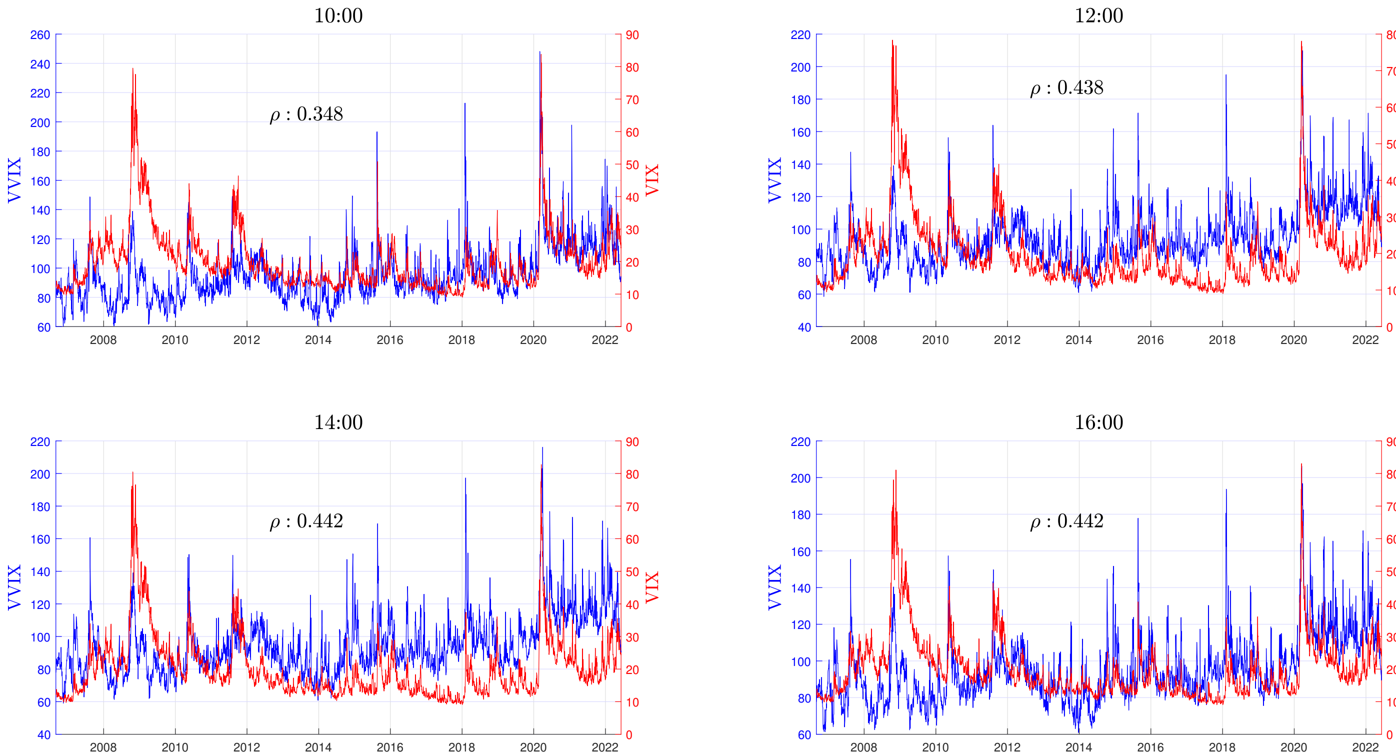
Figures and Tables

Figure 1: Trading Volume and Relative Bid-Ask Spread of VIX Options Over the Day



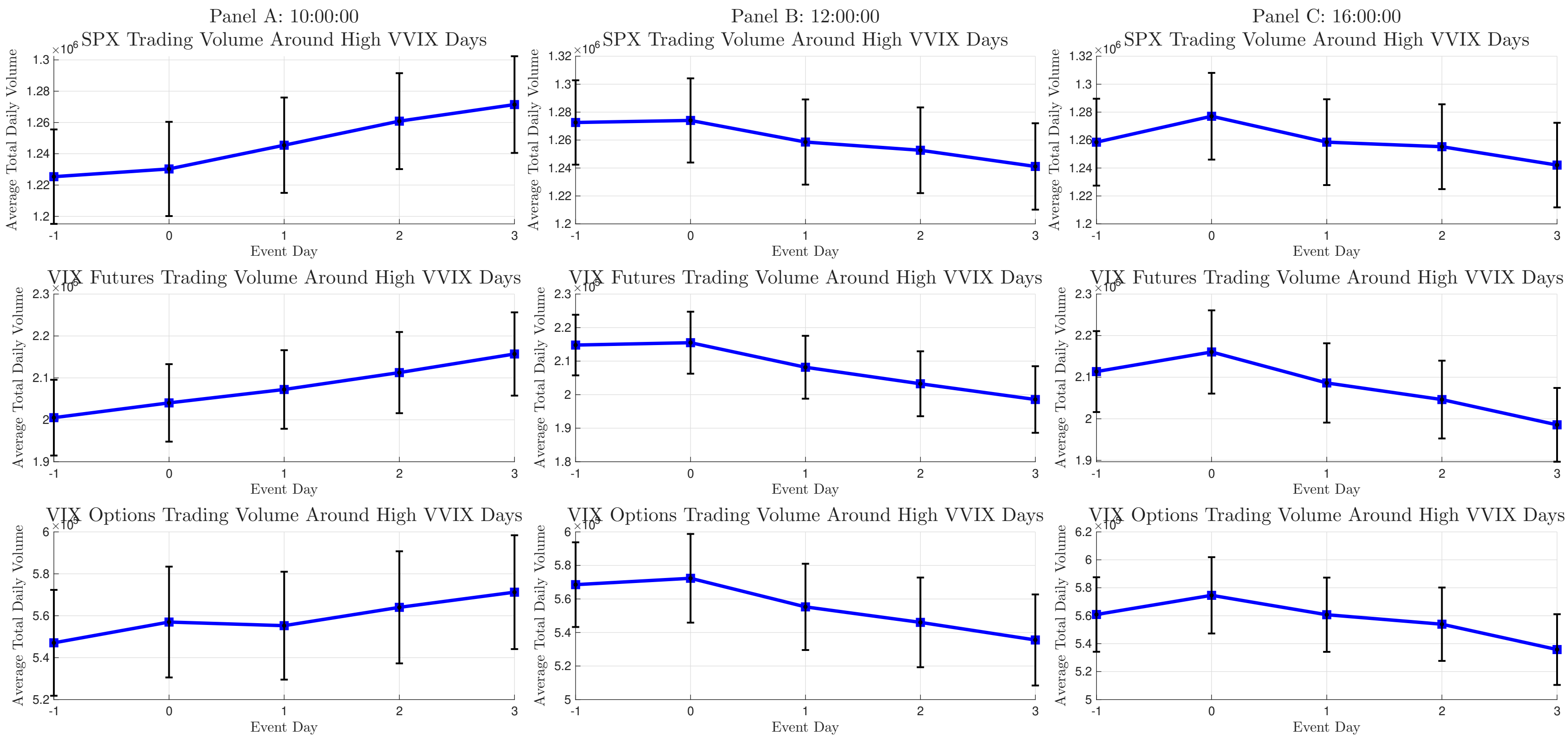
Notes: This figure plots in two panels the relative bid-ask spread (top panel), and the time series average of the trading volume in terms of number of contracts (bottom panel) of VIX options over the day. The relative bid-ask spread is computed as (Ask – Bid)/MidQuote. The sample period spans September 2006 to June 2022.

Figure 2: VVIX and VIX Time Series



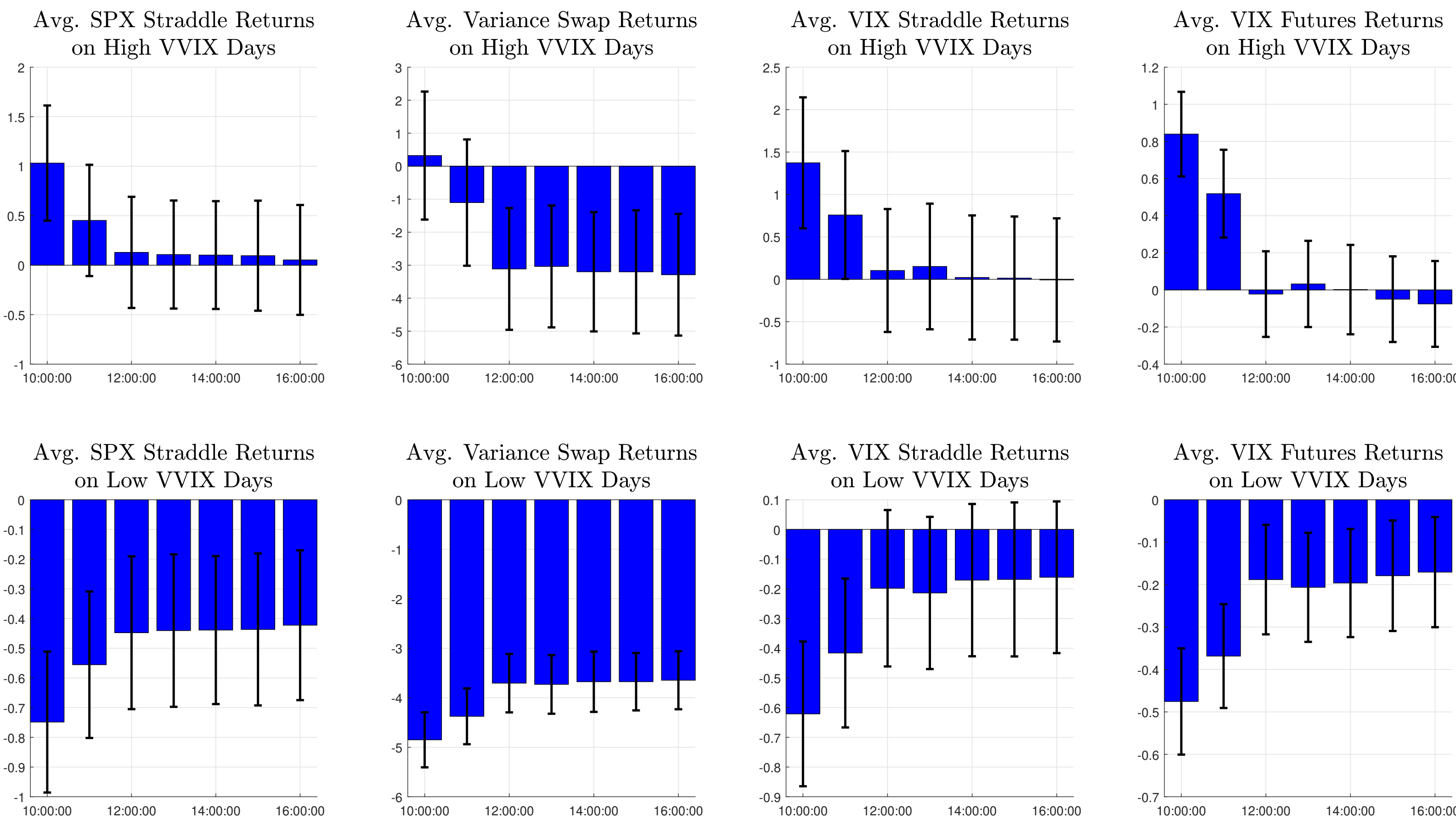
Notes: This figure plots in four panels the time series of the VVIX and VIX computed at four different times: 10:00, 12:00, 14:00 and 16:00. The value in the center of each subplot indicates the correlation between VVIX and VIX. The sample period spans September 2006 to June 2022.

Figure 3: Trading Volume around High VVIX Days



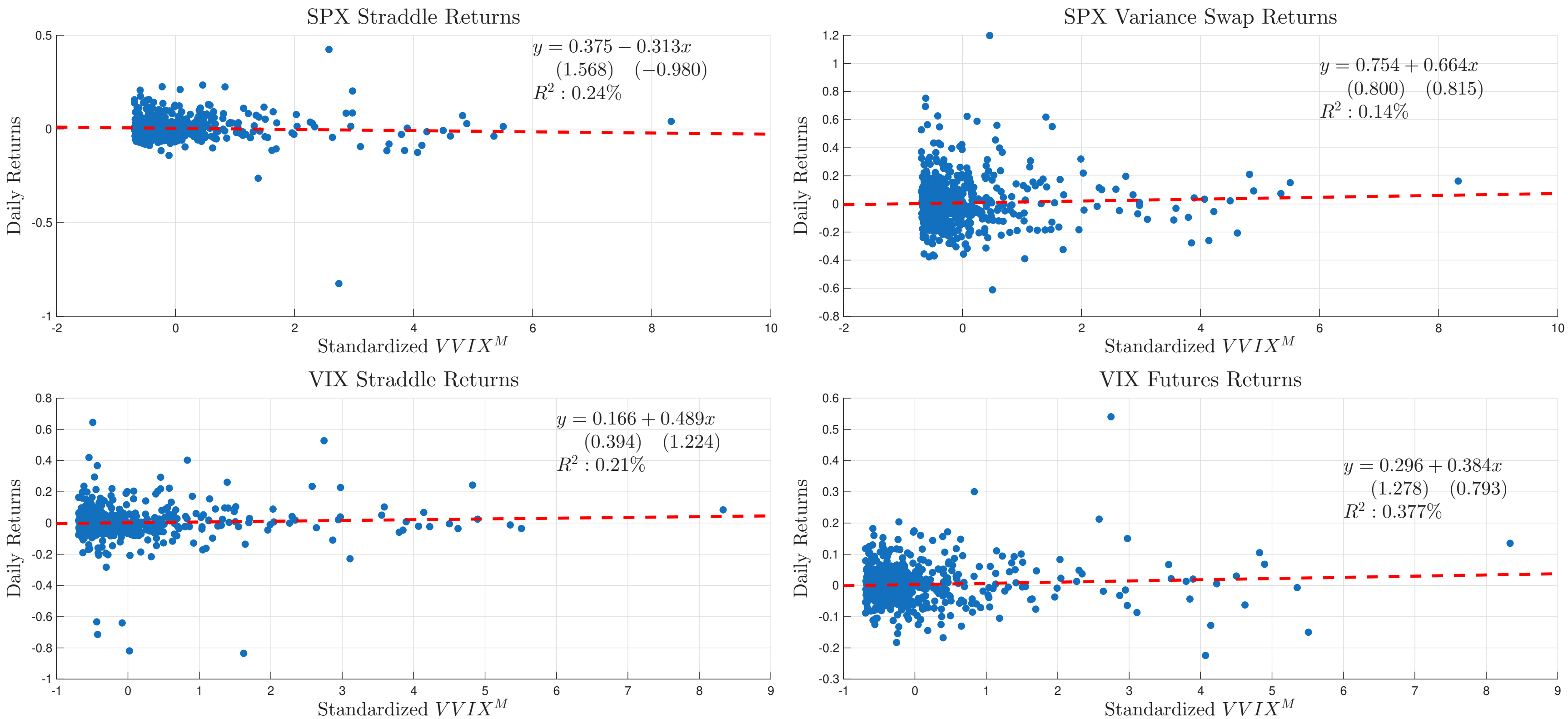
Notes: This figure displays average daily trading volume for SPX options (top row), VIX futures (middle row), and VIX options (bottom row) around days with elevated VVIX. The event day (day 0) is defined as days when VVIX exceeds its 75th percentile, with the conditioning time varying across panels: 10:00 EST (Panel A), 12:00 EST (Panel B), and 16:00 EST (Panel C). The event window spans one day before through three days after the event. Error bars denote 95% confidence intervals computed using bootstrap methods with 2,500 replications. The sample period is September 2006 to June 2022.

Figure 4: Average Return Above and Below the 75th percentile of VVIX



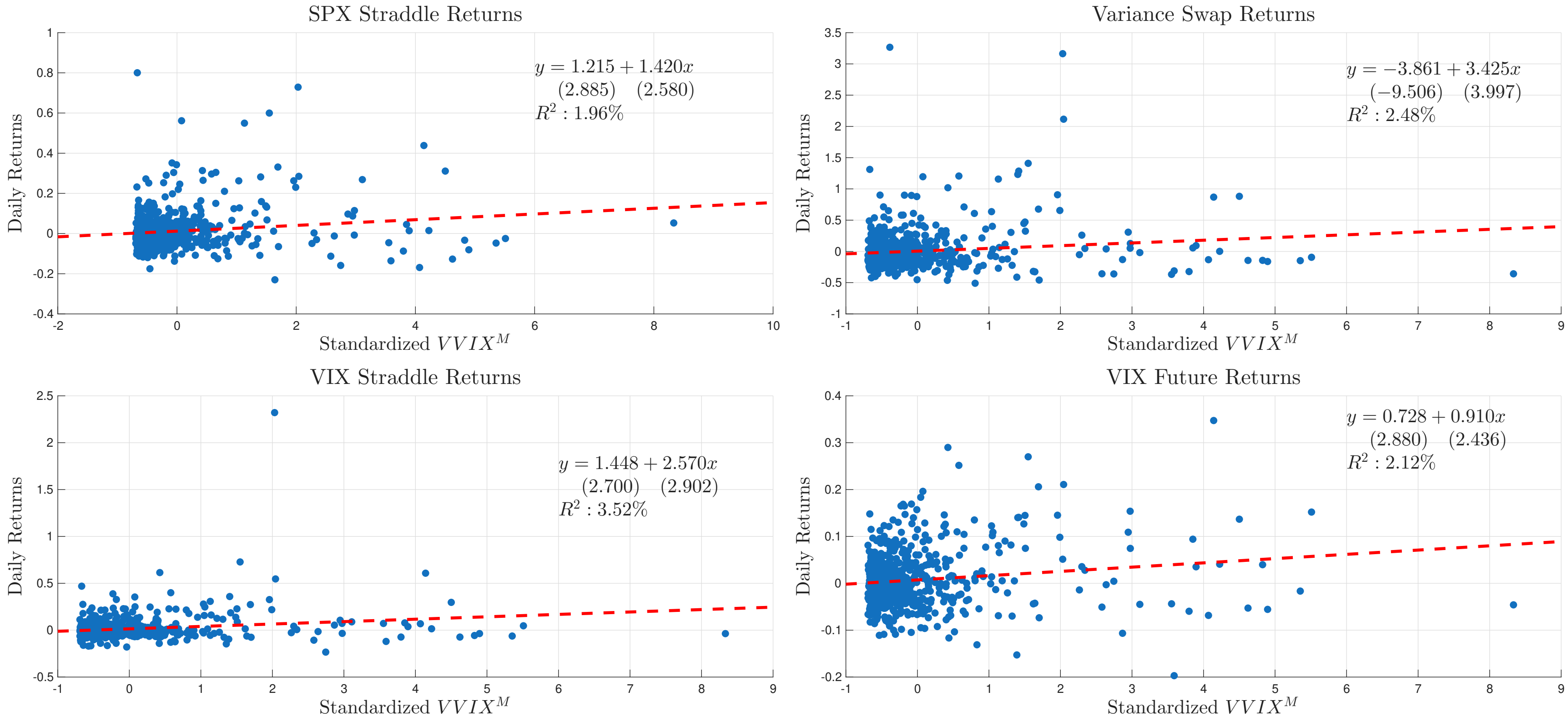
Notes:This figure plots the average $t + 1$ returns in the top (bottom) panels for days when VVIX at time t exceeds (falls below) its 75th percentile. The x-axis shows the different intraday times used to calculate VVIX. Standard errors are computed using bootstrap methods with 2,500 replications. The sample period spans September 2006 to June 2022.

Figure 5: Relationship Between Intraday Returns and Morning VVIX



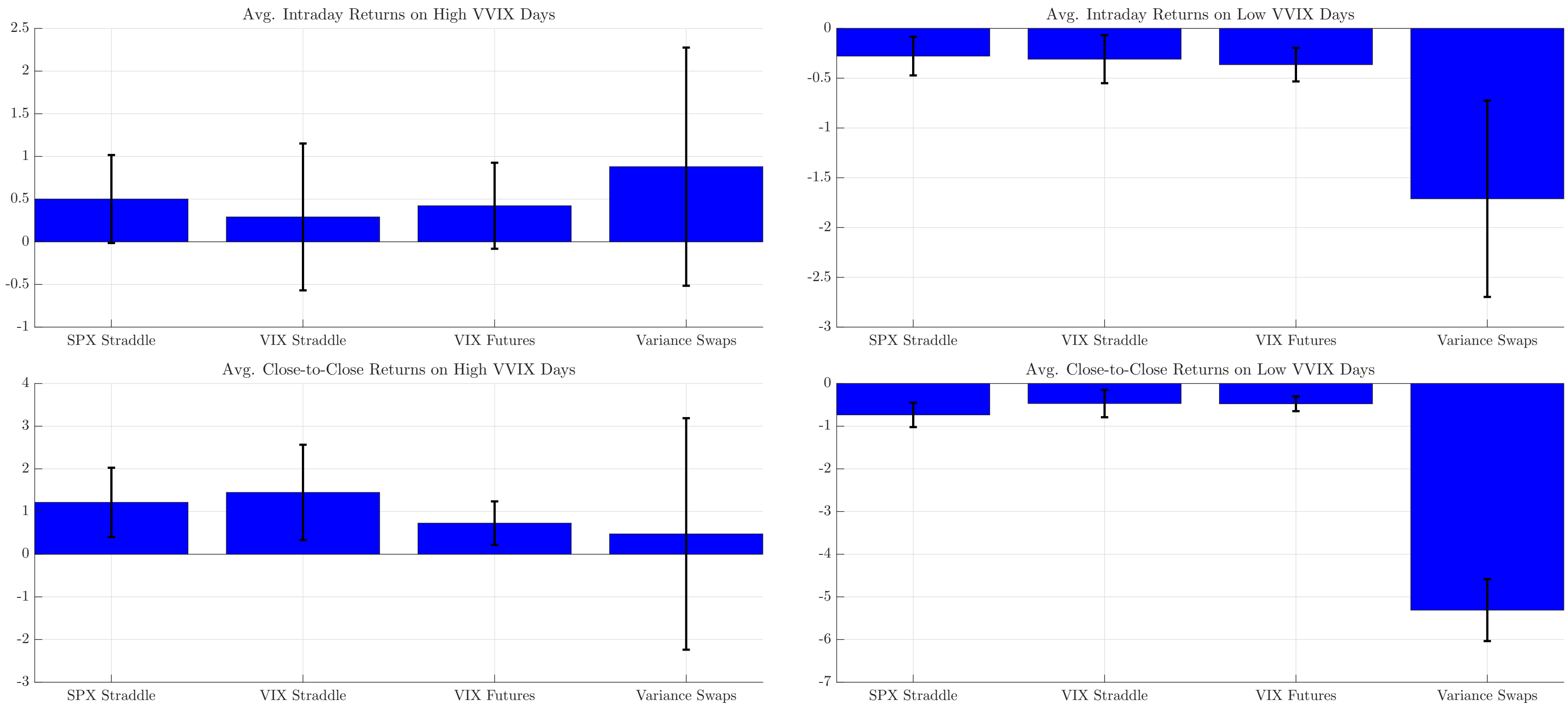
Notes: This figure presents scatter plots of intraday variance asset returns (10:00–16:00 EST) against standardized $VVIX^M$ on days when $VVIXM^M$ exceeds its 75th percentile. Each panel displays a different variance asset: SPX straddles (top left), variance swaps (top right), VIX straddles (bottom left), and VIX futures (bottom right). The dashed red line represents the OLS fitted regression line, with regression coefficients, t-statistics (in parentheses), and R^2 values reported in each panel. The sample period spans January 2013 to June 2022.

Figure 6: Relationship Between Close-to-Close Returns and Morning VVIX



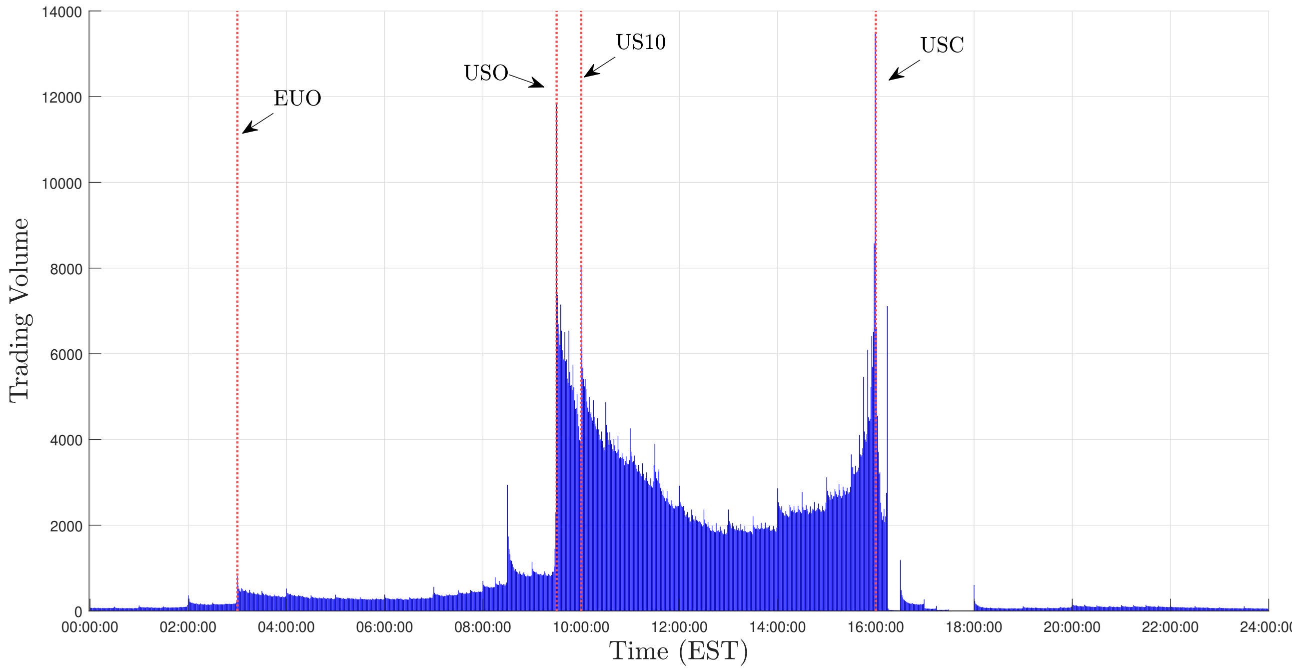
Notes: This figure presents scatter plots of close-to-close variance asset returns against standardized $VVIX^M$ on days when $VVIXM^M$ exceeds its 75th percentile. Each panel displays a different variance asset: SPX straddles (top left), variance swaps (top right), VIX straddles (bottom left), and VIX futures (bottom right). The dashed red line represents the OLS fitted regression line, with regression coefficients, t-statistics (in parentheses), and R^2 values reported in each panel. The sample period spans January 2013 to June 2022.

Figure 7: Average Returns on High and Low VVIX Days



Notes: This figure presents average variance asset returns on days with high (above 75th percentile) and low (below 75th percentile) morning VVIX ($VVIX^M$). The top panels display average intraday returns (10:00–16:00 EST), while the bottom panels display average close-to-close returns. High $VVIX^M$ days (left panels) correspond to long-only strategy returns; low $VVIX^M$ days (right panels) correspond to short-only strategy returns; we report average returns, so negative values indicate profits from short positions. Error bars represent 95% confidence intervals obtained via bootstrap with 2,500 replications. The sample period spans January 2013 to June 2022.

Figure 8: E-mini S&P 500 Futures Trading Volume



Notes: This figure depicts the time series average of the trading volume in terms of number of contracts (bottom panel) of E-mini Futures over the day. EUO indicates the European market open (3:00 EST), USO the U.S. market open (09:30 EST), US10 the U.S. market at 10:00, and USC the U.S. market close (16:00 EST). The sample period ranges from September 2006 to June 2022.

Table 1: Intraday VVIX In-Sample Predictive Regressions

	10:00	11:00	12:00	13:00	14:00	15:00	16:00
Panel A: SPX Straddle Returns							
β	1.072***	0.639***	0.252*	0.146	0.186	0.178	0.117
t-stat	5.742	3.763	1.657	0.988	1.298	1.193	0.746
$R^2_{adj}(\%)$	1.987	0.691	0.086	0.012	0.035	0.030	−0.001
Panel B: Variance Swap Returns							
β	2.978***	1.637***	−0.166	−0.490	−0.375	−0.390	−0.498
t-stat	4.472	2.975	−0.389	−1.254	−0.958	−0.937	−1.202
$R^2_{adj}(\%)$	2.068	0.607	−0.019	0.031	0.008	0.011	0.033
Panel C: VIX Straddle Returns							
β	1.346***	0.651***	−0.035	−0.098	−0.056	−0.060	−0.127
t-stat	4.930	3.111	−0.169	−0.484	−0.265	−0.275	−0.568
$R^2_{adj}(\%)$	2.455	0.555	−0.024	−0.012	−0.021	−0.020	−0.003
Panel D: VIX Futures Returns							
β	0.707***	0.469***	0.002	−0.082	−0.026	−0.031	−0.056
t-stat	6.056	3.432	0.019	−0.687	−0.234	−0.271	−0.465
$R^2_{adj}(\%)$	2.632	1.148	−0.025	0.011	−0.022	−0.020	−0.009

Notes: The table presents in-sample regression results examining the predictive power of VVIX for next-day excess returns ($r_{t+1} - r_{f,t+1}$) of one-month variance assets. We analyze four variance instruments: S&P 500 straddles, variance swaps, VIX straddles, and VIX futures. Results are organized in Panels A through D, each corresponding to one asset. The regressions use VVIX measured hourly from 10:00 to 16:00, which are standardized to have mean zero and unit variance. t-statistics are computed using HAC robust standard errors with 12 lags, and ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively. Finally, the bottom of each panel reports the adjusted-R^2 (R^2_{adj}). The sample period spans September 2006 to June 2022.

Table 2: Intraday VVIX Out-of-Sample Prediction R^2

	10:00	11:00	12:00	13:00	14:00	15:00	16:00
Panel A: SPX Straddle Returns							
μ_t	2.004***	0.473***	−0.246	−0.298	−0.267	−0.322	−0.362
μ	1.881***	0.348***	−0.372	−0.424	−0.393	−0.448	−0.488
Panel B: Variance Swap Returns							
μ_t	1.804***	0.355***	−0.315	−0.218	−0.238	−0.271	−0.243
μ	1.698***	0.247***	−0.424	−0.327	−0.347	−0.380	−0.352
Panel C: VIX Straddle Returns							
μ_t	2.175***	0.398**	−0.207	−0.190	−0.207	−0.262	−0.228
μ	2.115***	0.336**	−0.268	−0.252	−0.269	−0.324	−0.290
Panel D: VIX Futures Returns							
μ_t	2.408***	0.930***	−0.297	−0.260	−0.267	−0.276	−0.256
μ	2.335***	0.856***	−0.372	−0.334	−0.341	−0.351	−0.330

Notes: The table reports the out-of-sample R^2 (R^2_{oos}) following (Campbell and Thompson, 2008), computed as in Equation (3). The dependent variables are the one-month next-day excess returns ($r_{t+1} - r_{f,t+1}$) for four variance assets: S&P 500 straddles, variance swaps, VIX straddles, and VIX futures. We evaluate against two benchmarks: the historical mean through t, and the full sample historical mean. The model is estimated using Equation (2) with an expanding window, initialized with 252 days. We test statistical significance against each benchmark using the Clark and West (2007) statistic, where ***, **, *, denote significance at the 1%, 5%, and 10% levels, respectively, for the alternative hypothesis that VVIX models outperform the benchmark. The sample period spans September 2006 to June 2022.

Table 3: Trading Strategy

	SPX Straddle	VIX Straddle	VIX Futures	Variance Swaps
Panel A: Long-Short Strategy				
Benchmark	0.638	0.228	0.537	2.744
Strategy ($\varpi = 0.50$)	1.501	1.595	1.745	1.319
Strategy ($\varpi = 0.75$)	1.730	1.510	2.091	2.872
Panel B: Long only				
Strategy ($\varpi = 0.50$)	0.763	1.144	0.983	2.242
Strategy ($\varpi = 0.75$)	2.517	2.408	3.243	0.823
Panel C: Short only				
Strategy ($\varpi = 0.50$)	1.699	1.763	2.178	2.242
Strategy ($\varpi = 0.75$)	1.783	1.462	2.165	2.370

Notes: This table reports annualized Sharpe ratios for trading strategies based on morning VVIX ($VVIX^M$), measured at 10:00 EST. The benchmark is the unconditional strategy of systematically selling the variance asset, capturing the negative variance risk premium. Panel A presents the long-short strategy, which takes a long position in the variance asset when $VVIX^M$ exceeds the threshold ϖ and a short position otherwise. Panel B reports the long-only strategy, which buys the variance asset only on days when $VVIX^M$ exceeds ϖ. Panel C reports the short-only strategy, which sells the variance asset only on days when $VVIX^M$ falls below ϖ. We consider two thresholds: the median ($\varpi = 0.50$) and the 75th percentile ($\varpi = 0.75$) of the $VVIX^M$ distribution. All variance assets have a constant maturity of one month. Sharpe ratios are computed as the annualized mean excess return divided by the annualized standard deviation, with annualization factor $\sqrt{252}$. The sample period spans September 2006 to June 2022.

Table 4: Trading Strategy After Transaction Costs

	SPX Straddle	VIX Futures
Panel A: $c = 0.40\%$		
Benchmark	-0.203	0.537
Strategy ($\varpi = 0.50$)	0.658	1.607
Strategy ($\varpi = 0.75$)	0.885	1.990
Panel A: $c = 0.65\%$		
Benchmark	-0.728	0.537
Strategy ($\varpi = 0.50$)	0.131	1.521
Strategy ($\varpi = 0.75$)	0.357	1.927

Notes: This table reports annualized Sharpe ratios for two distinct variance-sensitive trading strategies (SPX straddles and VIX futures) after incorporating transaction costs (c). Panel uses a cost of 0.40%, corresponding to the median round-trip cost over the most recent three years of SPX data, while Panel B uses a cost of $c = 0.65\%$, corresponding to the median over the most recent 5 years. The benchmark strategy consists of always selling the variance asset. SPX straddles require daily rebalancing, so transaction costs $TC_{t+1} = c$. The VIX futures strategy, however, maintains a position until the signal is reversed, ie.g., $TC_{t+1} = c|P_{t+1} - P_t|$, where P_t takes the value of 1 if $VVIX^M > \varpi$, otherwise it takes the value of -1. The sample period spans September 2006 to June 2022.

Table 5: Predicting Variance Assets with $VVIX^M$ and Risk Controls

	Panel A: SPX Straddle Returns							Panel B: Variance Swap Returns						
$VVIX^M$	1.072***	1.152***	1.240***	1.018***	1.050***	1.153***	1.215***	2.978***	3.174***	3.573***	2.984***	3.012***	3.477***	3.738***
t-stat	5.742	5.673	5.777	5.398	5.627	6.505	5.795	4.472	4.521	4.529	4.651	4.501	5.688	5.347
r_t		−0.582***					−0.574***		−1.384***					−1.150**
t-stat		−4.875					−4.678		−2.989					−2.290
VRP_t			−0.550***				−0.439**			−1.950***				−1.321
t-stat			−3.188				−2.052			−3.140				−1.525
$SLOPE_{VIX}$				−0.257			−0.293*				0.031			−0.054
t-stat				−1.567			−1.701				0.062			−0.106
$IVSKEW_C$					−0.100		−0.235					0.154		−0.642
t-stat					−0.729		−1.634					0.404		−1.500
VIX^2						−0.226	−0.118						−1.393***	−0.967
t-stat						−1.332	−0.527						−2.612	−1.177
Adj R^2	1.987	2.545	2.443	2.072	1.978	2.040	3.028	2.068	2.487	2.858	2.044	2.049	2.443	3.120
	Panel C: VIX Straddle Returns							Panel D: VIX Futures Returns						
$VVIX^M$	1.346***	1.423***	1.522***	1.326***	1.370***	1.536***	1.611***	0.707***	0.750***	0.818***	0.680***	0.703***	0.764***	0.800***
t-stat	4.930	5.050	4.540	4.833	5.009	5.463	5.205	6.056	5.995	5.626	6.016	6.324	7.557	6.458
r_t		−0.477***					−0.463***		−0.276***					−0.227**
t-stat		−3.150					−2.840		−3.213					−2.303
VRP_t			−0.579**				−0.279			−0.366***				−0.301
t-stat			−2.375				−0.926			−3.043				−1.563
$SLOPE_{VIX}$				−0.095			−0.165				−0.127			−0.137
t-stat				−0.579			−0.901				−1.288			−1.294
$IVSKEW_C$					0.110		−0.121					−0.015		−0.097
t-stat					0.859		−0.831					−0.184		−1.204
VIX^2						−0.531***	−0.461						−0.160	−0.044
t-stat						−2.690	−1.586						−1.292	−0.228
Adj R^2	2.455	2.734	2.847	2.443	2.447	2.768	3.124	2.632	3.004	3.255	2.689	2.609	2.726	3.497

Notes: The table presents in-sample regression results examining the predictive power of $VVIX^M$ for next-day excess returns $(r_{i,t+1} - r_{f,t+1})$ of one-month variance assets while controlling for alternative predictors of variance assets. We analyze four variance instruments: S&P 500 straddles, variance swaps, VIX straddles, and VIX futures. Results are organized in four panels, each corresponding to one asset. The regressions use the VVIX computed at 10:00 ($VVIX^M$), and the set of control variables outlined in Section 4.1. All regressors are standardized to have mean 0 and unit variance. t-statistics are computed using HAC robust standard errors with 12 lags, and ***, **, * denote statistical significance at the 1%, 5%, and 10% level, respectively. Finally, the bottom of each panel reports the adjusted-R^2 (R^2_{adj}). The sample period spans September 2006 to June 2022.

Table 6: Predicting Variance Assets with $VVIX^M$ and Overnight Information

	Panel A: SPX Straddle Returns					Panel B: Variance Swap Returns				
$VVIX^M$	1.082***	1.081***	1.080***	1.078***	1.036***	3.003***	3.004***	3.029***	3.035***	3.146***
t-stat	5.756	5.834	5.711	5.755	5.350	4.508	4.552	4.583	4.637	5.031
$r^{EUO-USO}$	0.207					0.506				
t-stat	1.332					1.245				
$r^{EUO-US10}$		0.133					0.392			
t-stat		0.974					1.138			
$r^{USC-USO}$			0.120					0.748*		
t-stat			0.881					1.773		
$r^{USC-US10}$				0.080					0.681	
t-stat				0.672					1.867	
$RV^{EUO-USO}$					0.116					−0.549
t-stat					0.583					−0.733
Adj R^2	2.036	1.993	1.987	1.973	1.983	2.104	2.080	2.175	2.152	2.108

	Panel C: VIX Straddle Returns					Panel D: VIX Futures Returns				
$VVIX^M$	1.351***	1.349***	1.354***	1.353***	1.417***	0.712***	0.710***	0.723***	0.723***	0.728***
t-stat	4.953	4.986	4.950	4.983	4.936	6.061	6.105	6.133	6.179	7.219
$r^{EUO-USO}$	0.099					0.118				
t-stat	0.654					1.285				
$r^{EUO-US10}$		0.049					0.047			
t-stat		0.352					0.637			
$r^{USC-USO}$			0.119					0.245**		
t-stat			0.846					2.329		
$r^{USC-US10}$				0.085					0.192**	
t-stat				0.642					2.311	
$RV^{EUO-USO}$					−0.233					−0.071
t-stat					−0.990					−0.470
Adj R^2	2.444	2.434	2.450	2.441	2.498	2.681	2.619	2.926	2.802	2.632

Notes: The table presents in-sample regression results examining the predictive power of $VVIX^M$ for next-day excess returns $(r_{t+1} - r_{f,t+1})$ of one-month variance assets while controlling for overnight information. We analyze four variance instruments: S&P 500 straddles, variance swaps, VIX straddles, and VIX futures. Results are organized in four panels, each corresponding to one asset. The regressions use the VVIX computed at 10:00 ($VVIX^M$), and various control variables constructed from overnight returns from E-mini futures returns, as detailed in Section 4.2. Regressors are standardized to have mean 0 and unit variance. t-statistics are computed using HAC robust standard errors with 12 lags, and ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively. Finally, the bottom of each panel reports the adjusted-R^2 (R^2_{adj}). The sample period spans September 2006 to June 2022.

Table 7: Predicting Variance Assets with $VVIX^M$ and Order Imbalance Measures

	Panel A: SPX Straddle Returns							Panel B: Variance Swap Returns						
$VVIX^M$	1.072***	1.072***	1.071***	1.096***	1.074***	1.064***	1.060***	2.978***	2.975***	2.982***	3.010***	2.986***	2.969***	2.953***
t-stat	5.742	5.746	5.740	5.795	5.706	5.737	5.733	4.472	4.475	4.479	4.483	4.425	4.456	4.458
OI^{ES}_{EUO}		0.011							−0.277					
t-stat		0.080							−0.577					
OI^{ES}_{US10}			−0.024							0.275				
t-stat			−0.190							0.761				
OI^{ES}_{USC}				0.410***							0.547*			
t-stat				3.485							1.665			
OI^{VIX}_{US10}					−0.151							−0.438		
t-stat					−1.279							−1.481		
OI^{VIX}_{US11}						−0.289*							−0.365	
t-stat						−1.843							−0.983	
OI^{VIX}_{USC}							−0.152							−0.325
t-stat							−0.989							−0.817
Adj R^2	1.987	1.962	1.963	2.255	2.002	2.108	2.002	2.068	2.062	2.062	2.114	2.089	2.075	2.069

	Panel C: VIX Straddle Returns							Panel D: VIX Future Returns						
$VVIX^M$	1.346***	1.345***	1.348***	1.366***	1.351***	1.350***	1.347***	0.707***	0.706***	0.708***	0.720***	0.708***	0.706***	0.701***
t-stat	4.930	4.942	4.935	4.976	4.789	4.890	4.926	6.056	6.054	6.051	6.097	6.098	6.049	5.995
OI^{ES}_{EUO}		−0.064							−0.013					
t-stat		−0.389							−0.155					
OI^{ES}_{US10}			0.147							0.067				
t-stat			1.159							0.917				
OI^{ES}_{USC}				0.351***							0.227***			
t-stat				2.809							2.979			
OI^{VIX}_{US10}					−0.259							−0.100*		
t-stat					−1.601							−1.742		
OI^{VIX}_{US11}						0.150							−0.017	
t-stat						0.716							−0.229	
OI^{VIX}_{USC}							0.017							−0.077
t-stat							0.135							−0.885
Adj R^2	2.455	2.437	2.460	2.600	2.522	2.462	2.431	2.632	2.608	2.631	2.882	2.660	2.609	2.639

Notes: The table presents in-sample regression results examining the predictive power of $VVIX^M$ for next-day excess returns $(r_{t+1} - r_{f,t+1})$ of one-month variance assets while controlling for order imbalance measures. We analyze four variance instruments: S&P 500 straddles, variance swaps, VIX straddles, and VIX futures. Results are organized in four panels, each corresponding to one asset. The regressions use the VVIX computed at 10:00 ($VVIX^M$), and various order imbalance measures constructed from intraday volume from both E-mini futures and VIX options, as detailed in Section 4.3. Regressors are standardized to have zero mean and unit variance. t-statistics are computed using HAC robust standard errors with 12 lags, and ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. Finally, the bottom of each panel reports the adjusted-R^2 (R^2_{adj}). The sample period spans September 2006 to June 2022.

Table 8: Predicting Variance Assets with Risk Controls: Subsample Analysis

	Panel A: SPX Straddle Returns							Panel B: Variance Swap Returns						
$VVIX^M$	1.177^{***}	1.239^{***}	1.673^{***}	1.179^{***}	1.188^{***}	2.065^{***}	2.471^{***}	3.494^{***}	3.667^{***}	5.011^{***}	3.497^{***}	3.663^{***}	7.502^{***}	8.624^{***}
t-tstat	4.259	4.157	3.902	3.696	4.352	8.175	8.916	3.288	3.316	2.864	3.104	3.429	7.038	7.326
r_t		-0.383^{**}					-0.460^{***}		-1.088					-1.580^{**}
t-stat		-2.003					-2.594		-1.459					-2.015
VRP_t			-1.041^{***}				-0.624^{***}			-3.185^{*}				-1.227
t-stat			-2.591				-2.815			-1.876				-1.611
$SLOPE_{VIX}$				-0.299			-0.582^{***}				-0.392			-1.711^{***}
t-stat				-0.999			-2.655				-0.402			-3.662
$IVSKEW_C$					0.037		-0.263					0.589		-0.806^{*}
t-stat					0.226		-1.606					1.251		-1.781
VIX^2						-1.339^{***}	-1.497^{***}						-6.045^{***}	-6.804^{***}
t-stat						-5.558	-5.487						-5.911	-6.855
Adj R^2	2.409	2.614	3.846	2.519	2.362	4.143	5.656	2.336	2.513	3.822	2.318	2.350	6.291	7.574
	Panel C: VIX Straddle Returns							Panel D: VIX Future Returns						
$VVIX^M$	1.458^{***}	1.512^{***}	1.912^{***}	1.462^{***}	1.514^{***}	2.750^{***}	3.193^{***}	0.706^{***}	0.756^{***}	1.012^{***}	0.708^{***}	0.749^{***}	1.389^{***}	1.650^{***}
t-tstat	3.443	3.503	2.728	3.122	3.555	4.755	4.975	4.200	4.196	3.334	3.543	4.828	7.159	6.957
r_t		-0.323					-0.544^{**}		-0.324^{**}					-0.368^{**}
t-stat		-1.354					-2.224		-2.469					-2.519
VRP_t			-0.952				-0.295			-0.642^{**}				-0.264
t-stat			-1.442				-0.826			-2.039				-1.374
$SLOPE_{VIX}$				-0.432			-0.918^{***}				-0.210			-0.466^{***}
t-stat				-1.341			-4.159				-1.359			-3.033
$IVSKEW_C$					0.194		-0.166					0.149		-0.066
t-stat					1.068		-1.037					1.219		-0.603
VIX^2						-1.948^{***}	-2.330^{***}						-1.030^{***}	-1.171^{***}
t-stat						-3.369	-4.515						-4.099	-4.159
Adj R^2	2.404	2.473	3.165	2.571	2.396	4.811	5.977	2.344	2.787	3.829	2.507	2.393	5.155	6.976

Notes: The table presents in-sample regression results examining the predictive power of $VVIX^M$ for next-day excess returns ($r_{i,t+1} - r_{f,t+1}$) of one-month variance assets while controlling for alternative predictors of variance assets. We analyze four variance instruments: S&P 500 straddles, variance swaps, VIX straddles, and VIX futures. Results are organized in four panels, each corresponding to one asset. The regressions use the VVIX computed at 10:00 ($VVIX^M$), and the set control variables outlined in Section 4.1. Regressors are standardized to have zero mean and unit variance. $SLOPE_{VIX}$ is computed at 10:00. t-statistics are computed using HAC robust standard errors with 12 lags, and ***, **, * denote statistical significance at the 1%, 5%, and 10% levels, respectively. Finally, the bottom of each panel reports the adjusted-R^2 (R^2_{adj}). The sample period spans June 2014 to June 2022.

Table 9: Predicting Variance Assets with Overnight Information: Subsample Analysis

	Panel A: SPX Straddle Returns					Panel B: Variance Swap Returns				
$VVIX^M$	1.177***	1.173***	1.180***	2.081***	2.089***	3.494***	3.473***	3.502***	7.526***	7.528***
t-stat	4.259	4.295	4.288	8.263	8.415	3.288	3.303	3.308	6.900	6.884
$r_{VIX}^{EUO-US10}$		0.176					0.807			
t-stat		1.120					1.564			
$r_{ES}^{EUO-US10}$			0.083					0.191		
t-stat			0.557					0.443		
VXF^{EUO}				−1.388***					−6.190***	
t-stat				−5.946					−7.354	
VXF^{US10}					−1.390***					−6.150***
t-stat					−5.757					−7.065
Adj R^2	2.409	2.415	2.372	4.328	4.315	2.336	2.415	2.295	6.602	6.502
	Panel C: VIX Straddle Returns					**Panel D: VIX Futures Returns**				
$VVIX^M$	1.458***	1.451***	1.448***	2.916***	2.910***	0.706***	0.706***	0.710***	1.451***	1.456***
t-stat	3.443	3.475	3.454	5.038	5.148	4.200	4.201	4.231	7.766	7.488
$r_{VIX}^{EUO-US10}$		0.277					−0.001			
t-stat		0.875					−0.005			
$r_{ES}^{EUO-US10}$			−0.256					0.095		
t-stat			−1.463					0.755		
VXF^{EUO}				−2.238***					−1.145***	
t-stat				−4.661					−6.797	
VXF^{US10}					−2.213***					−1.144***
t-stat					−4.748					−6.110
Adj R^2	2.404	2.444	2.431	5.683	5.578	2.344	2.296	2.339	5.920	5.880

Notes: The table presents in-sample regression results examining the predictive power of $VVIX^M$ for next-day excess returns $(r_{i,t+1} - r_{f,t+1})$ of one-month variance assets while controlling for overnight information. We analyze four variance instruments: S&P 500 straddles, variance swaps, VIX straddles, and VIX futures. Results are organized in four panels, each corresponding to one asset. The regressions use the VVIX computed at 10:00 ($VVIX^M$), and the set control variables outlined in Section 4.2. Regressors are standardized to have zero mean and unit variance. t-statistics are computed using HAC robust standard errors with 12 lags, and ***, **, * denote statistical significance at the 1%, 5%, and 10% levels, respectively. Finally, the bottom of each panel reports the adjusted-R^2 (R^2_{adj}). The sample period spans June 2014 to June 2022.

Table 10: Predicting Variance Assets with Order Imbalance Measures: Subsample Analysis

	Panel A: SPX Straddle Returns						Panel B: Variance Swap Returns					
$VVIX^M$	1.177***	1.194***	1.195***	1.182***	1.176***	1.188***	3.476***	3.489***	3.540***	3.516***	3.491***	3.528***
t-stat	4.275	4.254	4.212	4.285	4.251	4.232	3.297	3.282	3.243	3.307	3.284	3.225
OI_{EUO}^{ES}	−0.007						−0.780					
t-stat	−0.035						−0.991					
OI_{USC}^{ES}		0.251						−0.072				
t-stat		1.518						−0.159				
OI_{US10}^{VIX}			−0.364***						−0.906**			
t-stat			−2.710						−2.371			
OI_{US10}^{SPX}				0.186						0.754*		
t-stat				1.305						1.732		
OI_{USC}^{SPX}					−0.073						−0.182	
t-stat					−0.453						−0.342	
OI_{EUO}^{VXF}						0.439						1.440
t-stat						1.505						1.610
Adj R^2	2.360	2.471	2.595	2.422	2.370	2.701	2.407	2.289	2.448	2.399	2.294	2.693
	Panel C: VIX Straddle Returns						Panel D: VIX Futures Returns					
$VVIX^M$	1.455***	1.471***	1.486***	1.471***	1.460***	1.472***	0.706***	0.719***	0.714***	0.710***	0.705***	0.709***
t-stat	3.468	3.453	3.294	3.453	3.456	3.335	4.193	4.221	4.233	4.232	4.189	4.216
OI_{EUO}^{ES}	−0.123						0.010					
t-stat	−0.452						0.071					
OI_{USC}^{ES}		0.190						0.188**				
t-stat		1.287						2.101				
OI_{US10}^{VIX}			−0.553***						−0.156*			
t-stat			−3.283						−1.837			
OI_{US10}^{SPX}				0.448*						0.137*		
t-stat				1.977						1.689		
OI_{USC}^{SPX}					0.081						−0.034	
t-stat					0.461						−0.347	
OI_{EUO}^{VXF}						0.586						0.116
t-stat						1.212						1.051
Adj R^2	2.373	2.397	2.708	2.587	2.363	2.752	2.296	2.465	2.412	2.386	2.301	2.361

Notes: The table presents in-sample regression results examining the predictive power of $VVIX^M$ for next-day excess returns ($r_{t+1} - r_{f,t+1}$) of one-month variance assets while controlling for order imbalance measures. We analyze four variance instruments: S&P 500 straddles, variance swaps, VIX straddles, and VIX futures. Results are organized in four panels, each corresponding to one asset. The regressions use the VVIX computed at 10:00 ($VVIX^M$), and various order imbalance measures constructed from intraday volume from both E-mini futures and VIX options, as detailed in Section 4.3. Regressors are standardized to have zero mean and unit variance. t-statistics are computed using HAC robust standard errors with 12 lags, and ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. Finally, the bottom of each panel reports the adjusted-R^2 (R^2_{adj}). The sample period spans June 2014 to June 2022.

Appendices

A Variance Assets

VIX^2 index approximates the price of a variance swap traded at time t and maturing at time T. Because options expiring exactly T months from t are not always traded, the VIX is calculated using a linear interpolation between variance swap rates for the two nearest expiration dates to T (see Carr and Madan, 1998). VIX^2 without annualization, an estimate of the variance swap price at time t, is therefore:

$$\hat{p}_{t,T} = \frac{T - S_1}{S_2 - S_1} \sum_K \frac{\Delta K_i}{K^2} \mathrm{O}_t(K; t + S_1) + \frac{S_2 - T}{S_2 - S_1} \sum_K \frac{\Delta K}{K^2} \mathrm{O}_t(K; t + S_2) \tag{A.1}$$

where $\mathrm{O}_t(K; t + S)$ is the price at t of the option with strike K and expiration date $t + S$ that is out of the money at time $t, \Delta K$ is the difference between K and the nearest strike price, and $S_1 \leq T \leq S_2$ are the two nearest expiration dates to T.

Note that Equation A.1 is the price of a specific, tradable, portfolio of out-of-the-money options with times to expiration equal to S_1 and S_2. Therefore, the return of a variance swap from day t to day $t+1$ can be approximated by the return of the day t replicating portfolio:

$$\begin{aligned}
&r_{T,t+1}^{\mathrm{VAR_SWAP}} \\
&= \frac{\sum_K \left(\frac{T-S_1}{S_2-S_1} \frac{\Delta K_i}{K^2} \mathrm{O}_{t+1}\left(K; t + S_1\right) + \frac{S_2-T}{S_2-S_1} \frac{\Delta K}{K^2} \mathrm{O}_{t+1}\left(K; t + S_2\right) \right)}{\sum_K \left(\frac{T-S_1}{S_2-S_1} \frac{\Delta K_i}{K^2} \mathrm{O}_{t}\left(K; t + S_1\right) + \frac{S_2-T}{S_2-S_1} \frac{\Delta K}{K^2} \mathrm{O}_{t}\left(K; t + S_2\right) \right)} - 1 \\
&= \sum_K w_{1,t}(K) \cdot r_{t+1}^{\mathrm{O}}\left(K; t + S_1\right) + w_{2,t}(K) \cdot r_{t+1}^{\mathrm{O}}\left(K; t + S_2\right), \\
&w_{1,t}(K) \equiv \frac{\frac{T-S_1}{S_2-S_1} \frac{\Delta K}{K^2} \mathrm{O}_t\left(K; t + S_1\right)}{\hat{p}_{t,T}}, w_{2,t}(K) \equiv \frac{\frac{S_2-T}{S_2-S_1} \frac{\Delta K}{K^2} \mathrm{O}_t\left(K; t + S_2\right)}{\hat{p}_{t,T}},
\end{aligned} \tag{A.2}$$

where $\mathrm{O}_t(K; t + S)$ is the price at t of the option with strike K and expiration date $t + S$ that is out of the money at time t, and

$$r_{t+1}^{\mathrm{O}}(K;t+S)=\frac{\mathrm{O}_{t+1}(K;t+S)}{\mathrm{O}_{t}(K;t+S)}-1 \tag{A.3}$$

On most days, there are no options expiring exactly T months later, and so the VIX calculation uses a linear combination of options with the two nearest expiration dates to $t+T$. This linear combination to form a portfolio at time t and compute its time $t+1$ returns, results in a "constant maturity" strategy.

The returns for each constant maturity VIX futures strategy are calculated as:

$$r_{T,t+1}^{\mathrm{VIXFUT}}=\frac{\frac{T-S_1}{S_2-S_1}\,\mathrm{VIX\_FUT}_{t+1}\left(t+S_1\right)+\frac{S_2-T}{S_2-S_1}\,\mathrm{VIX\_FUT}_{t+1}\left(t+S_2\right)}{\frac{T-S_1}{S_2-S_1}\,\mathrm{VIX\_FUT}_{t}\left(t+S_1\right)+\frac{S_2-T}{S_2-S_1}\,\mathrm{VIX\_FUT}_{t}\left(t+S_2\right)}-1, \tag{A.4}$$

where $VIX\_FUT_t(t+S)$ is the day t price of a VIX futures contract with maturity date $t+S$, and S_1 and S_2 are the two closest times to maturity to the target time to maturity T.

Finally, we compute the returns for each constant maturity S&P 500 and VIX straddle strategy using:

$$r_{T,t+1}^{\mathrm{STRADDLE}}=\frac{\frac{T-S_1}{S_2-S_1}\,\mathrm{STRADDLE}_{t+1}\left(t+S_1\right)+\frac{S_2-T}{S_2-S_1}\,\mathrm{STRADDLE}_{t+1}\left(t+S_2\right)}{\frac{T-S_1}{S_2-S_1}\,\mathrm{STRADDLE}_{t}\left(t+S_1\right)+\frac{S_2-T}{S_2-S_1}\,\mathrm{STRADDLE}_{t}\left(t+S_2\right)}-1 \tag{A.5}$$

where $\mathrm{STRADDLE}_t(t+S)$ is the day t price of an at-the-money straddle with expiration date $t+S$, and S_1 and S_2 are the two closest times to expiration to the target T. This equation applies to both S&P 500 and VIX options.

B Descriptive Statistics

Table B1: Correlation and AR(1) Coefficient

	$VVIX_{10}$	$VVIX_{11}$	$VVIX_{12}$	$VVIX_{13}$	$VVIX_{14}$	$VVIX_{15}$	$VVIX_{16}$
$VVIX_{10}$	0.900	0.833	0.798	0.783	0.799	0.800	0.809
$VVIX_{11}$		0.933	0.938	0.917	0.945	0.950	0.958
$VVIX_{12}$			0.935	0.967	0.984	0.973	0.968
$VVIX_{13}$				0.931	0.972	0.961	0.953
$VVIX_{14}$					0.936	0.985	0.977
$VVIX_{15}$						0.932	0.984
$VVIX_{16}$							0.935

Note: The table presents correlations (off-diagonal) and AR(1) coefficients (diagonal elements) for $VVIX$ measures computed at different intraday intervals, denoted by subscript values. The sample period spans September 2006 to June 2022.

Table B2: Variance Assets: Descriptive Statistics

	$T=1$	$T=2$	$T=3$	$T=6$	$T=1$	$T=2$	$T=3$	$T=6$
	Panel A: SPX Straddle Returns				Panel B: Variance Swap Returns			
Mean	−0.303	−0.159	−0.098	−0.005	−3.558	−1.884	−1.252	−0.646
Median	−1.713	−0.761	−0.456	−0.198	−7.149	−3.820	−2.660	−1.457
Std. Dev.	7.556	4.072	3.060	1.972	20.581	13.760	10.929	7.587
Sharpe Ratio	−0.637	−0.621	−0.506	−0.037	−2.745	−2.173	−1.818	−1.352
Skewness	3.809	3.267	3.098	2.335	4.732	3.922	2.999	2.212
Kurtosis	40.437	32.731	33.712	27.197	51.256	44.567	27.288	18.451
p-value	0.013	0.018	0.052	0.969	0.000	0.000	0.000	0.000
	Panel C: VIX Straddle Returns				Panel D: VIX Futures Returns			
Mean	−0.125	−0.086	−0.039	−0.018	−0.147	−0.070	−0.050	−0.009
Median	−1.506	−0.689	−0.410	−0.112	−0.646	−0.318	−0.262	−0.104
Std. Dev.	8.546	4.225	3.006	2.559	4.335	3.173	2.665	1.958
Sharpe Ratio	−0.233	−0.321	−0.208	−0.112	−0.539	−0.350	−0.299	−0.075
Skewness	8.800	5.645	3.812	0.765	1.239	1.250	1.193	0.790
Kurtosis	179.064	89.881	48.194	57.707	8.855	11.602	12.012	9.816
p-value	0.366	0.213	0.456	0.713	0.037	0.177	0.271	0.849

Notes: This table presents descriptive statistics for excess returns (in %) of four variance assets: S&P straddles (Panel A), variance swaps (Panel B), VIX straddles (Panel C), and VIX futures (Panel D). Returns are reported for 1-, 2-, 3-, and 6-month maturities (T). Sharpe ratios are annualized using $\sqrt{252}$. We test the null hypothesis of zero mean against a negative mean using bootstrapped standard errors (2,500 replications). The sample period spans September 2006 to June 2022.

Table B3: Variance Assets: Correlation Analysis

		SPX Straddle Returns			Variance Swap Returns			VIX Straddle Returns			VIX Futures Returns		
		$T=1$	$T=3$	$T=6$	$T=1$	$T=3$	$T=6$	$T=1$	$T=3$	$T=6$	$T=1$	$T=3$	$T=6$
SPX Straddle Returns	$T=1$	1.000	0.888	0.787	0.785	0.683	0.614	0.657	0.558	0.366	0.562	0.478	0.348
	$T=3$		1.000	0.955	0.758	0.753	0.710	0.632	0.623	0.436	0.655	0.598	0.464
	$T=6$			1.000	0.667	0.697	0.683	0.560	0.598	0.430	0.610	0.590	0.482
Var. Swap Returns	$T=1$				1.000	0.883	0.826	0.726	0.682	0.476	0.767	0.686	0.549
	$T=3$					1.000	0.946	0.700	0.760	0.539	0.878	0.828	0.681
	$T=6$						1.000	0.644	0.748	0.541	0.875	0.851	0.713
VIX Straddle Returns	$T=1$							1.000	0.707	0.431	0.570	0.492	0.374
	$T=3$								1.000	0.534	0.700	0.681	0.562
	$T=6$									1.000	0.502	0.509	0.445
VIX Futures Returns	$T=1$										1.000	0.935	0.780
	$T=3$											1.000	0.890
	$T=6$												1.000

Notes: This table presents correlations between excess returns of four variance assets: S&P straddles, variance swaps, VIX straddles, and VIX futures, across 1-, 3-, and 6-month maturities from September 2006 to June 2022.

Table B4: Intraday and Close-to-Close Variance Assets: Descriptive Statistics

	SPX Straddle	Variance Swaps	VIX Straddle	VIX Futures
Panel A: Intraday Returns (×100)				
Mean	−0.081	−1.064	−0.159	−0.167
Median	−0.413	−3.088	−0.262	−0.284
St. Dev.	4.895	20.507	6.991	4.426
Sharpe Ratio	−0.270	−0.823	−0.360	−0.600
Skewness	−2.716	3.337	−0.799	1.358
Kurtosis	76.908	34.582	40.471	15.909
p-value	0.414	0.012	0.281	0.000
Panel B: Close-to-Close Returns (×100)				
Mean	−0.245	−3.868	0.011	−0.179
Median	−1.502	−7.453	−1.399	−0.649
St. Dev.	7.417	21.739	9.099	4.478
Sharpe Ratio	−0.524	−2.825	0.019	−0.633
Skewness	3.069	4.973	9.469	1.416
Kurtosis	21.975	55.175	194.594	9.935
p-value	0.106	0.000	0.955	0.049

Notes: This table reports summary statistics for variance asset returns. Panel A presents intraday returns computed from 10:00 to 16:00 EST. Panel B presents close-to-close returns. Returns are expressed in percentage terms. We report the mean, median, standard deviation, annualized Sharpe ratios, skewness, kurtosis, and the p-value from a test of whether the mean return equals zero against a negative mean using bootstrapped standard errors (2,500 replications). All variance assets have constant one-month maturity. The sample period spans January 2013 to June 2022.

C Additional Controls

Table C1: Predicting Variance Assets with $VVIX^M$ including NOISE and LTV

	Panel A: SPX Straddle Returns									Panel B: Variance Swap Returns								
α	−0.304***	−0.304**	−0.304**	−0.304***	−0.304***	−0.304***	−0.304***	−0.304**	−0.304**	−3.557***	−3.557***	−3.557***	−3.557***	−3.557***	−3.557***	−3.557***	−3.557***	−3.557***
t-stat	−2.655	−2.480	−2.536	−2.734	−2.682	−2.667	−2.580	−2.500	−2.522	−11.332	−10.678	−10.523	−11.318	−11.265	−11.424	−10.787	−10.335	−10.394
$VVIX^M$	1.072***	1.152***	1.240***	1.018***	1.050***	1.088***	1.329***	1.294***	1.318***	2.978***	3.174***	3.573***	2.984***	3.012***	3.041***	3.930***	3.950***	4.000***
t-stat	5.742	5.673	5.777	5.398	5.627	5.775	6.150	5.285	5.616	4.472	4.521	4.529	4.651	4.501	4.502	5.089	4.536	5.020
r_t		−0.582***						−0.550***	−0.556***		−1.384***						−0.936*	−0.993*
t-stat		−4.875						−4.322	−4.319		−2.989						−1.862	−1.925
VRP_t			−0.550***					−0.653***	−0.267			−1.950***					−2.392***	−1.023
t-stat			−3.188					−2.884	−1.301			−3.140					−2.786	−1.397
$SLOPE_{VIX}$				−0.257				−0.360*	−0.313*				0.031				−0.263	−0.083
t-stat				−1.567				−1.975	−1.643				0.062				−0.481	−0.147
$SKEW_C$					−0.100			−0.089	−0.279*					0.154			0.047	−0.636
t-stat					−0.729			−0.653	−1.903					0.404			0.112	−1.415
$NOISE$						0.173		0.450**							0.694**		1.676***	
t-stat						1.296		2.150							2.170		2.635	
LTV							−0.592***		−0.491**							−2.184***		−1.666**
t-stat							−2.979		−2.301							−3.347		−2.220
Adj R^2	1.987	2.545	2.443	2.072	1.978	2.014	2.459	3.290	3.247	2.068	2.487	2.858	2.044	2.049	2.156	2.957	3.517	3.365
	Panel C: VIX Straddle Returns									Panel D: VIX Future Returns								
α	−0.123	−0.123	−0.123	−0.123	−0.123	−0.123	−0.123	−0.123	−0.123	−0.147**	−0.147**	−0.147**	−0.147**	−0.147**	−0.147**	−0.147**	−0.147**	−0.147**
t-stat	−0.939	−0.894	−0.905	−0.946	−0.933	−0.940	−0.917	−0.879	−0.888	−2.353	−2.226	−2.173	−2.415	−2.361	−2.390	−2.272	−2.188	−2.186
$VVIX^M$	1.346***	1.423***	1.522***	1.326***	1.370***	1.354***	1.675***	1.621***	1.694***	0.707***	0.750***	0.818***	0.680***	0.703***	0.724***	0.822***	0.878***	0.826***
t-stat	4.930	5.050	4.540	4.833	5.009	4.941	4.846	4.502	4.793	6.056	5.995	5.626	6.016	6.324	6.116	6.435	5.399	5.877
r_t		−0.477***						−0.394**	−0.397**		−0.276***						−0.202**	−0.224**
t-stat		−3.150						−2.351	−2.251		−3.213						−2.100	−2.354
VRP_t			−0.579**					−0.637**	−0.205			−0.366***					−0.465***	−0.261*
t-stat			−2.375					−1.998	−0.843			−3.043					−2.737	−1.842
$SLOPE_{VIX}$				−0.095				−0.202	−0.172				−0.127				−0.198*	−0.142
t-stat				−0.579				−1.058	−0.872				−1.288				−1.762	−1.271
$SKEW_C$					0.110			0.104	−0.095					−0.015			0.014	−0.106
t-stat					0.859			0.742	−0.624					−0.184			0.164	−1.146
$NOISE$						0.094		0.393*							0.185**		0.396***	
t-stat						0.795		1.761							2.426		2.981	
LTV							−0.755**		−0.637**							−0.265**		−0.131
t-stat							−2.522		−2.052							−1.794		−0.914
Adj R^2	2.455	2.734	2.847	2.443	2.447	2.443	3.064	3.132	3.275	2.632	3.004	3.255	2.689	2.609	2.789	2.910	4.138	3.542

Notes: The table presents in-sample regression results examining the predictive power of $VVIX^M$ for next-day excess returns $(r_{i,t+1} - r_{f,t+1})$ of one-month variance assets while controlling for alternative predictors of variance assets. We analyze four variance instruments: S&P 500 straddles, variance swaps, VIX straddles, and VIX futures. Results are organized in four panels, each corresponding to one asset. The regressions use the VVIX computed at 10:00 ($VVIX^M$), and the set of control variables outlined in Section 4.1. All regressors are standardized to have zero mean and unit variance. t-statistics are computed using HAC robust standard errors with 12 lags, and ***, **, * denote statistical significance at the 1%, 5%, and 10% levels, respectively. Finally, the bottom of each panel reports the adjusted-R^2 (R^2_{adj}). The sample period spans September 2006 to June 2022.

Table C2: Predicting Variance Assets with $VVIX^M$ including NOISE and LTV: Subsample Analysis

	Panel A: SPX Straddle Returns									Panel B: Variance Swap Returns								
$VVIX^M$	1.177	1.239	1.673	1.179	1.188	1.177	2.058	1.691	2.090	3.494	3.667	5.011	3.497	3.663	3.495	6.995	5.119	7.033
t-tstat	4.259	4.157	3.902	3.696	4.352	4.303	4.679	3.746	4.287	3.288	3.316	2.864	3.104	3.429	3.228	4.447	2.935	4.202
r_t		−0.383						−0.276	−0.172		−1.088						−0.493	0.088
t-stat		−2.003						−1.383	−0.876		−1.459						−0.605	0.095
VRP_t			−1.041					−0.986	−0.481			−3.185					−3.023	−0.641
t-stat			−2.591					−2.399	−1.200			−1.876					−1.725	−0.443
$SLOPE_{VIX}$				−0.299				−0.321	−0.310				−0.392				−0.419	−0.483
t-stat				−0.999				−1.066	−1.003				−0.402				−0.478	−0.568
$IVSKEW_C$					0.037			−0.007	−0.201					0.589			0.356	−0.553
t-stat					0.226			−0.040	−1.224					1.251			0.610	−1.281
NOISE						−0.050		−0.074							0.238		0.272	
t-stat						−0.286		−0.499							0.408		0.566	
LTV							−1.377		−1.112							−5.473		−5.319
t-stat							−3.169		−2.004							−4.442		−3.088
Adj R^2	2.409	2.614	3.846	2.519	2.362	2.365	4.350	3.937	4.731	2.336	2.513	3.822	2.318	2.350	2.299	5.748	3.737	5.732

	Panel C: VIX Straddle Returns									Panel D: VIX Future Returns								
$VVIX^M$	1.458	1.512	1.912	1.462	1.514	1.460	2.748	1.985	2.757	0.706	0.756	1.012	0.708	0.749	0.706	1.366	1.049	1.385
t-tstat	3.443	3.503	2.728	3.122	3.555	3.302	3.555	2.705	3.360	4.200	4.196	3.334	3.543	4.828	4.137	5.998	3.379	5.174
r_t		−0.323						−0.234	0.021		−0.324						−0.215	−0.172
t-stat		−1.354						−0.885	0.064		−2.469						−1.465	−1.242
VRP_t			−0.952					−0.888	0.112			−0.642					−0.566	−0.139
t-stat			−1.442					−1.350	0.244			−2.039					−1.792	−0.571
$SLOPE_{VIX}$				−0.432				−0.430	−0.488				−0.210				−0.248	−0.256
t-stat				−1.341				−1.352	−1.569				−1.359				−1.541	−1.501
$IVSKEW_C$					0.194			0.210	−0.171					0.149			0.133	−0.028
t-stat					1.068			1.031	−0.960					1.219			1.042	−0.280
NOISE						0.358		0.329							0.032		0.014	
t-stat						1.790		1.829							0.235		0.109	
LTV							−2.016		−2.190							−1.032		−0.926
t-stat							−2.779		−2.516							−4.129		−3.865
Adj R^2	2.404	2.473	3.165	2.571	2.396	2.504	5.127	3.397	5.284	2.344	2.787	3.829	2.507	2.393	2.301	5.322	4.122	5.656

Notes: The table presents in-sample regression results examining the predictive power of $VVIX^M$ for next-day excess returns $(r_{i,t+1} - r_{f,t+1})$ of one-month variance assets while controlling for alternative predictors of variance assets. We analyze four variance instruments: S&P 500 straddles, variance swaps, VIX straddles, and VIX futures. Results are organized in four panels, each corresponding to one asset. The regressions use the VVIX computed at 10:00 ($VVIX^M$), and the set of control variables outlined in Section 4.1. All regressors are standardized to have zero mean and unit variance. t-statistics are computed using HAC robust standard errors with 12 lags, and ***, **, * denote statistical significance at the 1%, 5%, and 10% levels, respectively. Finally, the bottom of each panel reports the adjusted-R^2 (R^2_{adj}). The sample period spans June 2014 to June 2022.

Table C3: Predicting Variance Assets with $VVIX^M$ and Day-of-the-Week Dummies

	Panel A: SPX Straddle Returns				Panel B: Variance Swap Returns			
$VVIX^M$	1.075***	1.063***	1.056***	1.057***	2.981***	2.952***	2.944***	2.935***
t-stat	5.748	5.721	5.675	5.680	4.475	4.462	4.424	4.430
MONDAY	0.968***			1.044***	0.827			1.175
t-stat	2.986			3.145	1.000			1.395
WEDNESDAY		1.424***		1.389***		4.210***		3.850***
t-stat		4.926		4.479		4.631		3.986
FRIDAY			−1.722***	−1.120***			−3.800***	−2.535***
t-stat			−5.406	−3.334			−4.370	−2.779
Adj R^2	2.213	2.542	2.793	3.290	2.068	2.727	2.589	3.019
	Panel C: VIX Straddle Returns				**Panel D: VIX Futures Returns**			
$VVIX^M$	1.346***	1.341***	1.336***	1.334***	0.706***	0.705***	0.707***	0.705***
t-stat	4.937	4.918	4.863	4.866	6.057	6.053	6.042	6.039
MONDAY	0.074			0.013	−0.192			−0.144
t-stat	0.204			0.035	−1.102			−0.757
WEDNESDAY		0.843***		0.622*		0.215		0.183
t-stat		2.599		1.847		1.252		0.999
FRIDAY			−1.051**	−0.888**			−0.004	0.009
t-stat			−2.492	−2.117			−0.020	0.047
Adj R^2	2.432	2.590	2.673	2.704	2.638	2.648	2.608	2.615

Notes: The table presents predictive regression results examining the predictive power of $VVIX^M$ for next-day excess returns ($r_{i,t+1} - r_{f,t+1}$) of one-month variance assets while controlling for the day-of-the-week effects. We analyze four different variance instruments: S&P 500 straddles, variance swaps, VIX straddles, and VIX futures. The control variables consist of three variables ($MONDAY$, $WEDNESDAY$, and $FRIDAY$) that equal 1 on their respective days and 0 otherwise. For each regression, we report coefficient estimates alongside their corresponding t-statistics, which are computed using HAC robust standard errors with 12 lags, and ***, **, * denote statistical significance at the 1%, 5%, and 10% levels, respectively. Additionally, we present the adjusted R^2 values in the final row of each panel. The sample period spans September 2006 to June 2022.

Table C4: Predicting Variance Assets with $VVIX^M$ Excluding Policy Meetings and Daylight Saving Days

	Panel A: SPX Straddle Returns			Panel B: Variance Swap Returns		
NO FOMC	1.121***			2.962***		
t-stat	5.272			4.084		
NO ECB		1.025***			2.755***	
t-stat		5.861			4.008	
NO DST			1.015***			2.947***
t-stat			6.016			4.373
Adj R^2	2.155	1.816	1.812	2.061	1.906	2.041
	Panel C: VIX Straddle Returns			**Panel D: VIX Future Returns**		
NO FOMC	1.373***			0.735***		
t-stat	4.330			5.927		
NO ECB		1.297***			0.641***	
t-stat		4.679			5.368	
NO DST			1.256***			0.655***
t-stat			4.295			6.420
Adj R^2	2.532	2.257	2.107	2.873	2.173	2.335

Notes: The table presents predictive regression results examining the predictive power of $VVIX^M$ for next-day excess returns ($r_{i,t+1} - r_{f,t+1}$) of one-month variance assets across different sample restrictions. We analyze four variance instruments: S&P 500 straddles, variance swaps, VIX straddles, and VIX futures. *NO FOMC* excludes days with FOMC meetings, *NO ECB* excludes days with ECB monetary policy announcements, and *NO DST* excludes periods when the U.S. and Europe operate on different daylight saving time schedules. Each panel reports coefficient estimates and corresponding t-statistics, which are computed using HAC robust standard errors with 12 lags, and ***, **, * denote statistical significance at the 1%, 5%, and 10% levels, respectively. Additionally, we present the adjusted R^2 values in the final row of each panel. The sample period spans September 2006 to June 2022.

D Longer Horizon Predictive Regressions

Table D1: Predicting Variance Assets with $VVIX^M$ and Controls, 2-months Maturity

	Panel A: SPX Straddle Returns											Panel B: Variance Swap Returns										
$VVIX^M$	0.638***	0.666***	0.744***	0.595***	0.620***	0.684***	0.645***	0.780***	0.702***	0.751***	0.759***	2.147***	2.312***	2.582***	2.127***	2.197***	2.489***	2.184***	2.786***	2.676***	2.833***	2.837***
t-stat	5.262	5.135	5.549	4.904	5.212	6.122	5.277	5.697	5.461	5.037	5.236	5.034	5.102	4.712	5.148	5.193	6.292	5.062	5.480	5.702	4.719	5.300
r_t		−0.179**							−0.166*	−0.153	−0.158		−1.034***							−0.839**	−0.684**	−0.743**
t-stat		−1.988							−1.698	−1.499	−1.561		−3.068							−2.294	−1.852	−1.989
VRP_t			−0.348***						−0.330**	−0.433***	−0.229			−1.426***						−0.949	−1.649***	−0.764
t-stat			−3.025						−2.242	−2.812	−1.565			−3.286						−1.503	−2.707	−1.537
$SLOPE_{VIX}$				−0.209**					−0.203*	−0.241**	−0.214*				−0.096					−0.215	−0.356	−0.231
t-stat				−2.125					−1.822	−2.167	−1.741				−0.290					−0.619	−0.941	−0.603
$IVSKEW_C$					−0.081				−0.141	−0.070	−0.173*					0.229				−0.246	0.195	−0.250
t-stat					−1.003				−1.554	−0.817	−1.880					0.856				−0.824	0.650	−0.784
VIX^2						−0.128			−0.029								−0.953***			−0.569		
t-stat						−1.116			−0.201								−2.605			−0.950		
NOISE							0.077			0.251*								0.405*			1.147**	
t-stat							0.878			1.930								1.867			2.497	
LTV								−0.326**			−0.251*								−1.467***			−1.012**
t-stat								−2.314			−1.728								−3.147			−2.028
Adj R^2	2.431	2.595	3.070	2.659	2.444	2.492	2.442	2.926	3.444	3.736	3.651	2.410	2.936	3.360	2.390	2.411	2.803	2.471	3.306	3.615	4.062	3.823
	Panel C: VIX Straddle Returns											Panel D: VIX Futures Returns										
$VVIX^M$	0.791***	0.841***	0.859***	0.788***	0.810***	0.844***	0.808***	0.937***	0.893***	0.955***	0.954***	0.562***	0.591***	0.626***	0.541***	0.560***	0.574***	0.576***	0.618***	0.598***	0.672***	0.619***
t-stat	5.344	5.424	4.970	5.599	5.480	6.332	5.467	5.644	6.155	5.398	5.788	5.476	5.400	5.269	5.679	5.696	6.512	5.614	5.817	5.915	5.370	5.554
r_t		−0.278**							−0.256*	−0.237*	−0.245*		−0.168**							−0.131*	−0.126*	−0.140*
t-stat		−2.288							−1.893	−1.792	−1.858		−2.423							−1.717	−1.676	−1.883
VRP_t			−0.223						−0.106	−0.269	−0.006			−0.210**						−0.209	−0.283**	−0.157
t-stat			−1.635						−0.595	−1.566	−0.048			−2.299						−1.354	−2.186	−1.263
$SLOPE_{VIX}$				−0.011					−0.059	−0.111	−0.070				−0.101					−0.105	−0.155*	−0.111
t-stat				−0.110					−0.543	−0.957	−0.610				−1.480					−1.418	−1.928	−1.425
$IVSKEW_C$					0.088				0.032	0.140*	0.005					−0.009				−0.021	0.034	−0.046
t-stat					1.142				0.321	1.671	0.060					−0.152				−0.325	0.517	−0.688
VIX^2						−0.149			−0.078								−0.035			0.067		
t-stat						−1.224			−0.428								−0.363			0.429		
NOISE							0.186**			0.351***								0.154***			0.293***	
t-stat							2.256			2.705								2.648			3.291	
LTV								−0.336*			−0.299								−0.128			−0.043
t-stat								−1.802			−1.546								−1.249			−0.370
Adj R^2	3.476	3.870	3.705	3.453	3.493	3.560	3.644	3.965	3.937	4.452	4.193	3.113	3.362	3.486	3.185	3.089	3.099	3.321	3.221	3.683	4.321	3.669

Notes: The table presents in-sample regression results examining the predictive power of $VVIX^M$ for next-day excess returns ($r_{i,t+1} - r_{f,t+1}$) of two-month variance assets while controlling for alternative predictors of variance assets. We analyze four variance instruments: S&P 500 straddles, variance swaps, VIX straddles, and VIX futures. Results are organized in four panels, each corresponding to one asset. The regressions use the VVIX computed at 10:00 ($VVIX^M$), and the set control variables outlined in Section 4.1. All regressors are standardized to have zero mean and unit variance. t-statistics are computed using HAC robust standard errors with 12 lags, and ***, **, * denote statistical significance at the 1%, 5%, and 10% levels, respectively. Finally, the bottom of each panel reports the adjusted-R^2 (R^2_{adj}). The sample period spans September 2006 to June 2022.

Table D2: Predicting Variance Assets with $VVIX^M$ and Controls, 3-months Maturity

Panel A: SPX Straddle Returns

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
$VVIX^M$	0.491***	0.500***	0.569***	0.451***	0.474***	0.514***	0.496***	0.582***	0.518***	0.566***	0.558***
t-stat	4.971	4.818	5.425	4.611	4.942	5.728	4.988	5.395	5.146	4.947	4.995
r_t		−0.058							−0.043	−0.038	−0.042
t-stat		−0.715							−0.462	−0.403	−0.451
VRP_t			−0.258***						−0.285**	−0.343***	−0.203
t-stat			−2.737						−2.289	−2.691	−1.626
$SLOPE_{VIX}$				−0.191**					−0.169*	−0.203**	−0.178*
t-stat				−2.423					−1.820	−2.237	−1.774
$IVSKEW_C$					−0.075				−0.096	−0.053	−0.127*
t-stat					−1.128				−1.327	−0.794	−1.760
VIX^2						−0.066			0.030		
t-stat						−0.692			0.254		
NOISE							0.065			0.203*	
t-stat							0.882			1.952	
LTV								−0.209*			−0.147
t-stat								−1.851			−1.279
Adj R^2	2.544	2.554	3.163	2.894	2.577	2.561	2.565	2.897	3.544	3.878	3.666

Panel B: Variance Swap Returns

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
$VVIX^M$	1.806***	1.966***	2.160***	1.788***	1.866***	2.051***	1.837***	2.270***	2.224***	2.385***	2.328***
t-stat	5.493	5.442	4.909	5.611	5.778	6.914	5.527	5.835	6.007	4.991	5.541
r_t		−0.949***							−0.767**	−0.663**	−0.717**
t-stat		−3.331							−2.535	−2.195	−2.376
VRP_t			−1.161***						−0.782	−1.284***	−0.647
t-stat			−3.314						−1.461	−2.658	−1.605
$SLOPE_{VIX}$				−0.088					−0.223	−0.353	−0.235
t-stat				−0.335					−0.795	−1.165	−0.772
$IVSKEW_C$					0.272				−0.044	0.276	−0.061
t-stat					1.265				−0.189	1.158	−0.239
VIX^2						−0.684**			−0.295		
t-stat						−2.316			−0.579		
NOISE							0.341*			0.968***	
t-stat							1.934			2.669	
LTV								−1.065***			−0.612
t-stat								−2.781			−1.553
Adj R^2	2.706	3.414	3.704	2.688	2.740	3.023	2.778	3.452	4.020	4.588	4.154

Panel C: VIX Straddle Returns

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
$VVIX^M$	0.580***	0.608***	0.627***	0.570***	0.607***	0.600***	0.591***	0.678***	0.626***	0.692***	0.681***
t-stat	4.198	4.399	4.291	4.536	4.420	5.195	4.286	5.138	5.452	4.986	5.506
r_t		−0.159*							−0.139	−0.136	−0.147*
t-stat		−1.798							−1.468	−1.502	−1.652
VRP_t			−0.154						−0.108	−0.173	0.007
t-stat			−1.477						−0.748	−1.404	0.070
b $SLOPE_{VIX}$				−0.050					−0.097	−0.142	−0.110
t-stat				−0.589					−1.036	−1.434	−1.103
$IVSKEW_C$					0.125**				0.138*	0.187***	0.093
t-stat					2.221				1.700	2.824	1.319
VIX^2						−0.055			0.060		
t-stat						−0.507			0.372		
NOISE							0.123*			0.262***	
t-stat							1.907			2.879	
LTV								−0.224			−0.183
t-stat								−1.560			−1.241
Adj R^2	3.699	3.945	3.912	3.701	3.840	3.704	3.841	4.126	4.183	4.752	4.367

Panel D: VIX Futures Returns

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
$VVIX^M$	0.465***	0.486***	0.520***	0.453***	0.467***	0.475***	0.478***	0.516***	0.499***	0.566***	0.520***
t-stat	5.462	5.336	5.291	5.712	5.684	6.530	5.616	5.718	5.979	5.566	5.555
r_t		−0.130**							−0.087	−0.085	−0.097
t-stat		−2.321							−1.382	−1.347	−1.571
VRP_t			−0.181**						−0.193	−0.249**	−0.136
t-stat			−2.372						−1.529	−2.390	−1.278
$SLOPE_{VIX}$				−0.058					−0.060	−0.106	−0.067
t-stat				−1.030					−0.941	−1.530	−0.993
$IVSKEW_C$					0.010				0.002	0.044	−0.026
t-stat					0.195				0.031	0.776	−0.445
VIX^2						−0.027			0.077		
t-stat						−0.351			0.612		
NOISE							0.136***			0.259***	
t-stat							2.773			3.457	
LTV								−0.117			−0.040
t-stat								−1.431			−0.392
Adj R^2	3.020	3.228	3.415	3.041	2.997	3.004	3.255	3.151	3.521	4.208	3.488

Notes: The table presents in-sample regression results examining the predictive power of $VVIX^M$ for next-day excess returns $(r_{i,t+1} - r_{f,t+1})$ of three-month variance assets while controlling for alternative predictors of variance assets. We analyze four variance instruments: S&P 500 straddles, variance swaps, VIX straddles, and VIX futures. Results are organized in four panels, each corresponding to one asset. The regressions use the VVIX computed at 10:00 ($VVIX^M$), and the set control variables outlined in Section 4.1. All regressors are standardized to have zero mean and unit variance. t-statistics are computed using HAC robust standard errors with 12 lags, and ***, **, * denote statistical significance at the 1%, 5%, and 10% levels, respectively. Finally, the bottom of each panel reports the adjusted-R^2 (R^2_{adj}). The sample period spans September 2006 to June 2022.

Table D3: Predicting Variance Assets with $VVIX^M$ and Controls, 6-months Maturity

	Panel A: SPX Straddle Returns										
$VVIX^M$	0.326***	0.315***	0.378***	0.292***	0.313***	0.330***	0.330***	0.367***	0.321***	0.362***	0.344***
t-stat	4.631	4.410	5.215	4.282	4.597	5.101	4.639	4.885	4.675	4.821	4.618
r_t		0.068							0.082	0.080	0.077
t-stat		1.045							1.050	1.012	1.001
VRP_t			−0.171**						−0.241**	−0.249***	−0.182**
t-stat			−2.561						−2.559	−2.689	−1.990
$SLOPE_{VIX}$				−0.163***					−0.123*	−0.149**	−0.130**
t-stat				−3.120					−1.902	−2.412	−1.915
$IVSKEW_C$					−0.060				−0.048	−0.038	−0.078*
t-stat					−1.361				−1.029	−0.887	−1.657
VIX^2						−0.010			0.084		
t-stat						−0.137			0.995		
NOISE							0.036			0.134**	
t-stat							0.636			1.826	
LTV								−0.093			−0.042
t-stat								−1.126			−0.537
Adj R^2	2.712	2.804	3.371	3.342	2.777	2.689	2.720	2.866	4.240	4.498	4.167

	Panel B: Variance Swap Returns										
$VVIX^M$	1.260***	1.385***	1.526***	1.251***	1.309***	1.410***	1.281***	1.543***	1.553***	1.692***	1.603***
t-stat	5.934	5.784	5.173	6.037	6.333	7.489	5.984	6.210	6.345	5.428	5.820
r_t		−0.747***							−0.577***	−0.528**	−0.569***
t-stat		−3.648							−2.649	−2.471	−2.683
VRP_t			−0.872***						−0.655*	−0.930***	−0.572**
t-stat			−3.778						−1.724	−2.884	−2.072
$SLOPE_{VIX}$				−0.045					−0.142	−0.245	−0.151
t-stat				−0.277					−0.811	−1.283	−0.817
$IVSKEW_C$					0.222				0.037	0.219	0.013
t-stat					1.443				0.217	1.238	0.073
VIX^2						−0.418**			−0.050		
t-stat						−2.099			−0.138		
NOISE							0.224*			0.684***	
t-stat							1.845			2.743	
LTV								−0.649**			−0.233
t-stat								−2.488			−0.887
Adj R^2	2.733	3.650	3.906	2.712	2.790	2.973	2.795	3.302	4.294	4.919	4.344

	Panel C: VIX Straddle Returns										
$VVIX^M$	0.333***	0.379***	0.354***	0.320***	0.350***	0.326***	0.343***	0.361***	0.350***	0.403***	0.365***
t-stat	3.173	3.328	3.633	3.497	3.409	3.475	3.268	3.948	4.037	4.513	4.244
r_t		−0.354**							−0.374**	−0.375**	−0.378**
t-stat		−2.088							−2.154	−2.186	−2.207
VRP_t			−0.067						0.013	−0.019	0.057
t-stat			−0.724						0.102	−0.167	0.587
$SLOPE_{VIX}$				−0.062					−0.135	−0.171*	−0.140
t-stat				−0.774					−1.444	−1.729	−1.498
$IVSKEW_C$					0.076*				0.127*	0.153**	0.103
t-stat					1.775				1.750	2.520	1.585
VIX^2						0.019			0.078		
t-stat						0.214			0.597		
NOISE							0.107*			0.193**	
t-stat							1.658			2.256	
LTV								−0.064			−0.016
t-stat								−0.443			−0.101
Adj R^2	1.671	3.530	1.708	1.703	1.731	1.651	1.820	1.697	3.811	4.202	3.762

	Panel D: VIX Futures Returns										
$VVIX^M$	0.281***	0.293***	0.345***	0.284***	0.281***	0.285***	0.290***	0.318***	0.324***	0.388***	0.336***
t-stat	6.321	6.138	5.760	6.334	6.533	6.539	6.539	6.185	5.823	6.118	5.348
r_t		−0.092*							−0.042	−0.047	−0.051
t-stat		−1.719							−0.779	−0.891	−0.972
VRP_t			−0.210***						−0.278***	−0.285***	−0.233***
t-stat			−4.030						−3.177	−3.980	−3.455
$SLOPE_{VIX}$				0.011					0.031	−0.008	0.027
t-stat				0.264					0.721	−0.170	0.633
$IVSKEW_C$					0.000				−0.022	−0.011	−0.054
t-stat					−0.004				−0.634	−0.275	−1.373
VIX^2						−0.011			0.136*		
t-stat						−0.215			1.711		
NOISE							0.091**			0.199***	
t-stat							2.306			3.695	
LTV								−0.084			0.039
t-stat								−1.573			0.712
Adj R^2	2.040	2.231	3.060	2.018	2.015	2.018	2.230	2.164	3.375	3.911	3.134

Notes: The table presents in-sample regression results examining the predictive power of $VVIX^M$ for next-day excess returns $(r_{i,t+1} - r_{f,t+1})$ of six-month variance assets while controlling for alternative predictors of variance assets. We analyze four variance instruments: S&P 500 straddles, variance swaps, VIX straddles, and VIX futures. Results are organized in four panels, each corresponding to one asset. The regressions use the VVIX computed at 10:00 ($VVIX^M$), and the set control variables outlined in Section 4.1. All regressors are standardized to have zero mean and unit variance. t-statistics are computed using HAC robust standard errors with 12 lags, and ***, **, * denote statistical significance at the 1%, 5%, and 10% levels, respectively. Finally, the bottom of each panel reports the adjusted-R^2 (R^2_{adj}). The sample period spans September 2006 to June 2022.

Table D4: Predicting Variance Assets with controls: Subsample Analysis, 2-months Maturity

	Panel A: SPX Straddle Returns											Panel B: Variance Swap Returns										
$VVIX^M$	0.676***	0.690***	1.010***	0.678***	0.684***	1.245***	0.676***	1.214***	1.490***	1.011***	1.246***	2.386***	2.513***	3.468***	2.389***	2.542***	5.118***	2.386***	4.844***	5.943***	3.573***	4.902***
t-stat	3.745	3.541	3.962	3.211	3.899	8.407	3.861	4.478	9.395	3.758	4.237	3.419	3.479	2.879	3.178	3.681	7.320	3.420	4.678	7.664	3.011	4.379
r_t		−0.083							−0.125	−0.004	0.065		−0.723							−1.032*	−0.238	0.211
t-stat		−0.519							−0.882	−0.025	0.428		−1.398							−1.785	−0.412	0.325
VRP_t			−0.701***						−0.469***	−0.691***	−0.399			−2.271*						−0.902	−2.147*	−0.530
t-stat			−2.859						−3.304	−2.692	−1.450			−1.936						−1.601	−1.766	−0.547
$SLOPE_{VIX}$				−0.224					−0.389***	−0.238	−0.218				−0.346					−1.282***	−0.433	−0.433
t-stat				−1.247					−2.644	−1.318	−1.144				−0.557					−3.752	−0.770	−0.773
$IVSKEW_C$					0.029				−0.144	0.015	−0.100					0.543				−0.366	0.415	−0.223
t-stat					0.264				−1.409	0.129	−1.014					1.594				−1.167	1.008	−0.748
VIX^2						−0.858***			−0.916***								−4.120***			−4.588***		
t-stat						−5.501			−4.995								−5.578			−6.441		
NOISE							−0.092			−0.113								−0.022			−0.019	
t-stat							−0.814			−1.233								−0.055			−0.060	
LTV								−0.841***			−0.654*								−3.842***			−3.690***
t-stat								−2.946			−1.842								−4.526			−3.219
Adj R^2	2.562	2.552	4.685	2.800	2.518	4.873	2.562	4.901	6.832	4.832	5.652	2.543	2.726	4.312	2.549	2.618	6.827	2.495	6.467	8.307	4.261	6.499
	Panel C: VIX Straddle Returns											Panel D: VIX Futures Returns										
$VVIX^M$	0.814***	0.845***	1.056***	0.816***	0.876***	1.442***	0.815***	1.523***	1.680***	1.121***	1.539***	0.563***	0.607***	0.715***	0.565***	0.596***	0.932***	0.563***	1.006***	1.103***	0.753***	1.017***
t-stat	4.743	4.787	3.355	4.282	5.288	7.615	4.597	4.589	8.031	3.443	4.324	4.391	4.356	3.539	3.826	5.275	6.026	4.374	6.712	5.963	3.531	5.785
r_t		−0.163							−0.239*	−0.101	0.035		−0.257**							−0.285**	−0.213*	−0.191*
t-stat		−1.438							−1.912	−0.839	0.269		−2.377							−2.509	−1.839	−1.782
VRP_t			−0.507						−0.169	−0.453	0.074			−0.320						−0.058	−0.231	0.104
t-stat			−1.438						−0.742	−1.359	0.328			−1.522						−0.351	−1.159	0.725
$SLOPE_{VIX}$				−0.256*					−0.518***	−0.289*	−0.312*				−0.225*					−0.396***	−0.276**	−0.277*
t-stat				−1.784					−3.242	−1.809	−1.778				−1.823					−2.675	−2.023	−1.889
$IVSKEW_C$					0.217**				0.072	0.243**	0.034					0.116				0.029	0.144	0.015
t-stat					2.102				0.691	2.313	0.295					1.262				0.338	1.589	0.215
VIX^2						−0.947***			−1.080***								−0.557**			−0.681***		
t-stat						−3.255			−4.665								−2.295			−2.656		
NOISE							0.171*			0.147								0.009			−0.023	
t-stat							1.673			1.521								0.098			−0.215	
LTV								−1.108**			−1.179**								−0.693***			−0.725***
t-stat								−2.444			−2.269								−3.589			−4.106
Adj R^2	3.499	3.589	4.516	3.801	3.681	6.143	3.607	7.338	7.679	5.088	7.679	2.826	3.360	3.496	3.237	2.890	4.355	2.779	5.352	6.133	4.287	6.064

Notes: The table presents in-sample regression results examining the predictive power of $VVIX^M$ for next-day excess returns ($r_{i,t+1} - r_{f,t+1}$) of two-month variance assets while controlling for alternative predictors of variance assets. We analyze four variance instruments: S&P 500 straddles, variance swaps, VIX straddles, and VIX futures. Results are organized in four panels, each corresponding to one asset. The regressions use the VVIX computed at 10:00 ($VVIX^M$), and the set control variables outlined in Section 4.1. Regressors are standardized to have zero mean and unit variance. $SLOPE_{VIX}$ is computed at 10:00. t-statistics are computed using HAC robust standard errors with 5 lags, and ***, **, * denote statistical significance at the 1%, 5%, and 10% levels, respectively. Finally, the bottom of each panel reports the adjusted-R^2 (R^2_{adj}). The sample period spans June 2014 to June 2022.

Table D5: Predicting Variance Assets with controls: Subsample Analysis, 3-months Maturity

	Panel A: SPX Straddle Returns											Panel B: Variance Swap Returns										
$VVIX^M$	0.501***	0.498***	0.766***	0.502***	0.508***	0.927***	0.500***	0.906***	1.109***	0.762***	0.936***	1.957***	2.090***	2.801***	1.959***	2.127***	4.087***	1.957***	3.890***	4.771***	2.929***	3.934***
t-stat	3.436	3.188	4.164	2.930	3.614	7.942	3.551	4.431	9.133	3.892	4.291	3.759	3.794	3.014	3.484	4.198	8.214	3.752	5.177	8.450	3.233	4.801
r_t		0.014							−0.011	0.073	0.125		−0.734*							−0.955**	−0.340	−0.024
t-stat		0.095							−0.089	0.481	0.897		−1.855							−2.106	−0.769	−0.050
VRP_t			−0.556***						−0.401***	−0.560***	−0.345			−1.772*						−0.624	−1.604*	−0.380
t-stat			−3.012						−3.497	−2.826	−1.517			−1.915						−1.374	−1.703	−0.502
$SLOPE_{VIX}$				−0.198					−0.312***	−0.206	−0.187				−0.264					−1.043***	−0.381	−0.384
t-stat				−1.469					−2.584	−1.500	−1.279				−0.561					−3.660	−0.865	−0.864
$IVSKEW_C$					0.026				−0.091	0.023	−0.063					0.594**				−0.100	0.502	0.017
t-stat					0.280				−1.090	0.253	−0.806					2.007				−0.383	1.458	0.069
VIX^2						−0.644***			−0.662***								−3.213***			−3.565***		
t-stat						−4.681			−4.200								−5.695			−6.278		
$NOISE$							−0.085			−0.102								−0.002			−0.001	
t-stat							−0.898			−1.374								−0.006			−0.003	
LTV								−0.634***			−0.483*								−3.022			−2.790***
t-stat								−2.850			−1.779								−4.627			−3.394
Adj R^2	2.522	2.476	4.932	2.876	2.480	4.859	2.547	4.913	7.126	5.283	6.054	2.788	3.126	4.540	2.791	2.980	7.030	2.740	6.742	8.619	4.636	6.729

	Panel C: VIX Straddle Returns											Panel D: VIX Futures Returns										
$VVIX^M$	0.523***	0.550***	0.687***	0.525***	0.583***	0.896***	0.523***	1.022***	1.077***	0.750***	1.037***	0.465***	0.499***	0.603***	0.467***	0.493***	0.770***	0.465***	0.837***	0.913***	0.633***	0.849***
t-stat	3.872	4.180	3.327	3.767	4.664	7.061	3.885	5.700	8.331	3.561	5.051	4.455	4.360	3.707	3.861	5.312	6.248	4.459	7.014	6.277	3.728	6.226
r_t		−0.162							−0.199*	−0.130	−0.070		−0.199**							−0.209**	−0.153	−0.141
t-stat		−1.449							−1.704	−1.210	−0.630		−2.341							−2.394	−1.596	−1.619
VRP_t			−0.344						−0.113	−0.276	0.087			−0.289*						−0.084	−0.222	0.053
t-stat			−1.330						−0.575	−1.188	0.582			−1.779						−0.693	−1.395	0.437
$SLOPE_{VIX}$				−0.229*					−0.413***	−0.285**	−0.295*				−0.190**					−0.325***	−0.233**	−0.230*
t-stat				−1.954					−2.663	−2.077	−1.956				−1.977					−2.656	−2.114	−1.951
$IVSKEW_C$					0.209***				0.149	0.250***	0.108					0.098				0.030	0.121	0.016
t-stat					2.718				1.672	3.135	1.131					1.349				0.417	1.608	0.277
VIX^2						−0.563**			−0.635***								−0.459**			−0.546**		
t-stat						−2.470			−3.225								−2.365			−2.524		
NOISE							0.085			0.058								−0.015			−0.043	
t-stat							1.112			0.772								−0.177			−0.456	
LTV								−0.780**			−0.799**								−0.582***			−0.593***
t-stat								−2.259			−2.199								−4.062			−3.860
Adj R^2	3.183	3.438	4.219	3.754	3.610	5.239	3.221	7.385	7.508	5.457	8.209	2.772	3.227	3.568	3.193	2.839	4.266	2.726	5.333	5.982	4.295	5.985

Notes: The table presents in-sample regression results examining the predictive power of $VVIX^M$ for next-day excess returns $(r_{i,t+1} - r_{f,t+1})$ of three-month variance assets while controlling for alternative predictors of variance assets. We analyze four variance instruments: S&P 500 straddles, variance swaps, VIX straddles, and VIX futures. Results are organized in four panels, each corresponding to one asset. The regressions use the VVIX computed at 10:00 ($VVIX^M$), and the set control variables outlined in Section 4.1. Regressors are standardized to have zero mean and unit variance. $SLOPE_{VIX}$ is computed at 10:00. t-statistics are computed using HAC robust standard errors with 5 lags, and ***, **, * denote statistical significance at the 1%, 5%, and 10% levels, respectively. Finally, the bottom of each panel reports the adjusted-R^2 (R^2_{adj}). The sample period spans June 2014 to June 2022.

Table D6: Predicting Variance Assets with controls: Subsample Analysis, 6-months Maturity

Panel A: SPX Straddle Returns

$VVIX^M$	0.312***	0.296***	0.503***	0.313***	0.317***	0.561***	0.312***	0.563***	0.677***	0.494***	0.588***
t-stat	3.124	2.795	4.810	2.674	3.300	6.509	3.248	4.598	8.176	4.433	4.614
r_t		0.099							0.092	0.127	0.156
t-stat		0.813							0.832	1.002	1.335
VRP_t			−0.402***						−0.333***	−0.412***	−0.297*
t-stat			−3.412						−3.876	−3.109	−1.795
$SLOPE_{VIX}$				−0.161*					−0.211**	−0.163*	−0.145
t-stat				−2.072					−2.471	−1.953	−1.605
$IVSKEW_C$					0.017				−0.039	0.021	−0.027
t-stat					0.282				−0.709	0.359	−0.534
VIX^2						−0.375***			−0.349***		
t-stat						−3.261			−2.868		
NOISE							−0.084			−0.095*	
t-stat							−1.225			−1.845	
LTV								−0.393***			−0.261
t-stat								−2.888			−1.552
Adj R^2	2.408	2.603	5.516	3.017	2.367	4.353	2.538	4.667	7.712	6.595	7.004

Panel B: Variance Swap Returns

$VVIX^M$	1.297***	1.405***	1.877***	1.299***	1.409***	2.618***	1.297***	2.552***	3.100***	1.966***	2.583***
t-stat	4.241	4.379	3.348	3.797	4.854	8.783	4.262	5.960	9.144	3.639	5.357
r_t		−0.607**							−0.689**	−0.346	−0.164
t-stat		−2.391							−2.201	−1.187	−0.553
VRP_t			−1.217**						−0.463	−1.059*	−0.312
t-stat			−2.077						−1.472	−1.744	−0.623
$SLOPE_{VIX}$				−0.255					−0.755***	−0.354	−0.347
t-stat				−0.943					−3.275	−1.384	−1.270
$IVSKEW_C$					0.392*				−0.018	0.349	0.049
t-stat					1.741				−0.097	1.400	0.269
VIX^2						−1.991***			−2.200***		
t-stat						−5.552			−5.316		
NOISE							−0.035			−0.049	
t-stat							−0.148			−0.229	
LTV								−1.961			−1.707***
t-stat								−4.545			−3.318
Adj R^2	2.689	3.222	4.506	2.747	2.870	6.260	2.643	6.344	8.129	4.761	6.485

Panel C: VIX Straddle Returns

$VVIX^M$	0.273**	0.295**	0.373***	0.274**	0.323***	0.410***	0.273**	0.651***	0.516***	0.422***	0.654***
t-stat	2.191	2.344	3.095	2.342	2.801	2.974	2.259	5.567	3.844	3.609	5.344
r_t		−0.182*							−0.180*	−0.176*	−0.144
t-stat		−1.696							−1.768	−1.815	−1.479
VRP_t			−0.210						−0.093	−0.139	0.158**
t-stat			−1.102						−0.506	−0.844	2.094
$SLOPE_{VIX}$				−0.137					−0.232	−0.186	−0.201
t-stat				−1.282					−1.659	−1.507	−1.466
$IVSKEW_C$					0.175***				0.181**	0.209***	0.096
t-stat					2.875				2.404	3.430	1.127
VIX^2						−0.207			−0.186		
t-stat						−1.228			−0.932		
NOISE							0.086			0.072	
t-stat							1.569			1.528	
LTV								−0.592*			−0.641*
t-stat								−1.812			−1.821
Adj R^2	1.457	2.069	2.101	1.791	1.978	1.893	1.557	5.601	3.849	3.640	6.641

Panel D: VIX Futures Returns

$VVIX^M$	0.314***	0.348***	0.457***	0.315***	0.331***	0.514***	0.314***	0.575***	0.632***	0.474***	0.586***
t-stat	5.887	6.124	4.922	5.080	6.739	6.156	5.830	7.875	6.266	5.344	7.230
r_t		−0.222***							−0.201***	−0.176***	−0.161**
t-stat		−3.551							−2.943	−2.662	−2.472
VRP_t			−0.301***						−0.173***	−0.248**	−0.106
t-stat			−3.057						−2.695	−2.544	−1.484
$SLOPE_{VIX}$				−0.089*					−0.164**	−0.107*	−0.110*
t-stat				−1.864					−2.540	−1.942	−1.861
$IVSKEW_C$					0.058				−0.003	0.049	−0.006
t-stat					1.106				−0.057	0.910	−0.124
VIX^2						−0.301***			−0.309**		
t-stat						−3.458			−2.555		
NOISE							0.011			0.005	
t-stat							0.228			0.105	
LTV								−0.408***			−0.310***
t-stat								−4.423			−3.493
Adj R^2	2.550	3.769	4.343	2.710	2.584	3.840	2.505	5.101	6.275	5.163	6.102

Notes: The table presents in-sample regression results examining the predictive power of $VVIX^M$ for next-day excess returns $(r_{i,t+1} - r_{f,t+1})$ of six-month variance assets while controlling for alternative predictors of variance assets. We analyze four variance instruments: S&P 500 straddles, variance swaps, VIX straddles, and VIX futures. Results are organized in four panels, each corresponding to one asset. The regressions use the VVIX computed at 10:00 ($VVIX^M$), and the set control variables outlined in Section 4.1. Regressors are standardized to have zero mean and unit variance. $SLOPE_{VIX}$ is computed at 10:00. t-statistics are computed using HAC robust standard errors with 5 lags, and ***, **, * denote statistical significance at the 1%, 5%, and 10% levels, respectively. Finally, the bottom of each panel reports the adjusted-R^2 (R^2_{adj}). The sample period spans June 2014 to June 2022.