Uncovering the Incremental Information Content of High-Frequency Options

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December 12, 2022

Abstract

We propose variances and jump option realized measures which can be seen as new "observable quantities" to summarize the information about investors' expectations from high-frequency option data. We show that the jump component of the option quadratic variation captures jumps related to the underlying asset and risk factor. We also propose the option realized semivariance and signed jumps to successfully capture the information contained in the sign of the high-frequency option returns. Using option data on SPDR S&P 500 ETF (SPY) and 15 individual equities, we show that the option realized measures have additional incremental information, neither contained in the stock nor in the end-of-day option data, which is important for predicting future variance, variance risk-premia and excess returns. In specific, the negative (positive) semivariance and signed jump of out-of-the-money call (put) options play a prominent role in predicting future variance, and both variance and equity risk-premia, consistent with a downside risk channel.

Keywords: High-Frequency Data; High-Frequency Options; Option Realized Variance; Option Realized Jumps; Downside Risk;
JEL classification: C58; G10; G12.

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1 Introduction

The state-contingent nature of the option payoff makes it highly informative about state prices and the price of risk. In addition, it is widely known that, beyond market return risk, investors require compensation for bearing variance and jump risks. Traditional approaches considering end-of-day option prices provide important insights about equity, variance, jump and tail risk premia.[1] However, the increasing availability of high-frequency option data affords the potential to convey accurate real-time information regarding investors' preferences, yielding a more comprehensive view of the joint dynamics between the realized and expected asset price. In other words, high-frequency option data capture information about investors' expectations and risk appetites' change in response to the intraday order flow and news arrivals, which are not contained in low frequency data.[2]

In this paper, we propose (noise-robust) option realized measures to summarize the rich information content of high-frequency option data. Our approach assumes that an option is an asset on its own (e.g., Coval and Shumway, 2001; Broadie et al., 2009), and therefore its variance is simply the variance of the option prices. Thus, employing high-frequency econometric techniques, we estimate the option realized variance and jump variation. We show that the jump component of the option quadratic variation captures discontinuities that are related to both the underlying asset and the underlying risk factor.[3] As the option realized variance and jump variation fail at capturing the information contained in the sign of the high-frequency option returns, we propose the option realized semivariance and signed jumps. These measures successfully capture the downside and upside risk of option contracts.[4] As the call (put) option moves in the same (opposite) direction of the underlying

[1]An incomplete list of studies on these topics are Bakshi et al. (2003), Christoffersen et al. (2012), Andersen et al. (2015, 2017), Bollerslev et al. (2015), among others.

[2]To illustrate, Figure 1, in Section 3, presents the intraday prices (underlying asset and options) of the market index and an individual equity on August 7, 2007. This day the Federal Reserve surprised the market by deciding to keep its target for the federal funds rate. This news triggered a negative market reaction that took about an hour to recover and is completely disregarded when considering end-of-day data.

[3]This result is in line with Andersen et al. (2015) who show that option prices, as functionals of the variance and jump intensity, inherit the behavior of these variables at small scales.

[4]The relevance of semivariances, and the broader class of downside risk measures, has a long history in

asset, the downside risk of a call (put) contract is captured by the negative (positive) option realized semivariance. This applies analogously to signed jumps.

Our empirical analysis is based on a novel high-frequency option data including the SPDR S&P 500 ETF (SPY), as a proxy for the US stock market index, and 15 individual US equities for over 16 years. We find that our option realized measures are good predictors of future realized variance (RV), variance risk-premia (VRP) and excess returns, and their predictive power is not contained in standard low- nor high-frequency predictors. In particular, we find that option realized measures, extracted from out-of-the-money (OTM) calls and puts, positively predict future variance, while negatively predicting variance and equity risk-premia. The negative sign found in the VRP is directly related to the RV. As the option realized measures positively predict future RV, an increase in RV, all else equal, would decrease the VRP, yielding a negative relationship between the option realized measures and future VRP. Moreover, the negative relationship between the option realized measures and future excess returns is inline with the so-called volatility puzzle. We rationalize this finding with that risk-averse agents reduce consumption/investments to increase precautionary savings in the presence of higher uncertainty about the stock market, thereby decreasing future returns.

In addition, our results suggest that the predictive power of the option realized semivariances and signed jumps is superior to that of their aggregate counterparts. In specific, we find that most of the predictive power is driven by the negative (positive) semivariance and signed jump of OTM call (put) options, confirming previous findings in the literature regarding the richer information content of downside risk measures (e.g., Ang et al., 2006; Lettau et al., 2014; Kilic and Shaliastovich, 2019).

The current high-frequency option pricing literature is very limited, focusing mainly on options written on indices (e.g., Andersen et al., 2015; Audrino and Fengler, 2015; Taylor

finance and several studies have shown that the upside and downside risks are very distinct factors, where generally downside risk plays a more important role in explaining risk-premia (e.g., Hogan and Warren, 1974; Ang et al., 2006; Lettau et al., 2014; Kilic and Shaliastovich, 2019; Bollerslev et al., 2020).

et al., 2018; Kapetanios et al., 2019; Amaya et al., 2022). The few exceptions considering options written on individual equities investigate issues related to market microstructure and trading costs (e.g., Anand et al., 2016; Muravyev and Pearson, 2020; Andersen et al., 2021). Thus, to the best of our knowledge, we are the first in studying the predictive information content of (noise-robust) option realized measures using high-frequency option data written on both the market index and individual equities.

The closest works to ours are Audrino and Fengler (2015) and Amaya et al. (2022), who employ high-frequency options written on the market index to construct an option realized variance. Audrino and Fengler (2015) examine the consistency of models by comparing the option realized variance against those implied by competing models. Amaya et al. (2022) investigate the impact of market microstructure noise and the information content of the option realized variance. We extend and complement these studies in a number of ways. First, besides the option realized variance, we propose the option realized jump, the option realized semivariances and signed jumps. The latter two measures capture the information contained in the sign of the high-frequency option returns.[5] Second, we examine the predictive information content of these measures, at both the index and individual equity levels, using a more extended and recent dataset. Third, we shed light on the impact of downside risk measures, estimated from signed high-frequency option returns, on future variance, equity and variance risk-premia. Fourth, we provide evidence about the incremental information of the option realized (signed) measures by showing that the pricing of variance and specially jump risks are important predictors of equity and variance risk-premia.

Our paper intersects with several strands of the literature on important areas in asset pricing and financial econometrics. We relate to the extensive literature identifying jumps from option prices (e.g., Bates, 1996; Duffie et al., 2000; Pan, 2002; Bakshi et al., 2003; Eraker et al., 2003; Christoffersen et al., 2012),[6] as well as to the strands of the literature

[5]Consistent with economic intuition, large differences in the option realized semivariances and signed jumps are typically associated with macroeconomic announcements, highlighting the importance of discriminating between positive and negative option returns.

[6]For an incomplete list of studies using (end-of-day) option pricing data to estimate jumps see Aït-

explaining risk compensation for this additional source of risk in equity premia (e.g., Bali and Hovakimian, 2009; Santa-Clara and Yan, 2010; Andersen et al., 2015; Cremers et al., 2015; Andersen et al., 2017) and variance-risk premia (e.g., Bollerslev and Todorov, 2011b; Bollerslev et al., 2015; Andersen et al., 2015; Almeida et al., 2022). We also relate to the literature employing high-frequency data to better estimate variance and jump measures (e.g., Andersen et al., 2001, 2003; Barndorff-Nielsen and Shephard, 2004; Barndorff-Nielsen et al., 2010; Weller, 2019; Almeida et al., 2022, *inter alia*). Finally, we touch upon the literature looking at the information content of decomposed risk measures (e.g., Ang et al., 2006; Feunou et al., 2013; Lettau et al., 2014; Bollerslev et al., 2015; Patton and Sheppard, 2015; Farago and Tédongap, 2018; Kilic and Shaliastovich, 2019; Bollerslev et al., 2020).

The remainder of the paper is organized as follows. Section 2 presents the theoretical framework adopted for the construction of the option realized measures. Section 3 describes the data and the estimated option realized measures. In Sections 4, 5, and 6, we study the information content of the option realized measures with respect to future realized variances, variance risk premia, and excess equity returns, respectively. Section 7 concludes the paper. Additional results are relegated to the paper Appendix.

2 Theoretical Background

This section presents the construction of our proposed option realized measures. First, we define the theoretical framework and outline the option quadratic variation. In specific, we show that the option realized measures contain incremental information about (signed) jumps that stem from both the underlying asset and underlying risk factor. Second, we present the option realized measures in their standard and noise-robust forms.

We assume that the price of an asset S and its underlying risk factor X, are two Itô semimartingale processes that evolve continuously under the objective measure $\mathbb{P}$, and are

Sahalia (2002), Eraker (2004), Johannes (2004), Wu (2006), Bollerslev and Todorov (2011a,b), Bollerslev and Todorov (2014), Andersen et al. (2017, 2019, 2020), and Todorov (2022).

outlined by the following stochastic differential equations:

$$\frac{dS_t}{S_{t-}} = \mu_S(X_{t-})dt + \sum_{i=1}^{m} \sigma_{S,i}(X_{t-})dW_{i,t} + dJ_{S,t}^{+} + dJ_{S,t}^{-}, \tag{1}$$

$$dX_t = \mu_X(X_{t-})dt + \sum_{i=1}^{m} \sigma_{X,i}(X_{t-})dW_{i,t} + dJ_{X,t}^{+} + dJ_{X,t}^{-}, \tag{2}$$

where $\mu_S(X_{t-})$ and $\mu_X(X_{t-})$ are predictable drift coefficients for the respective price and underlying risk factor. $\{W_{i,t}\}_{t\geq 0, i\in\{1,\ldots,m\}}$ are independent standard Brownian motions under the measure $\mathbb{P}$, and $\{\sigma_{S,i}(X_{t-})\}_{i\in\{1,\ldots,m\}}$ and $\{\sigma_{X,i}(X_{t-})\}_{i\in\{1,\ldots,m\}}$ are diffusive coefficients for the same processes. $J_{S,t}^{+}$ and $J_{S,t}^{-}$ ($J_{X,t}^{+}$ and $J_{X,t}^{-}$) are two jump processes for the price (risk factor) that capture the positive and negative jump sizes and, of course, their sum equals the total jump part:

$$J_{S,t}^{+} = \sum_{n=1}^{N_{S,t}} Z_{S,n}\mathbb{I}_{\{Z_{S,n}>0\}}, \quad J_{S,t}^{-} = \sum_{n=1}^{N_{S,t}} Z_{S,n}\mathbb{I}_{\{Z_{S,n}<0\}}, \tag{3}$$

$$J_{X,t}^{+} = \sum_{n=1}^{N_{X,t}} Z_{X,n}\mathbb{I}_{\{Z_{X,n}>0\}}, \quad J_{X,t}^{-} = \sum_{n=1}^{N_{X,t}} Z_{X,n}\mathbb{I}_{\{Z_{X,n}<0\}}, \tag{4}$$

where $\{N_{S,t}\}_{t\geq 0}$ and $\{N_{X,t}\}_{t\geq 0}$ are Cox processes, $\{Z_{S,n}\}_{n=1}^{\infty}$ and $\{Z_{X,n}\}_{n=1}^{\infty}$ are the jump size of the price and risk factor, respectively. In addition, we assume the jump intensities are state dependent, i.e. $\lambda_S(X_{t-})$ and $\lambda_X(X_{t-})$, but the jump sizes are state independent.

Following standard conditions, the option price of the asset S at time t is given by $O_{t,k,\tau}$. Assuming frictionless trading in the options market (Andersen et al., 2015), the option prices are given by:

$$O_t \equiv O_{t,k,\tau}(S_t, X_t) = \begin{cases} \mathbb{E}^{\mathbb{Q}}\left[e^{-\int_t^{t+\tau} r_u du}(S_{t+\tau} - K)^{+} \middle| S_t, X_t\right], & \text{if } K > S_{t+\tau}, \\ \mathbb{E}^{\mathbb{Q}}\left[e^{-\int_t^{t+\tau} r_u du}(K - S_{t+\tau})^{+} \middle| S_t, X_t\right], & \text{if } K \leq S_{t+\tau}, \end{cases} \tag{5}$$

where τ is time-to-maturity, K is the strike price, $S_{t+\tau}$ is the spot price of the underlying asset at time $t+\tau$, $k = K/S_t$ is the contract moneyness, r_u is the risk-free rate, and $\mathbb{Q}$ is the risk-neutral probability measure.

As our aim is to construct measures of the option realized variance and semivariances, we start by deriving the option quadratic variation. Using Itô's lemma for semimartingale processes (for more details, see proposition 8.19 in Cont and Tankov, 2003), the quadratic variation of the option can be characterized as follows:[7]

$$
\begin{aligned}
[o,o]_t = & \underbrace{\sum_{i=1}^{m}\int_0^t \left(\frac{\partial o_u}{\partial s}(S_u,X_u)\right)^2 \sigma_{S,i}^2(X_{u-})du + \sum_{i=1}^{m}\int_0^t \left(\frac{\partial o_u}{\partial x}(S_u,X_u)\right)^2 \sigma_{X,i}^2(X_{u-})du \\
& + 2\sum_{i=1}^{m}\int_0^t \left(\frac{\partial o_u}{\partial s}(S_u,X_u)\right)\left(\frac{\partial o_u}{\partial x}(S_u,X_u)\right)\sigma_{S,i}(X_{u-})\sigma_{X,i}(X_{u-})du}_{OCV_t} \\
& + \underbrace{\sum_{0\le u\le t}\left[(o_u(S_u,X_u)-o_u(S_{u-},X_{u-}))^+\right]^2 + \sum_{0\le u\le t}\left[(o_u(S_u,X_u)-o_u(S_{u-},X_{u-}))^-\right]^2}_{OJV_t=OJV_t^+ + OJV_t^-}.
\end{aligned}
\tag{6}
$$

Proof: See Appendix B.

We use $(\,\cdot\,)^+$ and $(\,\cdot\,)^-$ to denote the positive and negative jump, respectively. As can be seen in equation (6), the evolution of the option quadratic variation depends on two components. The first component contains three terms that capture the diffusive or normal changes in the information set, while the second component relates to the rough arrival of information. It is important to note that the jump component of $[o,o]_t$ captures jumps that are related to both the underlying asset and the underlying risk-factor. In addition, equation (6) allows to differentiate the direction of the jumps, which is crucial for measuring downside risk. As noted by Andersen et al. (2015), negative price jumps and positive price jumps impact the option quadratic variation differently. This different impact is due to the leverage effect; negative returns correlate with increases in volatility, while positive returns correlate with reductions in volatility.

Although the option quadratic variation is not directly observable, it can be consistently

[7] $o_t \equiv \log(O_t)$. To ease notation, we suppress the subscripts k and τ. In addition, we have purposely omitted $\frac{1}{o_s^2(S_{u-},X_{u-})}$ from the three elements of the diffusive component. This term is obtained by taking the derivative of o_t w.r.t. x and s, and its quadratic form arises because of the quadratic variation.

estimated from high-frequency option data. The next subsection is devoted to this purpose.

2.1 Option Realized Measures

An option is an asset whose payoff depends on the value of another asset, i.e. the underlying asset. Despite this dependence, an option can be seen as an asset on its own, meaning that the variance of an option is simply the variance of the option prices. In other words, using high-frequency option data and the realized variance approach (e.g. Barndorff-Nielsen and Shephard, 2002; Andersen et al., 2003) we can consistently estimate the option quadratic variation for a specific level of moneyness and maturity:[8]

$$\mathcal{ORV}_t = \sum_{j=1}^{N} |r^o_{t,j}|^2 \xrightarrow{p} [o, o]_t, \tag{7}$$

where $r^o_{t,j} = \log(O_{t,j\Delta_N}) - \log(O_{t,(j-1)\Delta_N})$, $j = 1, 2, \ldots, N$ is the j-th high-frequency option return, $\Delta_N \equiv 1/N$ is the time interval and N is the total number of intraday increments per day. As the $\mathcal{ORV}$ is a consistent estimator of the option quadratic variation, the jump component of the $\mathcal{ORV}$ contains information about jumps in both the underlying asset and underlying risk factor, which suggests that the jump component of the $\mathcal{ORV}$ contains non trivial information as it is not possible to identify risk factor jumps using the realized variance of the underlying asset. Motivated by the incremental information of the jump component, we separate jumps from the diffusive part of the option quadratic variation as:

$$\mathcal{ORJ}_t = \max\left(\mathcal{ORV}_t - \mathcal{OBV}_t, 0\right) \xrightarrow{p} OJV_t, \tag{8}$$

where $\mathcal{OBV}_t = N/(N-1)(\pi/2)\sum_{j=2}^{N} |r^o_{t,j}||r^o_{t,j-1}|$, is the option bi-power variation, which is a consistent estimator of the diffusive component (e.g., Barndorff-Nielsen and Shephard, 2004).

[8] Andersen et al. (2001, 2003) and Barndorff-Nielsen and Shephard (2002) show that under suitable conditions the realized variance is an unbiased and highly efficient estimator of the quadratic variation.

The $\mathcal{ORV}_t$ and $\mathcal{OBV}_t$ rely on even functions of high-frequency option returns, i.e. squares and absolute values, which of course eliminate any information that may be contained in the sign of these returns. To overcome this issue, we propose the option realized semivariance. As shown in Barndorff-Nielsen et al. (2010), these measures decompose the $\mathcal{ORV}$ into two components that relate only to positive and negative high-frequency option returns. The option realized semivariances, therefore, capture the downside and upside risk of an option contract. Since the call (put) option moves in the same (opposite) direction as the underlying asset, the downside risk of a call (put) contract is captured by the negative (positive) option realized semivariance.

Let $p(x) = \max\{x, 0\}$ and $n(x) = \min\{x, 0\}$ denote the component-wise positive and negative of a real vector x. Then, the option realized semivariances can be outlined as:

$$\begin{aligned} \mathcal{ORV}_t^+ &= \sum_{j=1}^{N} p\left(r_{t,j}^o\right)^2 \xrightarrow{p} \frac{1}{2} OCV_t + OJV_t^+, \\ \mathcal{ORV}_t^- &= \sum_{j=1}^{N} n\left(r_{t,j}^o\right)^2 \xrightarrow{p} \frac{1}{2} OCV_t + OJV_t^-. \end{aligned} \tag{9}$$

These estimators provide a complete decomposition of $\mathcal{ORV} = \mathcal{ORV}^+ + \mathcal{ORV}^-$, and this decomposition holds for any N and in the limit. As shown in equation (9) the option realized semivariance includes variation due to both the continuous part of the option price process and the jump component. However, the continuous part is not decomposable into positive and negative components,[9] which suggests that this component can be removed by taking the difference between both option realized semivariances. The remaining component is what we define as the option realized signed jumps:

$$\mathcal{ORSJ}_t = \mathcal{ORV}_t^+ - \mathcal{ORV}_t^- \xrightarrow{p} OJV_t^+ - OJV_t^-. \tag{10}$$

[9] This implies that each of the option realized semivariances converges to one-half of the continuous part of the option quadratic variation plus the sum of squared signed jumps.

Finally, we proceed by separating the positive and negative signed jumps as follows:

$$\begin{aligned} \mathcal{ORJ}_t^+ &= p\left(\mathcal{ORSJ}_t\right), \\ \mathcal{ORJ}_t^- &= n\left(\mathcal{ORSJ}_t\right). \end{aligned} \tag{11}$$

We use the decomposition of the option realized variance (equation (9)) and signed jumps (equation (11)) to gain new insights on the importance of variance and jump measures related to signed option returns. We refer to them as option realized signed measures.

2.2 Market Microstructure Noise

This section presents noise-robust estimates of our proposed option realized measures. It is well documented in the literature that standard high-frequency based volatility measures tend to be biased in the presence of market microstructure noise (e.g., Zhang et al., 2005; Hansen and Lunde, 2006; Aït-Sahalia and Xiu, 2019). Among other things, price discreteness forces the observed price to deviate from the "true" price (e.g., Gottlieb and Kalay, 1985; Easley and O'Hara, 1992). As a consequence, the observed volatility is upward biased vis-à-vis the true volatility by an amount that depends on the tick size and the sampling frequency. Thus, market microstructure noise may have a non-negligible impact even when sampling at the "optimal" five-minute returns (e.g., Andersen et al., 2001).

We assume that the observed log option price, $o_t = \log(O_t)$, is a discontinuous Itô semimartingale, contaminated by additive microstructure noise:

$$o_t = o_t^* + u_t, \tag{12}$$

where o_t^* is the efficient option price and u_t is the noise component with $\mathbb{E}[u_t] = 0$ and $\mathbb{E}[u_t^2] = \omega^2$, and $o_t^* \perp u_t$. To estimate our noise-robust option realized measures, we rely on the subsampling approach of Zhang et al. (2005) based on five-minute frequency. We select this approach for two reasons. First, it has been shown to produce reasonable estimates of volatility with high accuracy in different empirical applications (e.g., Andersen et al., 2011).[10] Second, the subsampling approach does not involve any overlapping, so we avoid having a single option return contributing to both positive and negative semivariances.

For each trading day, we select option prices at a frequency $\Delta_N = 5$ minutes and construct $\theta = 3$ overlapping price grids at an inferior frequency, that is, $\delta = \theta\Delta_N$:

$$\begin{array}{ccc} 09{:}31{:}00 & 09{:}36{:}00 & 09{:}41{:}00 \\ 09{:}46{:}00 & 09{:}51{:}00 & 09{:}56{:}00 \\ 10{:}01{:}00 & 10{:}06{:}00 & 10{:}15{:}00 \\ \vdots & \vdots & \vdots \end{array}$$

With observations sampled every 5 minutes, this estimator employs three overlapping grids constructed at a 15-minute frequency. The option subsampling realized measures are defined as the average of the standard measures over the θ grids defined above, that is:

$$\begin{aligned} \widehat{\mathcal{ORV}}_t &= \frac{1}{\theta}\sum_{i=1}^{\theta}\mathcal{ORV}_{t,i}(\delta), \qquad \widehat{\mathcal{OBV}}_t = \frac{1}{\theta}\sum_{i=1}^{\theta}\mathcal{OBV}_{t,i}(\delta), \\ \widehat{\mathcal{ORV}}_t^{+} &= \frac{1}{\theta}\sum_{i=1}^{\theta}\mathcal{ORV}_{t,i}^{+}(\delta), \quad \widehat{\mathcal{ORV}}_t^{-} = \frac{1}{\theta}\sum_{i=1}^{\theta}\mathcal{ORV}_{t,i}^{-}(\delta). \end{aligned} \tag{13}$$

Similarly, the option subsampling realized jump and signed jumps are estimated as follows:

$$\begin{aligned} \widehat{\mathcal{ORJ}}_t &= \max\left(\widehat{\mathcal{ORV}}_t - \widehat{\mathcal{OBV}}_t, 0\right), \\ \widehat{\mathcal{ORJ}}_t^{+} &= p\left(\widehat{\mathcal{ORSJ}}_t\right), \\ \widehat{\mathcal{ORJ}}_t^{-} &= n\left(\widehat{\mathcal{ORSJ}}_t\right), \end{aligned} \tag{14}$$

where $\widehat{\mathcal{ORSJ}}_t = \widehat{\mathcal{ORV}}_t^{+} - \widehat{\mathcal{ORV}}_t^{-}$.

[10] Christensen et al. (2014) show that when the aim is to estimate the quadratic variation, the subsampling approach of Zhang et al. (2005) is to first-order equivalent to the realized kernel (Barndorff-Nielsen et al., 2008) and the preaveraging approach (Jacod et al., 2009). In addition, Amaya et al. (2022) show that the subsampling estimators, implemented using high-frequency options, based on 5-minute returns provide a good bias-variance trade-off, which is consistent with the work of Liu et al. (2015).

In what follows, we rely on the option subsampling realized measures. Please note that for ease of notation, we drop the hat from the measures when referring to these quantities.

3 Data

This section presents the data adopted in the study. In subsection 3.1, we illustrate the high-frequency option data together with the filtering procedure. Similarly, subsection 3.2 reports the equity high-frequency data and its cleaning process. Finally, subsection 3.3 depicts the option realized measures and their interaction with the underlying measures.

3.1 High-Frequency Options

Our data consists of high-frequency options written on the SPDR S&P 500 ETF (SPY) and on 15 individual equities provided by CBOE LiveVol. The raw option data include minute-by-minute bid-ask quotes and volumes over the trading day (09:31 to 16:00) for the period January 11, 2005 and December 31, 2021 for SPY.[11] For the individual equities, the data span from January 2, 2004 to December 31, 2021.[12]

As discussed in the introduction, high-frequency option data affords the potential of reflecting real-time information regarding investors' expectations in a more accurate manner than low frequency data. To illustrate, Figure 1 presents in four panels the intraday prices (underlying asset and options) of SPY (top panels) and AAPL (bottom panels), at the 1-minute original interval. The day corresponds to an FOMC meeting, held on August 7, 2007, where the Federal Reserve decided to keep its target for the federal fund rates, in contrast to what the market had been anticipating.[13] The impact of this unexpected news triggered

[11] Options written on SPY are only available from January 11, 2005, and are the most liquid options on the market.

[12] The 15 individual equities are Apple Inc. (AAPL), Amazon Inc. (AMZN), Boeing Co (BA), Caterpillar Inc (CAT), Goldman Sachs Group Inc (GS), Home Depot Inc (HD), IBM Corp (IBM), Johnson & Johnson (JNJ), JP Morgan Chase and Co (JPM), The Coca Cola Co (KO), Microsoft Corp (MSFT), United Health Group (UNH), Verizon Communications Inc (VZ), Wells Fargo & Co (WFC) and Exxon Mobil Co (XOM).

[13] The Federal Open Market Committee decided on that day to keep its target for the federal funds rate at 5-1/4 percent. The Committee statement on forward-guidance was moderately suggesting for an expansion

Figure 1: **High-Frequency Underlying and Option Prices around an FOMC Event**

Notes: This figure shows the time series of the underlying and options prices for the stock market index (SPY) and Apple Inc. (AAPL) equity during an FOMC meeting on August 7, 2007. The selected options are OTM calls ($K/S = 1.10$) and puts ($K/S = 0.9$). The data tick size is kept at the original 1-minute.

a negative (positive) jump for the underlying asset and the call price (put price) of both SPY and AAPL, with the prices reversing to previous levels after around one hour, i.e., 15:00h. This is one of the many examples that can be drawn from our dataset to highlight the importance of high-frequency option data in capturing these price joint dynamics that are related to news arrivals, which are otherwise ignored by end-of-day option data.

Following the low and high-frequency option literature (e.g., Bakshi et al., 1997; Carr and Wu, 2011; Christoffersen et al., 2012; Andersen et al., 2021), we implement the following

(e.g. "...the economy seems likely to continue to expand at a moderate pace over coming quarters, supported by solid growth in employment and incomes and a robust global economy.") However, there were policy concerns mainly on the inflation pressures (e.g. "...a sustained moderation in inflation pressures has yet to be convincingly demonstrated", and "...the Committee's predominant policy concern remains the risk that inflation will fail to moderate as expected.")

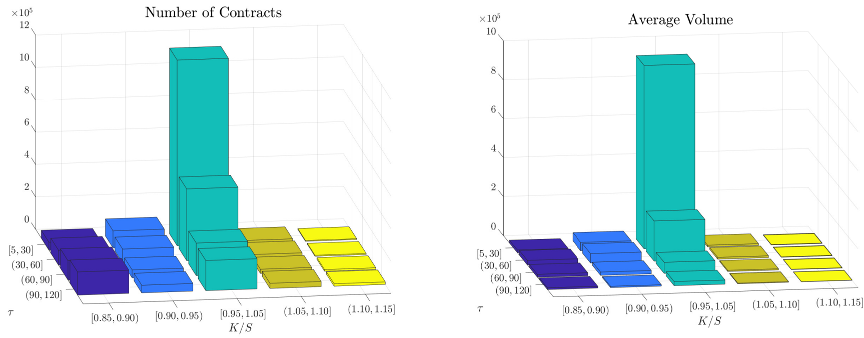
filters. We only consider bid and ask quotes between 09:31 and 16:00; we remove contracts with an average intraday mid-quote price smaller than 3/8; we remove contracts with nil open interest; we require the bid price to be higher than zero and lower than the ask price; we keep options with a maturity of at least 5 days and up to 120 days; we keep options that are at-the-money (ATM) and OTM;[14] we remove Mini option and Jumbo contracts as per consistency with other assets; we remove options that violate arbitrage conditions.[15]

Figure 2 depicts the number of contracts and average trading volume stratified by moneyness and maturity for respectively SPY and the average of the 15 individual equities. As can be seen, the shorter maturities $\tau \in [5, 30]$ concentrates the biggest proportion of contracts for both SPY and individual equities. The trading volume corroborates this finding. For instance, the number of contracts within this region is 1,325,516 –with an average trading volume of 201,936– for SPY, and 243,708 –with an average trading volume of 9,607– across the 15 individual equities. For the shortest maturity region ($\tau \in [5, 30]$), the ATM range ($K/S \in [0.95, 1.05]$) concentrates the biggest proportion of contracts and trading volume for both SPY and the average of the individual equities. By contrast, the OTM range ($K/S \in [0.90, 0.95)$ and $K/S \in [1.05, 1.10)$) shows different features for SPY and the individual equities. Whereas SPY OTM put contracts account for 85% and 83% of all OTM contracts and average trading volume, respectively, these proportions drop to 60% and 45% for individual equities.

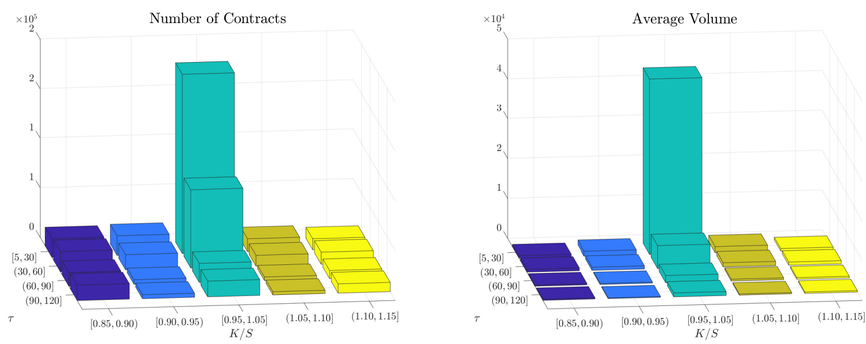
[14]Following previous literature adopting American options (e.g., Bakshi et al., 2003; Conrad et al., 2013), we do not adjust for early exercise premia in our option prices. According to Bakshi et al. (2003), the magnitude of such premia in OTM options is negligible, and even when early exercise premia are not modest (i.e., OTM option in the neighborhood of ATM) the portfolio weighting in these options is small by construction. In addition, Andersen et al. (2015) show that the early exercise premia of high-frequency options is always substantially smaller than bid-ask spreads and does not exceed 0.2% of an option price.

[15]Most of these filters are common in the option pricing literature. The open interest constraint ensures that there is genuine interest in the option contract (Carr and Wu, 2011). Options that are close to maturity or that have a very long expiration date are removed, consistently with Carr and Wu (2011) and Christoffersen et al. (2012), among others. We remove options with a negative bid-ask spread and that violate no-arbitrage constraints, as these option prices are invalid and inconsistent with theory. Finally, we remove in-the-money (ITM) contracts, as they tend to be more illiquid than OTM and ATM contracts (e.g., Christoffersen et al., 2012; Ornthanalai, 2014).

Figure 2: **Description of High-Frequency Option Data**



(a) **Market Index (SPY)**



(b) **Individual Equities**

Notes: This figure reports in two panels the number of option contracts and the average contracts volume for SPY and for the average of the individual equities. The descriptive are reported for all available contracts grouped across moneyness $K/S \in \{0.85,\ 0.90,\ 1.00,\ 1.10,\ 1.15\}$ and maturities $\tau \in \{30,\ 60,\ 90,\ 120\}$. The sample period is from January 11, 2005 to December 31, 2021, for SPY, and from January 2, 2004 to December 31, 2021 for the individual equities.

The descriptive statistics suggest that put options written on SPY may contain a richer information set than calls. Conversely, the information content of option contracts on individual equities distribute more symmetrically across moneyness, implying that the measures estimated from either call or put options may be equally informative (e.g., Bakshi et al., 2003).

3.2 High-Frequency Underlying Data

We collect high-frequency equity data at the tick level from Refinitiv DataScope for SPY and 15 individual equities. The sample period matches the high-frequency options data, i.e. January 11, 2005 to December 31, 2021 for SPY, and January 2, 2004 to December 31, 2021 for the individual equities. In following Barndorff-Nielsen et al. (2008), the common cleaning process for high-frequency stock data is detailed as follows. We delete ticks with a time stamp outside 09:30–16:00h; if one or multiple transactions have occurred in that second, we calculate the volume-weighted average price within that second; for the volume-weighted average price, we use the entry from the nearest previous second; we delete entries for which the price deviated by more than 10 mean absolute deviations from a rolling centered median (excluding the observation under consideration) of 50 observations (25 observations before and 25 after). Finally, we employ the previous tick interpolation to aggregate our data using a 5-minute interval. The choice of the 5-minute interval for stock is customary in the literature and is motivated by the good bias-variance trade-off observed at this interval (e.g. Andersen et al., 2003; Liu et al., 2015).

3.3 Introducing the Option Realized Measures

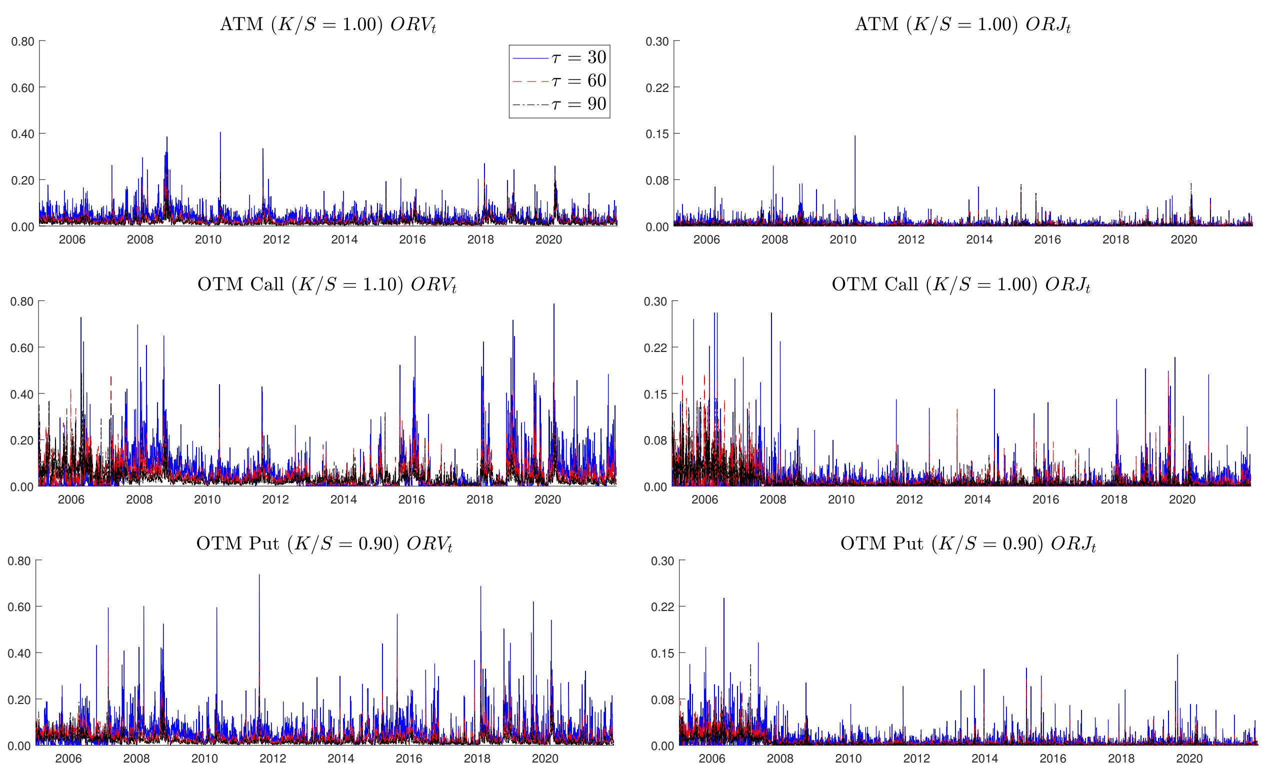
To deal with the large cross-section of option data spanning various maturities and moneyness levels, we construct a surface of option realized measures across both dimensions. In specific, for a given day, we collect an option realized measure, say $\mathcal{ORV}$, for all options in our dataset and perform a smoothed interpolation across moneyness levels and maturities.[16]

[16] We perform a locally smoothing quadratic regression by adopting the Matlab Lowess procedure on the square root of $\mathcal{ORV}$ and then use these values to obtain a result in $\mathcal{ORV}$ units. The Matlab functions performs a local regression using weighted linear least squares with a second degree polynomial model which is robust to other choices of smoothing.

Finally, we extract a daily balanced panel across moneyness and maturity with three equally spaced points over the moneyness dimension $K/S \in \{0.90,\ 1.00, 1.10\}$, corresponding to OTM puts, ATM and OTM calls, for maturities of $\tau \in \{30,\ 60,\ 90\}$.

Figure 3 depicts the SPY $\mathcal{ORV}$ and $\mathcal{ORJ}$ for the aforementioned levels of moneyness and maturities. Irrespective whether we look at the time series of the $\mathcal{ORV}$ or $\mathcal{ORJ}$, we observe that these measures share similar dynamics across both maturities and moneyness levels. As expected, the measures with shorter maturities display greater values. The time series of OTM option realized measures depict larger fluctuations relative to their ATM counterpart, particularly in turbulent times such as the global financial crisis and the Covid-19 pandemic.

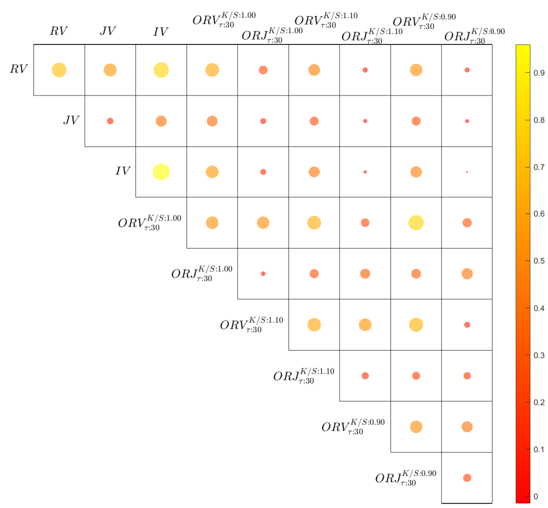
Figure 3: **SPY Option Realized Measures**



Notes: This figure shows the time series of the option realized measures namely $\mathcal{ORV}$ and $\mathcal{ORJ}$ with respect to SPY. The time series are presented for measures estimated across moneyness $K/S \in \{0.90,\ 1.00,\ 1.10\}$ and maturities $\tau \in \{30,\ 60,\ 90\}$. The sample period is from January 11, 2005 to December 31, 2021, at a daily frequency.

To rationalize the interaction between the option and the underlying realized measures, Figures 4 and 5 report the correlations and the AR(1) coefficient (main diagonal) for SPY and the average of the individual equities. For completeness, we also compare with the ATM implied volatility (IV), in variance form. For SPY, unsurprisingly, ATM $\mathcal{ORV}$ displays the highest level of correlation with both RV and IV, with values corresponding to 62% and 56%, respectively.[17] By contrast, when $\mathcal{ORV}$ is computed using OTM calls or puts, the correlation with RV decreases to 46% and 52%, respectively. A qualitatively similar finding is observed when comparing OTM $\mathcal{ORV}$ and IV.

Figure 4: **SPY Correlations and AR(1) Coefficients**

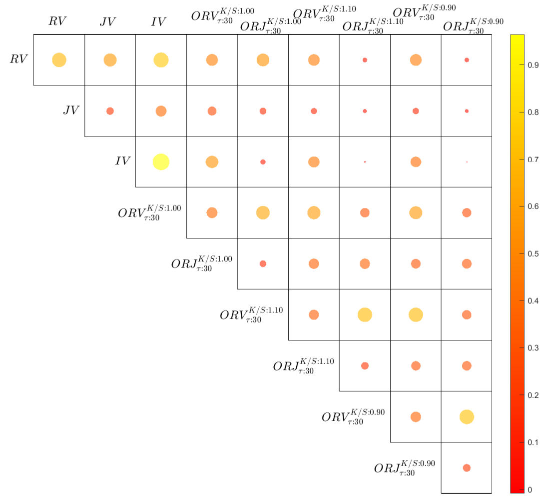


Notes: This figure presents the correlations between RV, JV, IV, and selected $\mathcal{ORV}$ and $\mathcal{ORJ}$ variables for SPY. The selected maturity for the option realized measures corresponds to $\tau = 30$ days, while the selected moneyness corresponds to OTM call options ($K/S = 1.10$), ATM options ($K/S = 1.00$), and OTM put options ($K/S = 0.90$). RV and JV are computed from SPY 5-minute returns. The main diagonal entries report the AR(1) coefficient of the variables. The sample period is from January 11, 2005 to December 31, 2021, at a daily frequency.

A plausible explanation for the decrease in the correlation level can be attributed to the fact that the jump component of OTM $\mathcal{ORV}$ contributes more to the option quadratic

[17] The correlation between IV and RV equals 79%.

Figure 5: **Individual Equity Correlations and AR(1) Coefficients**



Notes: This figure presents the correlations between RV, JV, IV, and selected $\mathcal{ORV}$ and $\mathcal{ORJ}$ variables for the average of the individual equities. The selected maturity for the option realized measures corresponds to $\tau = 30$ days, while the selected moneyness corresponds to OTM call options ($K/S = 1.10$), ATM options ($K/S = 1.00$), and OTM put options ($K/S = 0.90$). RV and JV are computed from 5-minute returns. The main diagonal entries report the AR(1) coefficient of the variables. The sample period is from January 2, 2004 to December 31, 2021, at a daily frequency.

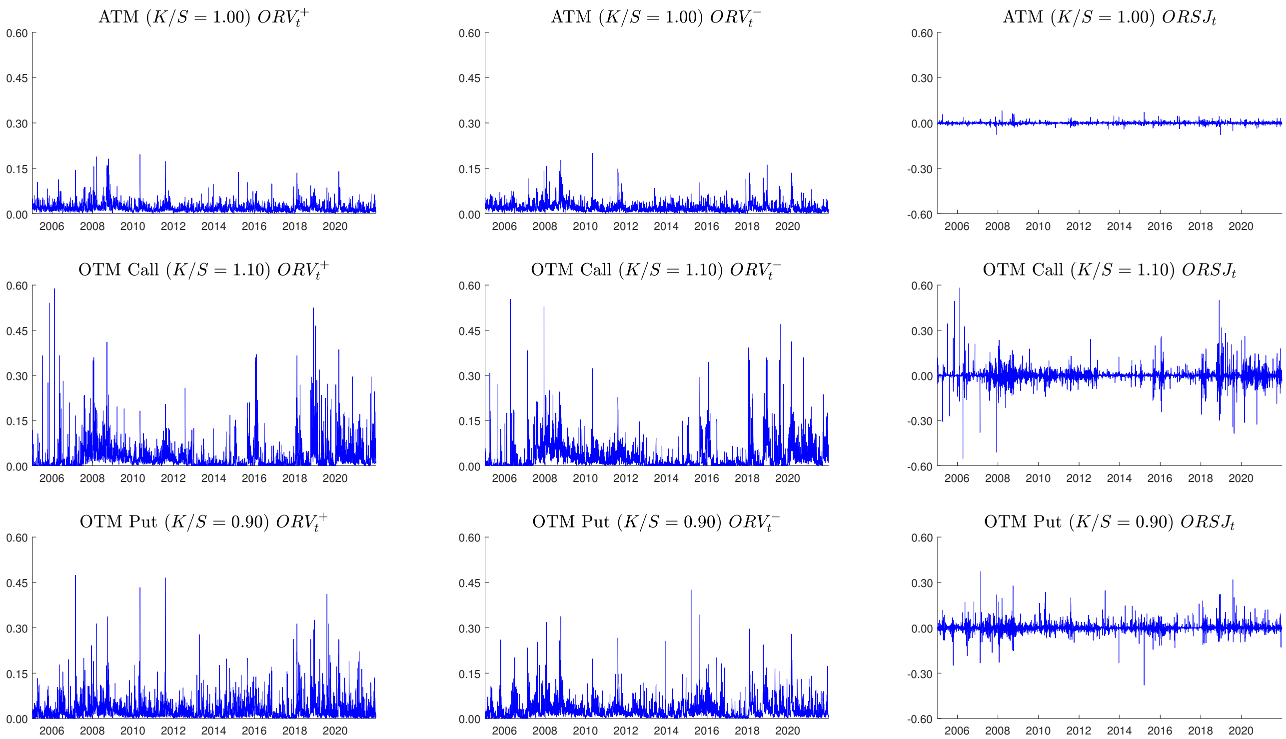
variation and these jumps are not captured by the RV. The smaller AR(1) coefficient observed in OTM $\mathcal{ORV}$ supports this explanation as jumps dynamics are known to be much less persistent than continuous sample path dynamics (e.g., Andersen et al., 2007). Similar conclusions can be drawn from Figure 5 for the relationship between the option and the underlying realized measures of the individual equities.

Finally, Figure 6 plots the SPY option realized semivariances and signed jumps.[18] For ease of presentation, and motivated by the graphical evidence in Figure 3, we focus on the dynamics of our estimates across the same levels of moneyness with a maturity of 30 days. We corroborate similar patterns even when the option realized measures are decomposed by sign. That is, OTM option realized semivariances and signed jumps fluctuate more than

[18] For the sake of space, we plot the $\mathcal{ORSJ}$, which contains both signed jumps, namely $\mathcal{ORJ}^+$ and $\mathcal{ORJ}^-$, depicted above and below the zero value, respectively.

their ATM counterparts reaching, in absolute terms, higher values.

Figure 6: **SPY Option Realized Signed Measures**



Notes: This figure shows the time series of the option realized semivariances ($\mathcal{ORV}^+$and $\mathcal{ORV}^-$) and signed jumps ($\mathcal{ORSJ}$) with respect to SPY. The time series are presented for measures estimated across moneyness $K/S \in \{0.90,\ 1.00,\ 1.10\}$ and maturity equal to $\tau \in 30$ days. The sample period is from January 11, 2005 to December 31, 2021, at a daily frequency.

In summary, the previous descriptive analysis suggests that option realized measures estimated using OTM calls and puts within 30-day maturity afford a richer information set relative to measures based on alternative moneyness and maturity levels. Thus, in what follows, we focus on option realized measures estimated from OTM calls ($K/S = 1.10$) and OTM puts ($K/S = 0.90$) with a maturity of 30 days.

4 Predicting the Realized Variance

This section is devoted to assessing the predictive information content of the option realized measures on future SPY and individual equity realized variances. We start by examining the predictive power of the $\mathcal{ORV}$ and $\mathcal{ORJ}$, to then focus our attention on the option realized semivariances and signed jumps.

Our baseline model is an extension of the so-called HAR model of Corsi (2009), which incorporates a daily jump component (JV) and the OptionMetrics ATM 30-day implied volatility (IV), in variance form.[19] This framework encompasses several specifications that improve upon the standard HAR model (e.g., Andersen et al., 2007; Busch et al., 2011, *inter alia*). Therefore, this setup allows us to assess the increased forecasting ability of the option realized measures even after controlling for predictors that are commonly adopted in the literature of forecasting RV. Let $RV_{t+1:t+h}$ define the multi-period normalized (scaled by the horizon) realized variance measures as the average of the corresponding one-period measures:

$$RV_{t+1:t+h} = h^{-1}\left[RV_{t+1} + RV_{t+2} + \cdots + RV_{t+h}\right],$$

where h corresponds to the forecasting horizon, i.e. $h \in \{1, 5, 22\}$ denoting one-day, one-week, and one-month ahead. The baseline model is outlined as:

$$RV_{t+1:t+h} = \beta_0 + \beta_d RV_t^{(\mathrm{d})} + \beta_w RV_t^{(\mathrm{w})} + \beta_m RV_t^{(\mathrm{m})} + \beta_{JV} JV_t + \beta_{IV} IV_t + \varepsilon_{t+1:t+h}, \qquad (15)$$

where $RV^{(d)}$, $RV^{(w)}$, and $RV^{(m)}$ are the respective past daily, weekly, and monthly RV as defined in Corsi (2009). JV is the jump component and IV is the implied volatility, in variance form. For individual equities, the baseline model is estimated using panel regressions with firm fixed effects.[20]

[19] The stock jump variation is defined as $JV_t \equiv \max\left[0, RV_t - BV_t\right]$ following Barndorff-Nielsen and Shephard (2004). IV is the average of the ATM call and put implies volatilities. OptionMetrics computes implied volatilities using a binomial tree, taking into account discrete dividend payments and the possibility of early exercise and using historical LIBOR/Eurodollar rates for interest rate inputs.

[20] To ease notation, we have suppressed the i subscript that characterizes the standard panel regression

4.1 Option Realized Measures

To assess the predictive power of the option realized measures on future SPY and individual equities RV, we further augment the baseline model separately with $\mathcal{ORV}$ and $\mathcal{ORJ}$:

$$RV_{t+1:t+h} = \beta_0 + \beta_d RV_t^{(\mathrm{d})} + \beta_w RV_t^{(\mathrm{w})} + \beta_m RV_t^{(\mathrm{m})} + \beta_{JV} JV_t + \beta_{IV} IV_t + \beta_{\mathcal{ORV}} \mathcal{ORV}_t + \varepsilon_{t+1:t+h}, \tag{16}$$

$$RV_{t+1:t+h} = \beta_0 + \beta_d RV_t^{(\mathrm{d})} + \beta_w RV_t^{(\mathrm{w})} + \beta_m RV_t^{(\mathrm{m})} + \beta_{JV} JV_t + \beta_{IV} IV_t + \beta_{\mathcal{ORJ}} \mathcal{ORJ}_t + \varepsilon_{t+1:t+h}, \tag{17}$$

where the $\mathcal{ORV}$ and $\mathcal{ORJ}$ are the option subsampling realized variance and jump component, and the remaining measures are defined as in equation (15).[21]

Tables 1 and 2 convey in three panels the regression results for SPY and the individual equities. Panels A, B, and C of each table report the one-day ($h = 1$), one-week ($h = 5$), and one-month ($h = 22$) coefficients and their corresponding robust t-statistics in parentheses. The t-statistics in Table 1 are estimated using Newey-West robust standard errors.[22] The regression results reported in Table 2 are estimated using a panel regression framework with firm fixed effects, and the t-statistics are estimated using clustered robust standard errors. Adjusted R^2s (R^2_{adj}) are reported in the last row of the tables. The first column of each panel presents the results for the baseline model. The other columns report the results with respect to the OTM call and put $\mathcal{ORV}$ and $\mathcal{ORJ}$.

First, we focus our attention on the stock market index (Table 1). The coefficients of past RVs are generally significant, confirming the high persistence feature of RV. In

models. This applies to all the equations shown in our empirical exercises.

[21] To avoid issues with extreme observations, throughout the study we winsorize the option realized measures at the 0.5% and 99.5% levels.

[22] The t-statistics are estimated using Newey and West (1987) HAC robust standard errors, with a lag-length equal to $\max\left[\left\lfloor 4\left(\frac{T}{100}\right)^{\frac{2}{9}}\right\rfloor, h\right]$. The first term corresponds to the optimal length of the Barlett kernel, and h denotes the forecast horizon.

addition, we find that whereas IV displays a strong and positive relationship with future RV, JV predicts negatively the future RV and is only significant at the daily horizon. The strong predictability of IV decays as the forecasting horizon lengthens. However, it provides evidence on the importance of augmenting the HAR model with forward-looking information (e.g., Busch et al., 2011).

Turning our attention to models augmented with $\mathcal{ORV}$ and $\mathcal{ORJ}$, we observe that the OTM put $\mathcal{ORV}$ is found to be a good RV predictor for all forecast horizons. By contrast, the OTM call $\mathcal{ORV}$ emerges to be significant only at longer horizons. The coefficients of the $\mathcal{ORV}$ are always positive regardless of the option contract. This implies that an increase in the $\mathcal{ORV}$ leads to an increase in the future SPY price variations. For instance, a 2-standard deviation increase in OTM put $\mathcal{ORV}$ ($h = 22$) predicts a rise of approximately 28% in the annual RV. Similarly, we find that the coefficients of the $\mathcal{ORJ}$ are generally positive, albeit insignificant. The richer information content observed in the SPY OTM put $\mathcal{ORV}$, relative to that of call OTM $\mathcal{ORV}$, is consistent with a hedging trading activity on the stock market index.

The results for the individual equities, reported in Table 2, confirm that past RV and IV are strong predictors of future RV. Moreover, both $\mathcal{ORV}$ measures are significant and positively related to the individual equities' future RV. By contrast, $\mathcal{ORJ}$ displays no predictive power. These results hold across all forecasting horizons. It is interesting to note that the uncovered significant predictive power of OTM call $\mathcal{ORV}$ shows a richer information set than that found in OTM put $\mathcal{ORV}$.

Table 1: Predicting SPY RV with Option Realized Measures

		Call ($K/S = 1.10$)		Put ($K/S = 0.90$)			Call ($K/S = 1.10$)		Put ($K/S = 0.90$)			Call ($K/S = 1.10$)		Put ($K/S = 0.90$)	
	Panel A: $h = 1$					Panel B: $h = 5$					Panel C: $h = 22$				
α	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(−3.351)	(−3.708)	(−3.226)	(−3.945)	(−3.282)	(−1.917)	(−2.547)	(−1.863)	(−2.930)	(−1.934)	(2.825)	(1.343)	(2.730)	(0.434)	(2.384)
β_d	0.228	0.220	0.227	0.193	0.227	0.283	0.273	0.285	0.243	0.281	0.072	0.037	0.070	0.022	0.072
	(2.837)	(2.753)	(2.799)	(2.396)	(2.805)	(3.475)	(3.285)	(3.475)	(2.940)	(3.476)	(1.665)	(0.814)	(1.587)	(0.424)	(1.580)
β_w	0.402	0.403	0.402	0.406	0.402	0.374	0.376	0.374	0.379	0.374	0.291	0.296	0.291	0.296	0.291
	(3.177)	(3.179)	(3.176)	(3.228)	(3.178)	(2.342)	(2.356)	(2.344)	(2.409)	(2.341)	(2.122)	(2.181)	(2.123)	(2.197)	(2.124)
β_m	−0.310	−0.308	−0.310	−0.297	−0.310	−0.191	−0.188	−0.191	−0.176	−0.191	0.015	0.026	0.016	0.034	0.015
	(−2.709)	(−2.700)	(−2.714)	(−2.629)	(−2.708)	(−1.159)	(−1.136)	(−1.162)	(−1.065)	(−1.158)	(0.084)	(0.142)	(0.087)	(0.189)	(0.084)
β_{JV}	−1.260	−1.266	−1.259	−1.269	−1.259	−0.788	−0.796	−0.788	−0.799	−0.787	0.803	0.777	0.804	0.790	0.803
	(−2.036)	(−2.049)	(−2.038)	(−2.080)	(−2.037)	(−1.441)	(−1.476)	(−1.439)	(−1.507)	(−1.444)	(1.383)	(1.472)	(1.387)	(1.463)	(1.383)
β_{IV}	0.664	0.660	0.664	0.666	0.665	0.624	0.619	0.624	0.627	0.627	0.243	0.227	0.243	0.246	0.243
	(5.194)	(5.212)	(5.189)	(5.261)	(5.182)	(5.303)	(5.271)	(5.301)	(5.244)	(5.301)	(2.229)	(2.077)	(2.230)	(2.245)	(2.212)
$\beta_{\mathcal{ORV}}$		0.065		0.233			0.090		0.269			0.285		0.330	
		(1.355)		(2.924)			(1.309)		(2.476)			(1.790)		(1.747)	
$\beta_{\mathcal{ORJ}}$			0.061		0.090			−0.083		0.147			0.148		0.011
			(0.380)		(0.645)			(−0.580)		(0.748)			(0.799)		(0.042)
R^2_{adj}	63.434%	63.461%	63.427%	63.673%	63.428%	67.177%	67.228%	67.172%	67.455%	67.175%	47.678%	48.803%	47.683%	48.482%	47.665%

Notes: This table presents the results of the HAR regression models in the spirit of Corsi (2009), as illustrated in regression models 15, 16, and 17, where the dependent variable is the SPY realized variance over future horizons with $h \in (1, 5, 22)$ days ahead presented in Panel A, B, and C, respectively. $\mathcal{ORV}$ is the option realized variance for SPY OTM calls ($K/S = 1.10$) and OTM puts ($K/S = 0.90$). $\mathcal{ORJ}$ is the option realized jump component for SPY OTM calls ($K/S = 1.10$) and OTM puts ($K/S = 0.90$). $RV_t^{(\mathrm{d})}$, $RV_t^{(\mathrm{w})}$, and $RV_t^{(\mathrm{m})}$ are the daily, weekly, and monthly levels of realized variances. JV_t is the jump variation over the last day. IV is the ATM options implied volatility, in variance form, with a maturity of 30 days, over the last day. t-stats are reported in parentheses and reflect robust Newey-West standard errors. Adjusted-R^2 are reported in the last row (%). The sample period is from January 11, 2005 to December 31, 2021, at a daily frequency.

Table 2: Predicting Equity RV with Option Realized Measures

		Call ($K/S=1.10$)		Put ($K/S=0.90$)			Call ($K/S=1.10$)		Put ($K/S=0.90$)			Call ($K/S=1.10$)		Put ($K/S=0.90$)	
	Panel A: $h=1$					Panel B: $h=5$					Panel C: $h=22$				
β_d	0.348	0.343	0.347	0.343	0.347	0.211	0.205	0.210	0.204	0.210	0.087	0.083	0.087	0.082	0.087
	(6.455)	(6.273)	(6.390)	(6.259)	(6.406)	(5.663)	(5.380)	(5.610)	(5.397)	(5.626)	(4.390)	(4.115)	(4.343)	(4.247)	(4.354)
β_w	0.151	0.151	0.151	0.151	0.151	0.246	0.246	0.246	0.246	0.246	0.131	0.131	0.131	0.131	0.131
	(1.698)	(1.691)	(1.695)	(1.692)	(1.697)	(3.596)	(3.577)	(3.591)	(3.582)	(3.594)	(4.425)	(4.411)	(4.426)	(4.429)	(4.424)
β_m	−0.077	−0.079	−0.078	−0.077	−0.077	0.027	0.026	0.027	0.028	0.027	0.173	0.171	0.172	0.173	0.173
	(−2.623)	(−2.646)	(−2.625)	(−2.598)	(−2.620)	(0.457)	(0.428)	(0.452)	(0.459)	(0.458)	(3.036)	(3.005)	(3.034)	(3.033)	(3.036)
β_{JV}	−0.294	−0.296	−0.296	−0.295	−0.295	−0.158	−0.161	−0.160	−0.159	−0.159	−0.030	−0.032	−0.030	−0.030	−0.030
	(−1.442)	(−1.456)	(−1.454)	(−1.448)	(−1.446)	(−1.403)	(−1.439)	(−1.419)	(−1.420)	(−1.408)	(−0.391)	(−0.418)	(−0.395)	(−0.399)	(−0.392)
β_{IV}	0.597	0.602	0.599	0.600	0.598	0.665	0.671	0.667	0.669	0.666	0.385	0.390	0.386	0.389	0.385
	(10.278)	(10.412)	(10.295)	(10.392)	(10.292)	(12.677)	(12.688)	(12.647)	(12.691)	(12.666)	(6.162)	(6.206)	(6.142)	(6.244)	(6.153)
β_{ORV}		0.105		0.152			0.136		0.177			0.097		0.149	
		(2.847)		(2.306)			(2.874)		(2.232)			(3.112)		(2.630)	
β_{OJV}			0.130		0.118			0.116		0.099			0.021		0.028
			(1.597)		(1.206)			(1.618)		(1.251)			(0.465)		(0.514)
R^2_{adj}	57.396%	57.423%	57.404%	57.427%	57.399%	61.512%	61.554%	61.518%	61.550%	61.513%	52.039%	52.081%	52.039%	52.093%	52.039%

Notes: This table presents the results of the HAR regression models in the spirit of Corsi (2009), as illustrated in regression models 15, 16, and 17, where the dependent variable is the individual stock realized variance over future horizons with $h \in (1, 5, 22)$ days ahead presented in Panel A, B, and C, respectively. $\mathcal{ORV}$ is the option realized variance for the individual equities OTM calls ($K/S = 1.10$) and OTM puts ($K/S = 0.90$). $\mathcal{ORJ}$ is the option realized jump component for the individual equities OTM calls ($K/S = 1.10$) and OTM puts ($K/S = 0.90$). $RV_t^{(\mathrm{d})}$, $RV_t^{(\mathrm{w})}$, and $RV_t^{(\mathrm{m})}$ are the daily, weekly, and monthly levels of realized variances. JV_t is the jump variation over the last day. IV is the ATM options implied volatility, in variance form, with a maturity of 30 days, over the last day. The models are estimated in a panel framework with firms fixed effect. t-stats are reported in parentheses and reflect robust Newey-West standard errors. Adjusted-R^2 are reported in the last row (%). The sample period is from January 2, 2004 to December 31, 2021, at a daily frequency.

This finding is in line with the higher information content placed in individual equity calls as opposed to puts (Bakshi et al., 2003).[23] In addition, Bollen and Whaley (2004) explain this difference based on differential demands (net buying pressure) for index options vis-à-vis stock options documenting that most trading in index options involves puts, whereas most trading in stock options involves calls. Therefore, changes in implied volatility of S&P 500 options are most strongly affected by buying pressure for index puts, while changes in implied volatility of stock options are dominated by call option demand. We reflect this evidence in our empirical findings as well as in the stock market index and individual equity options volume and number of contracts illustrated in Figures 2a and 2b.

In sum, from this first empirical analysis, we find that the $\mathcal{ORV}$ measures contain incremental information to predict the future assets' realized variances, and their information content is neither contained in past RV nor IV. The improvements afforded by the models containing the $\mathcal{ORV}$ measures directly translate in a better model fit. We find that the R^2_{adj} of these models are usually 24 to 81 basis points higher than that of the baseline model. Conversely, we do not find any predictive power enclosed in the $\mathcal{ORJ}$ measures. Previous research reported that jumps were of only limited value for forecasting RV (e.g. Andersen et al., 2007; Busch et al., 2011; Patton and Sheppard, 2015). This suggests that the impact of jumps depends critically on their sign, and such impact may be offset in a measure that does not distinguish between positive and negative jumps. This motivates our next empirical section in which we aim to shed more light on the predictive power of the signed jumps and, in general, on the options realized signed measures.

[23] The less negative individual equity skew tempers the way individual OTM puts are priced vis-à-vis OTM calls.

4.2 Option Realized Signed Measures

In this section, we take a step further in our analysis and we investigate the predictive ability of the options realized signed measures. To do so, we adopt the following models:

$$RV_{t+1:t+h} = \beta_0 + \beta_d RV_t^{(\mathrm{d})} + \beta_w RV_t^{(\mathrm{w})} + \beta_m RV_t^{(\mathrm{m})} + \beta_{JV} JV_t + \beta_{IV} IV_t + \beta_{\mathcal{ORV}^+} \mathcal{ORV}^+{}_t + \beta_{\mathcal{ORV}^-} \mathcal{ORV}^-{}_t + \varepsilon_{t+1:t+h}, \tag{18}$$

$$RV_{t+1:t+h} = \beta_0 + \beta_d RV_t^{(\mathrm{d})} + \beta_w RV_t^{(\mathrm{w})} + \beta_m RV_t^{(\mathrm{m})} + \beta_{JV} JV_t + \beta_{IV} IV_t + \beta_{\mathcal{ORJ}^+} \mathcal{ORJ}^+{}_t + \beta_{\mathcal{ORJ}^-} \mathcal{ORJ}^-{}_t + \varepsilon_{t+1:t+h}, \tag{19}$$

where the $\mathcal{ORV}^+$ and $\mathcal{ORV}^-$ are respectively the positive and negative option realized semivariance, and the $\mathcal{ORJ}^+$ and $\mathcal{ORJ}^-$ are the positive and negative option realized signed jumps. The remaining variables are defined as in equation (15).

Tables 3 and 4 report the SPY and individual equity results. The structure of the tables follows that presented in Section 4.1. As shown in Table 3, the coefficients of the negative semivariance ($\mathcal{ORV}^-$) of a call and the positive semivariance ($\mathcal{ORV}^+$) of a put are always significant and positively predict the future RV. In other words, the predictive power of the $\mathcal{ORV}$ is completely contained in the negative (positive) semivariance of a call (put) option and it can only be uncovered when the $\mathcal{ORV}$ is decomposed according to the sign of the option returns. These results are in line with a downside risk channel.

The signed jumps display a similar pattern. That is, $\mathcal{ORJ}^-$ for calls and $\mathcal{ORJ}^+$ for puts are the main risk components containing predictive information about future RV at any horizon. Whereas the coefficient of the put $\mathcal{ORJ}^+$ is positive, the coefficient of the call $\mathcal{ORJ}^-$ is negative. Please note that the $\mathcal{ORJ}^-$ is negative by construction, implying that a negative coefficient increases future RV. Two observations can be drawn from these findings. First, both call $\mathcal{ORJ}^-$ and put $\mathcal{ORJ}^+$ are associated with an increase in future RV, corroborating the downside risk effect. Second, when the jump component is considered in aggregate ($\mathcal{ORJ}$), we fail to uncover any predictive information content irrespective of the option contract, thereby highlighting the relevance of our proposed decomposition.

The further incremental information afforded by the option realized signed jumps, relative to the $\mathcal{ORJ}$, is also highlighted by the model performance. For instance, focusing on $h = 22$ and a call option (Table 1), we observe that the inclusion of the $\mathcal{ORJ}$ yields a very marginal increase in the regression R^2_{adj} relative to the baseline model ($R^2_{adj} = 47.68\%$). By contrast, the R^2_{adj} of the model including the OTM call $\mathcal{ORJ}^+$ and $\mathcal{ORJ}^-$ increases to 48.26% (see Panel C, Table 3). This is an example of how our option realized signed jumps improve upon the fit of both the baseline model and the model using only the $\mathcal{ORJ}$.

Moreover, it appears that the coefficients associated with the signed jumps reflect a greater effect compared to the semivariances in predicting future realized variances when both are found to be significant. This finding corroborates even further the importance of decomposing the $\mathcal{ORJ}$ component to display greater forecasting significance. Overall, for both the semivariances and signed jumps, it turns out that the channel we pin down is in line with a downside risk effect. The results for the individual equities (Table 4) corroborate the downside rick channel, as the information content of semivariances and signed jumps appear to be placed in the negative components of the calls ($\mathcal{ORV}^-$ and $\mathcal{ORJ}^-$) and the positive components of the puts ($\mathcal{ORV}^+$ and $\mathcal{ORJ}^+$).

Our findings show that the future realized variance of both the stock market index and individual equities is strongly related to the risk of past "bad" shocks. Following our aforementioned mechanism, future realized variance will react more to past negative (positive) information in the call (put) options. Similarly to previous studies on the importance of asymmetric risk in the stock market (e.g. Ang et al., 2006), we show that investors care differently about downside losses versus upside gains. Moreover, we confirm that the impact of a price risk factor on future variance depends on the sign of the risk factor (e.g. Patton and Sheppard, 2015) given that a negative (positive) price variation or jump of a call (put) leads to higher future asset volatility.

Table 3: Predicting SPY RV with Option Realized Signed Measures

		Call ($K/S = 1.10$)		Put ($K/S = 0.90$)			Call ($K/S = 1.10$)		Put ($K/S = 0.90$)			Call ($K/S = 1.10$)		Put ($K/S = 0.90$)	
	Panel A: $h = 1$					Panel B: $h = 5$					Panel C: $h = 22$				
α	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(−3.351)	(−3.734)	(−3.512)	(−3.956)	(−3.652)	(−1.917)	(−2.549)	(−2.436)	(−2.746)	(−2.558)	(2.825)	(1.172)	(2.405)	(0.549)	(2.036)
β_d	0.228	0.221	0.223	0.197	0.213	0.283	0.273	0.279	0.245	0.272	0.072	0.036	0.062	0.025	0.056
	(2.837)	(2.819)	(2.804)	(2.482)	(2.742)	(3.475)	(3.278)	(3.405)	(2.942)	(3.264)	(1.665)	(0.781)	(1.431)	(0.499)	(1.242)
β_w	0.402	0.409	0.407	0.409	0.409	0.374	0.380	0.378	0.382	0.380	0.291	0.300	0.293	0.299	0.296
	(3.177)	(3.243)	(3.234)	(3.275)	(3.304)	(2.342)	(2.387)	(2.372)	(2.439)	(2.414)	(2.122)	(2.213)	(2.152)	(2.214)	(2.181)
β_m	−0.310	−0.303	−0.304	−0.291	−0.294	−0.191	−0.183	−0.186	−0.170	−0.178	0.015	0.031	0.021	0.038	0.029
	(−2.709)	(−2.696)	(−2.700)	(−2.599)	(−2.637)	(−1.159)	(−1.111)	(−1.126)	(−1.025)	(−1.071)	(0.084)	(0.168)	(0.114)	(0.214)	(0.161)
β_{JV}	−1.260	−1.243	−1.243	−1.253	−1.262	−0.788	−0.778	−0.776	−0.782	−0.788	0.803	0.793	0.801	0.809	0.793
	(−2.036)	(−2.040)	(−2.034)	(−2.049)	(−2.056)	(−1.441)	(−1.458)	(−1.442)	(−1.478)	(−1.459)	(1.383)	(1.517)	(1.446)	(1.485)	(1.416)
β_{IV}	0.664	0.646	0.649	0.654	0.651	0.624	0.608	0.614	0.616	0.613	0.243	0.216	0.232	0.236	0.235
	(5.194)	(5.247)	(5.254)	(5.215)	(5.211)	(5.303)	(5.117)	(5.138)	(5.049)	(5.065)	(2.229)	(1.963)	(2.104)	(2.144)	(2.134)
$\beta_{\mathcal{ORV}^+}$		−0.209		0.532			−0.129		0.542			0.097		0.550	
		(−1.802)		(3.407)			(−1.162)		(2.711)			(0.729)		(2.076)	
$\beta_{\mathcal{ORV}^-}$		0.349		−0.098			0.315		−0.004			0.508		0.100	
		(2.442)		(−0.550)			(2.121)		(−0.020)			(2.113)		(0.495)	
$\beta_{\mathcal{ORJ}^+}$			−0.028		0.846			−0.012		0.688			0.249		0.727
			(−0.271)		(3.168)			(−0.111)		(2.482)			(1.354)		(2.055)
$\beta_{\mathcal{ORJ}^-}$			−0.530		−0.080			−0.409		−0.027			−0.615		−0.254
			(−2.267)		(−0.394)			(−1.914)		(−0.129)			(−2.135)		(−0.937)
R^2_{adj}	63.434%	63.646%	63.697%	63.802%	63.857%	67.177%	67.323%	67.304%	67.561%	67.417%	47.678%	48.990%	48.264%	48.588%	48.166%

Notes: This table presents the results of the HAR regression models in the spirit of Corsi (2009), as illustrated in regression models 15, 18, and 19, where the dependent variable is the SPY realized variance over future horizons with $h \in (1, 5, 22)$ days ahead presented in Panel A, B, and C, respectively. $\mathcal{ORV}^+$and $\mathcal{ORV}^-$are the option realized semivariances for SPY OTM calls ($K/S = 1.10$) and OTM puts ($K/S = 0.90$). $\mathcal{ORJ}^+$and $\mathcal{ORJ}^-$are the option realized signed jumps for SPY OTM calls ($K/S = 1.10$) and OTM puts ($K/S = 0.90$). $RV_t^{(d)}$, $RV_t^{(w)}$, and $RV_t^{(m)}$ are the daily, weekly, and monthly levels of realized variances. JV_t is the jump variation over the last day. IV is the ATM options implied volatility, in variance form, with a maturity of 30 days, over the last day. t-stats are reported in parentheses and reflect robust Newey-West standard errors. Adjusted-R^2 are reported in the last row (%). The sample period is from January 11, 2005 to December 31, 2021, at a daily frequency.

Table 4: Predicting Equity RV with Option Realized Signed Measures

		Call ($K/S=1.10$)		Put ($K/S=0.90$)			Call ($K/S=1.10$)		Put ($K/S=0.90$)			Call ($K/S=1.10$)		Put ($K/S=0.90$)	
	Panel A: $h=1$					Panel B: $h=5$					Panel C: $h=22$				
β_d	0.348	0.344	0.346	0.344	0.344	0.211	0.205	0.209	0.205	0.208	0.087	0.083	0.086	0.082	0.084
	(6.455)	(6.283)	(6.351)	(6.294)	(6.363)	(5.663)	(5.389)	(5.543)	(5.431)	(5.569)	(4.390)	(4.105)	(4.275)	(4.272)	(4.283)
β_w	0.151	0.151	0.151	0.152	0.153	0.246	0.246	0.246	0.247	0.247	0.131	0.130	0.131	0.131	0.132
	(1.698)	(1.692)	(1.694)	(1.706)	(1.712)	(3.596)	(3.578)	(3.589)	(3.588)	(3.605)	(4.425)	(4.407)	(4.420)	(4.453)	(4.468)
β_m	−0.077	−0.078	−0.078	−0.076	−0.075	0.027	0.026	0.027	0.028	0.029	0.173	0.171	0.172	0.173	0.174
	(−2.623)	(−2.642)	(−2.634)	(−2.562)	(−2.539)	(0.457)	(0.433)	(0.454)	(0.469)	(0.475)	(3.036)	(3.009)	(3.033)	(3.042)	(3.050)
β_{JV}	−0.294	−0.296	−0.296	−0.295	−0.295	−0.158	−0.160	−0.159	−0.159	−0.159	−0.030	−0.031	−0.030	−0.030	−0.031
	(−1.442)	(−1.453)	(−1.450)	(−1.451)	(−1.459)	(−1.403)	(−1.431)	(−1.412)	(−1.423)	(−1.421)	(−0.391)	(−0.409)	(−0.394)	(−0.401)	(−0.408)
β_{IV}	0.597	0.601	0.600	0.598	0.597	0.665	0.671	0.667	0.668	0.665	0.385	0.390	0.386	0.387	0.386
	(10.278)	(10.407)	(10.352)	(10.394)	(10.353)	(12.677)	(12.677)	(12.589)	(12.653)	(12.669)	(6.162)	(6.197)	(6.138)	(6.200)	(6.161)
β_{ORV^+}		0.085		0.328			0.070		0.259			0.032		0.240	
		(1.482)		(2.901)			(1.312)		(2.580)			(0.901)		(3.271)	
β_{ORV^-}		0.108		−0.133			0.215		0.029			0.189		−0.003	
		(2.039)		(−2.363)			(2.830)		(0.446)			(2.696)		(−0.051)	
β_{ORJ^+}			0.156		0.518			0.086		0.344			0.022		0.361
			(1.866)		(2.979)			(1.057)		(2.752)			(0.457)		(4.143)
β_{ORJ^-}			−0.193		0.003			−0.191		0.004			−0.141		−0.073
			(−2.528)		(0.042)			(−2.112)		(0.078)			(−2.216)		(−1.229)
R^2_{adj}	57.396%	57.418%	57.411%	57.443%	57.456%	61.512%	61.555%	61.519%	61.551%	61.535%	52.039%	52.091%	52.045%	52.099%	52.090%

Notes: This table presents the results of the HAR regression models in the spirit of Corsi (2009), as illustrated in regression models 15, 18, and 19, where the dependent variable is the individual stock realized variance over future horizons with $h \in (1, 5, 22)$ days ahead presented in Panel A, B, and C, respectively. $\mathcal{ORV}^+$and $\mathcal{ORV}^-$are the option realized semivariances for the individual equities OTM calls ($K/S = 1.10$) and OTM puts ($K/S = 0.90$). $\mathcal{ORJ}^+$and $\mathcal{ORJ}^-$are the option realized signed jumps for the individual equities OTM calls ($K/S = 1.10$) and OTM puts ($K/S = 0.90$). $RV_t^{(d)}$, $RV_t^{(w)}$, and $RV_t^{(m)}$ are the daily, weekly, and monthly levels of realized variances. JV_t is the jump variation over the last day. IV is the ATM options implied volatility, in variance form, with a maturity of 30 days, over the last day. The models are estimated in a panel framework with firms fixed effect. t-stats are reported in parentheses and reflect robust Newey-West standard errors. Adjusted-R^2 are reported in the last row (%). The sample period is from January 2, 2004 to December 31, 2021, at a daily frequency.

In summary, the option realized measures succeed in enhancing the information set of options-based low-frequency variables (e.g. IV) or stock-based high-frequency variables (e.g. RV and JV) for predicting RV. We show that our proposed measures are generally found to be significant in predicting future variance even when considered next to variables commonly adopted to augment the HAR model (e.g. Busch et al., 2011). However, our results suggest that the information content enclosed in the option realized measures is even stronger when we construct them by considering the sign of the option return variations.[24]

5 Predicting the Variance Risk Premium

This section examines the predictive power of the option realized measures on future variance risk-premia (VRP), which is defined as the difference between the ex-ante risk-neutral expectation of the future return variance and ex-post realized return variance over the interval $[t+1, t+h]$:[25]

$$VRP_{t+1:t+h} = \frac{1}{h}\left(\mathrm{E}_t^{\mathbb{Q}}\left[RV_{t+1:t+h}\right] - RV_{t+1:t+h}\right),$$

where the risk-neutral expectation is proxied by the IV in variance form scaled at the daily level and the RV is the daily realized variance estimated using 5-min returns as in (e.g. Bollerslev et al., 2009).

We study the predictability of the future index and individual equity variance risk premia, as measured by VRP, over forecasting horizons of one-day ($h = 1$), one-week ($h = 5$)

[24] We have repeated the entire analysis with respect to the predictability of future realized variances by considering now ATM options instead of OTM. ATM options prices are selected from an interpolation between the closest call and put price near to the ATM region as in Figlewski (2010). The results are qualitatively similar and for sake of brevity not reported in the paper. However, they are available upon request.

[25] We compute the risk premia as a short position in a variance swap, namely, as the difference between risk neutral and physical expectations of returns (e.g. Bollerslev et al., 2009; Bekaert and Hoerova, 2014). Other studies follow the definition as in Carr and Wu (2008), namely, as the difference between physical and risk neutral expectations of return variation. The same definition is applied in Kilic and Shaliastovich (2019).

and one-month ($h = 22$) ahead. Our baseline model is outlined as:

$$VRP_{t+1:t+h} = \beta_0 + \beta_{RV} RV_t + \beta_{JV} JV_t + \beta_{VRP} VRP_t + \varepsilon_{t+1:t+h}, \tag{20}$$

where RV, JV and VRP are the past daily realized variance, jump variance and variance risk-premia. For individual equities, the baseline model is estimated using panel regressions with firm fixed effects.[26]

5.1 Option Realized Measures

In the following models, we add the aggregate option realized measures of interest, namely the $\mathcal{ORV}$ and the $\mathcal{ORJ}$. The models are specified as follows:

$$VRP_{t+1:t+h} = \beta_0 + \beta_{RV} RV_t + \beta_{JV} JV_t + \beta_{VRP} VRP_t + \beta_{\mathcal{ORV}} \mathcal{ORV}_t + \varepsilon_{t+1:t+h}, \tag{21}$$

$$VRP_{t+1:t+h} = \beta_0 + \beta_{RV} RV_t + \beta_{JV} JV_t + \beta_{VRP} VRP_t + \beta_{\mathcal{ORJ}} \mathcal{ORJ}_t + \varepsilon_{t+1:t+h}, \tag{22}$$

where $\mathcal{ORV}$ and $\mathcal{ORJ}$ are the option subsampling realized variance and jump component. The remaining variables are defined as in equation (20). Tables 5 and 6 report in three panels the regression results for SPY and the individual equities. Panels A, B, and C of each table convey the one-day ($h = 1$), one-week ($h = 5$), and one-month ($h = 22$) coefficients and their corresponding robust t-statistics in parentheses. The t-statistics in Table 5 are estimated using Newey-West robust standard errors,[27] while for Table 6 the t-statistics are estimated using clustered robust standard errors. The last row reports the adjusted R^2 (R^2_{adj}). The first column of each panel presents the results for the baseline model, while the other columns report the results with the respect to the OTM call and put $\mathcal{ORV}$ and $\mathcal{ORJ}$.

As can be seen, the lag of the VRP is strongly significant across all forecasting horizons.

[26] To avoid multicollinearity issues, we consider the RV and IV separately in the regression model. Results for IV are qualitatively similar and are reported in Appendix C.

[27] We refer to Section 4.1 for more details on the lags for the HAC standard errors.

This result is not surprising as the VRP is also a very persistent measure. On the other hand, we find that RV and IV are only significant at the month and daily horizon, respectively. These results hold true for both SPY and individual stocks. Turning to the option realized measures, we note that the SPY OTM put $\mathcal{ORV}$ is always significant and its inclusion increases the monthly R^2_{adj} of the baseline model by 73 basis points. The richer information content of SPY put $\mathcal{ORV}$ is, again, in line with the greater trading pressure and information content enclosed in the stock index puts (e.g. Bakshi et al., 2003; Bollen and Whaley, 2004). The results for the individual stocks indicate that both the OTM call and put $\mathcal{ORV}$ are significant predictors of future VRP across all horizons.

It is noteworthy that the coefficients of the $\mathcal{ORV}$ are always negative irrespective of the option contract and forecasting horizon. We rationalize this finding as follows. As noted in Section 4, $\mathcal{ORV}$ positively predict future RV (see Tables 1 and 2). Thereby, an increase in the $\mathcal{ORV}$, *ceteris paribus*, would increase the RV, this quantity would then enter the VRP equation with a negative sign, yielding a decrease in future VRP. Conversely, we find that for RV and JV, the sign of the coefficients changes depending on the horizon. Overall, the $\mathcal{ORJ}$ displays a negligible impact on future VRP. These findings validate the next section studying the impact of the option realized signed measures on future VRP.

Table 5: Predicting SPY VRP with Option Realized Measures

		Call ($K/S=1.10$)		Put ($K/S=0.90$)			Call ($K/S=1.10$)		Put ($K/S=0.90$)			Call ($K/S=1.10$)		Put ($K/S=0.90$)	
	Panel A: $h=1$					Panel B: $h=5$					Panel C: $h=22$				
α	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(3.569)	(3.972)	(3.486)	(4.241)	(3.555)	(4.119)	(4.542)	(4.033)	(4.669)	(4.109)	(3.373)	(4.057)	(3.465)	(3.724)	(3.255)
β_{RV}	−0.052	−0.048	−0.051	−0.035	−0.052	0.053	0.055	0.053	0.068	0.053	0.201	0.211	0.202	0.212	0.201
	(−0.666)	(−0.610)	(−0.661)	(−0.449)	(−0.667)	(0.619)	(0.626)	(0.616)	(0.793)	(0.616)	(4.334)	(4.620)	(4.355)	(4.769)	(4.321)
β_{JV}	1.225	1.227	1.224	1.234	1.225	0.759	0.761	0.760	0.768	0.759	−0.140	−0.132	−0.140	−0.134	−0.140
	(2.719)	(2.728)	(2.725)	(2.784)	(2.721)	(1.599)	(1.602)	(1.598)	(1.630)	(1.602)	(−0.731)	(−0.721)	(−0.732)	(−0.738)	(−0.740)
β_{VRP}	0.349	0.349	0.348	0.335	0.348	0.484	0.484	0.484	0.472	0.481	0.394	0.395	0.394	0.385	0.392
	(3.194)	(3.202)	(3.184)	(3.109)	(3.184)	(5.536)	(5.533)	(5.532)	(5.401)	(5.462)	(6.800)	(6.905)	(6.792)	(6.623)	(6.652)
$\beta_{\mathcal{ORV}}$		−0.003		−0.021			−0.001		−0.019			−0.007		−0.013	
		(−0.607)		(−2.930)			(−0.241)		(−2.381)			(−1.167)		(−1.890)	
$\beta_{\mathcal{ORJ}}$			−0.009		−0.005			0.004		−0.021			−0.005		−0.018
			(−0.677)		(−0.422)			(0.364)		(−1.383)			(−0.471)		(−1.393)
R^2_{adj}	13.190%	13.185%	13.263%	13.692%	13.254%	23.627%	23.614%	23.684%	24.206%	23.732%	34.677%	35.090%	34.735%	35.404%	34.811%

Notes: This table presents the results of the regression models 20, 21, and 22, where the dependent variable is the SPY variance risk premium defined as: $VRP_{t+1:t+h} = \frac{1}{h}\left(\mathrm{E}_t^{\mathbb{Q}}\left[RV_{t+1:t+h}\right] - RV_{t+1:t+h}\right)$, over future horizons with $h \in (1, 5, 22)$ days ahead presented in Panel A, B, and C, respectively. $\mathcal{ORV}$ is the option realized variance for SPY OTM calls ($K/S = 1.10$) and OTM puts ($K/S = 0.90$). $\mathcal{ORJ}$ is the option realized jump component for SPY OTM calls ($K/S = 1.10$) and OTM puts ($K/S = 0.90$). RV, is the daily level of realized variances. JV_t is the jump variation over the last day. VRP is the variance risk premium over the previous day. t-stats are reported in parentheses and reflect robust Newey-West standard errors. Adjusted-R^2 are reported in the last row (%). The sample period is from January 11, 2005 to December 31, 2021, at a daily frequency.

Table 6: Predicting Equity VRP with Option Realized Signed Measures

		Call ($K/S = 1.10$)		Put ($K/S = 0.90$)			Call ($K/S = 1.10$)		Put ($K/S = 0.90$)			Call ($K/S = 1.10$)		Put ($K/S = 0.90$)	
	Panel A: $h = 1$					Panel B: $h = 5$					Panel C: $h = 22$				
β_{RV}	-0.054	-0.053	-0.054	-0.052	-0.054	0.015	0.016	0.015	0.017	0.015	0.090	0.091	0.090	0.091	0.090
	(-1.276)	(-1.244)	(-1.281)	(-1.234)	(-1.277)	(0.412)	(0.448)	(0.404)	(0.458)	(0.408)	(3.883)	(3.914)	(3.873)	(3.914)	(3.878)
β_{JV}	0.217	0.219	0.218	0.217	2.17	0.085	0.087	0.086	0.085	0.085	0.044	0.045	0.045	0.045	0.045
	(1.158)	(1.172)	(1.171)	(1.165)	(1.162)	(0.753)	(0.781)	(0.767)	(0.767)	(0.757)	(0.523)	(0.537)	(0.531)	(0.527)	(0.525)
β_{VRP}	0.348	0.345	0.347	0.345	0.348	0.337	0.334	0.336	0.334	0.337	0.252	0.251	0.252	0.251	0.252
	(12.511)	(12.404)	(12.303)	(12.376)	(12.359)	(7.842)	(7.723)	(7.758)	(7.739)	(7.800)	(14.730)	(14.582)	(14.510)	(14.673)	(14.601)
$\beta_{\mathcal{ORV}}$		-0.009		-0.014			-0.010		-0.013			-0.005		-0.006	
		(-2.578)		(-2.164)			(-3.061)		(-2.268)			(-2.230)		(-2.311)	
$\beta_{\mathcal{ORJ}}$			-0.013		-0.012			-0.012		-0.011			-0.006		-0.005
			(-1.597)		(-1.230)			(-1.861)		(-1.332)			(-1.176)		(-0.789)
R^2_{adj}	15.352%	15.395%	15.369%	15.410%	15.358%	14.133%	14.215%	14.155%	14.207%	14.139%	12.925%	12.978%	12.940%	12.965%	12.928%

Notes: This table presents the results of the regression models 20, 21, and 22, where the dependent variable is the individual equity variance risk premium defined as: $VRP_{t+1:t+h} = \frac{1}{h}\left(\mathrm{E}_t^{\mathbb{Q}}\left[RV_{t+1:t+h}\right] - RV_{t+1:t+h}\right)$, over future horizons with $h \in (1, 5, 22)$ days ahead presented in Panel A, B, and C, respectively. $\mathcal{ORV}$ is the option realized variance for individual equities OTM calls ($K/S = 1.10$) and OTM puts ($K/S = 0.90$). $\mathcal{ORJ}$ is the option realized jump component for the individual equities OTM calls ($K/S = 1.10$) and OTM puts ($K/S = 0.90$). RV, is the daily level of realized variances. JV_t is the jump variation over the last day. VRP is the variance risk premium over the previous day. t-stats are reported in parentheses and reflect robust Newey-West standard errors. Adjusted-R^2 are reported in the last row (%). The sample period is from January 2, 2004 to December 31, 2021, at a daily frequency.

5.2 Option Realized Signed Measures

In this section, we test the role of the option realized semivariances and signed jumps to predict future variance risk premia by employing the following models:

$$VRP_{t+1:t+h} = \beta_0 + \beta_{RV} RV_t + \beta_{JV} JV_t + \beta_{VRP} VRP_t + \beta_{\mathcal{ORV}^+} \mathcal{ORV}_t^+ + \beta_{\mathcal{ORV}^-} \mathcal{ORV}_t^- + \varepsilon_{t+1:t+h}, \tag{23}$$

$$VRP_{t+1:t+h} = \beta_0 + \beta_{RV} RV_t + \beta_{JV} JV_t + \beta_{VRP} VRP_t + \beta_{\mathcal{ORJ}^+} \mathcal{ORJ}_t^+ + \beta_{\mathcal{ORJ}^-} \mathcal{ORJ}_t^- + \varepsilon_{t+1:t+h}, \tag{24}$$

where $\mathcal{ORV}^+$ and $\mathcal{ORV}^-$ are respectively the positive and negative option realized semivariance, and the $\mathcal{ORJ}^+$ and $\mathcal{ORJ}^-$ are the positive and negative option realized signed jumps. The remaining variables are defined as in equation (20).

The results for SPY and individual equities are reported respectively in Tables 7 and 8. The tables are structured as in Section 5.1. In line with our previous findings, Table 7 shows that $\mathcal{ORV}^-$ and $\mathcal{ORJ}^-$ ($\mathcal{ORV}^+$ and $\mathcal{ORJ}^+$) of calls (puts) are strong predictors of future VRP. In addition, we also document a few cases in which the positive (negative) semivariances of calls (puts) render a significant coefficient. Nevertheless, when this happens, the coefficients placed on the negative (positive) $\mathcal{ORV}$ of calls (puts) are generally larger and more significant, indicating an overall downside risk net effect.

Our results also confirm the greater information content of SPY puts compared to calls. For instance, when call $\mathcal{ORV}^-$ and put $\mathcal{ORV}^+$ are found significant, both the t-statistic and the coefficient associated with the put $\mathcal{ORV}^+$ are larger. As an example, at $h = 1$, the coefficient associated with $\mathcal{ORV}^+$ for puts is almost double the one of $\mathcal{ORV}^-$ for calls. In addition, the t-statistic of the former is -3.796, while for the latter is -2.347. A similar pattern is confirmed when comparing the t-statistic and coefficients of the signed jumps. This finding is directly reflected in a greater R^2_{adj} associated with the models including information from SPY puts. To illustrate, when the baseline model is augmented with option signed jumps estimated using OTM puts, the R^2_{adj} of the models outperform that of the benchmark by 138.7, 112.2, and 87 basis points at the daily, weekly, and monthly horizon, respectively.

Table 8 presents the predictive results for the individual equity signed measures. Overall, we confirm the same findings documented for the stock market index. That is, a prevalent downside risk channel through which the option realized signed measures lead to a decrease of future VRP across the predictive horizons and option moneyness selected.[28]

5.3 Robustness Checks

Given that other variables may explain the dynamics of the VRP, in this section we further assess the predictability of the option realized measures after controlling for other variables specially related to the options market, asset distribution asymmetry and tail-risk. In particular, we consider the ATM 30-day implied volatility (IV), in variance form, as defined in Section 4, the risk-neutral skewness (RNS) (Bakshi et al., 2003) and the Jump-Tail Index (JTI) (Du and Kapadia, 2012).[29] We report the empirical results in Tables C1 and C3 for SPY, and Tables C2 and C4 for individual equity in Appendix C.

Tables C1 and C4 report the SPY and individual equity results for the $\mathcal{ORV}$ and $\mathcal{ORJ}$. For SPY, we corroborate the predictive ability of the OTM put $\mathcal{ORV}$ even when controlling for IV, RNS and JTI. Similarly, for the individual equities, we also confirm the significant information content of $\mathcal{ORV}$ for both OTM calls and puts. The coefficients of the $\mathcal{ORV}$s are found negative across all forecasting horizons. Moreover, we find that the inclusion of these controls renders the $\mathcal{ORJ}$ significant, albeit the significance is weak and only detected at shorter horizons.

[28]Results based on ATM option realized measures confirm the main findings of this section, and are available upon request.

[29]More details about these variables can be found in Appendix A.

Table 7: Predicting SPY VRP with Option Realized Signed Measures

		Call ($K/S=1.10$)		Put ($K/S=0.90$)			Call ($K/S=1.10$)		Put ($K/S=0.90$)			Call ($K/S=1.10$)		Put ($K/S=0.90$)	
	Panel A: $h=1$					Panel B: $h=5$					Panel C: $h=22$				
α	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(3.569)	(4.025)	(3.780)	(4.254)	(3.840)	(4.119)	(4.567)	(4.540)	(4.543)	(4.471)	(3.373)	(4.047)	(4.108)	(3.723)	(3.523)
β_{RV}	−0.052	−0.045	−0.042	−0.037	−0.044	0.053	0.058	0.060	0.067	0.058	0.201	0.213	0.207	0.211	0.204
	(−0.666)	(−0.567)	(−0.551)	(−0.471)	(−0.567)	(0.619)	(0.657)	(0.695)	(0.783)	(0.674)	(4.334)	(4.705)	(4.548)	(4.760)	(4.513)
β_{JV}	1.225	1.208	1.211	1.219	1.228	0.759	0.744	0.746	0.754	0.756	−0.140	−0.142	−0.143	−0.143	−0.139
	(2.719)	(2.737)	(2.731)	(2.731)	(2.757)	(1.599)	(1.582)	(1.580)	(1.592)	(1.593)	(−0.731)	(−0.777)	(−0.770)	(−0.772)	(−0.750)
β_{VRP}	0.349	0.355	0.355	0.341	0.344	0.484	0.489	0.489	0.476	0.482	0.394	0.398	0.397	0.388	0.392
	(3.194)	(3.312)	(3.315)	(3.179)	(3.204)	(5.536)	(5.614)	(5.610)	(5.466)	(5.558)	(6.800)	(7.041)	(6.946)	(6.715)	(6.812)
$\beta_{\mathcal{ORV}^+}$		0.023		−0.057			0.020		−0.052			0.005		−0.031	
		(2.030)		(−3.796)			(2.359)		(−3.435)			(0.746)		(−2.920)	
$\beta_{\mathcal{ORV}^-}$		−0.029		0.022			−0.023		0.018			−0.021		0.007	
		(−2.347)		(1.369)			(−1.953)		(1.764)			(−2.102)		(1.113)	
$\beta_{\mathcal{ORJ}^+}$			0.002		−0.089			0.007		−0.065			−0.005		−0.038
			(0.299)		(−3.312)			(1.047)		(−2.964)			(−0.569)		(−2.286)
$\beta_{\mathcal{ORJ}^-}$			0.050		0.005			0.035		−0.011			0.028		0.000
			(2.280)		(0.258)			(2.005)		(−0.703)			(2.274)		(0.026)
R^2_{adj}	13.190%	13.619%	13.909%	14.200%	14.577%	23.627%	24.032%	24.174%	24.810%	24.749%	34.677%	35.473%	35.382%	35.778%	35.547%

Notes: This table presents the results of the regression models 20, 23, and 24, where the dependent variable is the SPY variance risk premium defined as: $VRP_{t+1:t+h} = \frac{1}{h}\left(\mathrm{E}_t^{\mathbb{Q}}\left[RV_{t+1:t+h}\right] - RV_{t+1:t+h}\right)$, over future horizons with $h \in (1,5,22)$ days ahead presented in Panel A, B, and C, respectively. $\mathcal{ORV}^+$and $\mathcal{ORV}^-$are the option realized semivariances for SPY OTM calls ($K/S = 1.10$) and OTM puts ($K/S = 0.90$). $\mathcal{ORJ}^+$and $\mathcal{ORJ}^-$are the option realized signed jumps for SPY OTM calls ($K/S = 1.10$) and OTM puts ($K/S = 0.90$). RV, is the daily level of realized variances. JV_t is the jump variation over the last day. VRP is the variance risk premium over the previous day. t-stats are reported in parentheses and reflect robust Newey-West standard errors. Adjusted-R^2 are reported in the last row (%). The sample period is from January 11, 2005 to December 31, 2021, at a daily frequency.

Table 8: Predicting Equity VRP with Option Realized Signed Measures

		Call ($K/S=1.10$)		Put ($K/S=0.90$)			Call ($K/S=1.10$)		Put ($K/S=0.90$)			Call ($K/S=1.10$)		Put ($K/S=0.90$)	
	Panel A: $h=1$					Panel B: $h=5$					Panel C: $h=22$				
β_{RV}	-0.054	-0.053	-0.054	-0.053	-0.054	0.015	0.017	0.015	0.016	0.015	0.090	0.091	0.090	0.091	0.090
	(-1.276)	(-1.246)	(-1.284)	(-1.244)	(-1.273)	(0.412)	(0.451)	(0.404)	(0.449)	(0.415)	(3.883)	(3.919)	(3.881)	(3.904)	(3.887)
β_{JV}	0.217	0.218	0.218	0.217	0.218	0.085	0.086	0.085	0.085	0.086	0.044	0.045	0.044	0.045	0.045
	(1.158)	(1.169)	(1.167)	(1.167)	(1.177)	(0.753)	(0.774)	(0.760)	(0.767)	(0.764)	(0.523)	(0.532)	(0.524)	(0.527)	(0.530)
β_{VRP}	0.348	0.346	0.346	0.346	0.345	0.337	0.334	0.336	0.335	0.336	0.252	0.251	0.252	0.251	0.252
	(12.511)	(12.413)	(12.408)	(12.447)	(12.446)	(7.842)	(7.731)	(7.747)	(7.754)	(7.779)	(14.730)	(14.614)	(14.603)	(14.729)	(14.706)
$\beta_{\mathcal{ORV}^+}$		-0.007		-0.031			-0.004		-0.020			-0.002		-0.013	
		(-1.194)		(-2.754)			(-1.015)		(-2.515)			(-0.570)		(-2.921)	
$\beta_{\mathcal{ORV}^-}$		-0.010		0.012			-0.018		-0.001			-0.010		0.004	
		(-1.948)		(1.457)			(-2.972)		(-0.280)			(-2.746)		(1.939)	
$\beta_{\mathcal{ORJ}^+}$			-0.013		-0.050			-0.006		-0.026			-0.001		-0.016
			(-1.676)		(-2.855)			(-1.001)		(-2.531)			(-0.224)		(-3.256)
$\beta_{\mathcal{ORJ}^-}$			0.019		0.003			0.018		-0.003			0.006		-0.006
			(2.292)		(0.288)			(2.152)		(-0.515)			(1.540)		(-1.725)
R^2_{adj}	15.352%	15.387%	15.378%	15.442%	15.471%	14.133%	14.221%	14.153%	14.211%	14.180%	12.925%	12.989%	12.929%	12.986%	12.981%

Notes: This table presents the results of the regression models 20, 23, and 24, where the dependent variable is the individual equity variance risk premium defined as: $VRP_{t+1:t+h} = \frac{1}{h}\left(\mathrm{E}_t^{\mathbb{Q}}\left[RV_{t+1:t+h}\right] - RV_{t+1:t+h}\right)$, over future horizons with $h \in (1, 5, 22)$ days ahead presented in Panel A, B, and C, respectively. $\mathcal{ORV}^+$and $\mathcal{ORV}^-$ are the option realized semivariances for the individual equities OTM calls ($K/S = 1.10$) and OTM puts ($K/S = 0.90$). $\mathcal{ORJ}^+$ and $\mathcal{ORJ}^-$ are the option realized signed jumps for the individual equities OTM calls ($K/S = 1.10$) and OTM puts ($K/S = 0.90$). RV, is the daily level of realized variances. JV_t is the jump variation over the last day. VRP is the variance risk premium over the previous day. t-stats are reported in parentheses and reflect robust Newey-West standard errors. Adjusted-R^2 are reported in the last row (%). The sample period is from January 2, 2004 to December 31, 2021, at a daily frequency.

We now focus on the performance of the option realized signed measures, reported in Tables C3 and C4, for respectively SPY and the individual equities. As shown in Tables C3, we confirm the downside risk channel being the main channel through which our semivariances convey predictive power, that is $\mathcal{ORV}^-$ for calls and $\mathcal{ORV}^+$ for puts. For the signed jumps, again, we uncover their significant predictive information content when decomposed. Their predictive ability is not affected by the additional controls included in the model, and the relevant information is still placed into $\mathcal{ORJ}^-$ for calls and $\mathcal{ORJ}^+$ for puts. The results are corroborated for the individual equities in Table C4.

To conclude, we have shown that even when our model includes additional variables, our option realized (signed) measures still play a significant role in predicting VRP. The information content included in the options realized measures is not contained in other measures of asymmetry or risk extracted from low-frequency options data. The coefficients' sign is preserved and we still confirm the clear downside risk channel through which our signed measures predict the future VRP of both SPY and individual equities.[30]

6 Predicting Excess Returns

Hitherto, we have shown that the option realized measures are good predictors of future RV and VRP, and their information content is neither contained in low- nor high-frequency variance and jump measures. This section investigates the predictive power of the option realized (signed) measures on future excess returns. Predicting equity premium has always been a central topic in financial economics. As a consequence, the literature have identified several factors that explain future equity premium (e.g. Harvey et al., 2016).

Thus, our predictive model considers a number of additional explanatory variables and firm characteristics commonly employed in the literature. These include the weekly reversal (REV) (e.g. Lehmann, 1990; Jegadeesh, 1990), momentum (MoM) (e.g. Jegadeesh and Tit-

[30]The results in terms of predictive power for the option realized (signed) measures remain qualitatively and quantitatively unchanged when we replace the RNS with the $Skew$ (or $SPRD$) in our regressions. For more details about these variables, see Appendix A.

man, 1993), illiquidity (Illiq) (e.g. Amihud, 2002), stock market value (Size) (e.g., Fama and French, 1993), and option volume (OptV) (e.g. Pan and Poteshman, 2006). These variables are computed using data collected from CRSP database. The construction of each of these variables follow standard procedures, as further detailed in Appendix A. We construct the controls for both SPY and the individual equities. Our baseline model is outlined as:

$$R_{t+1:t+h} = \alpha + \beta_{RV} RV_t + \beta_{JV} JV_t + \beta_{IV} IV_t + \beta_{REV} REV_t + \beta_{MoM} MoM_t + \beta_{Illiq} Illiq_t + \beta_{Size} Size_t + \beta_{OptV} OptV_t + \varepsilon_{t+1:t+h}, \quad (25)$$

where $R_{t+1:t+h}$ is the (log) excess return, and we use one-month T-bill rate as a proxy for the risk-free rate; as usual, $h \in (1, 5, 22)$ is our predictive horizon, and for forecasts larger than one day, we cumulate the excess return from $t+1$ to $t+h$ (scaled by the horizon) as in Bollerslev et al. (2009, 2014). RV, JV and IV are the respective past daily realized variance, jump variation and the OptionMetrics ATM 30-day implied volatility, in variance form. For the individual equities, the baseline model is estimated panel regressions with firm fixed effects.[31]

6.1 Option Realized Measures

This section investigates the role of the option realized measures for predicting future excess returns. To do so, we augment equation (25) with the $\mathcal{ORV}$ and $\mathcal{ORJ}$ as follows:

$$R_{t+1:t+h} = \alpha + \mathbf{\Lambda}' \mathbf{\Pi}_t + \beta_{\mathcal{ORV}} \mathcal{ORV}_t + \varepsilon_{t+1:t+h}, \quad (26)$$

$$R_{t+1:t+h} = \alpha + \mathbf{\Lambda}' \mathbf{\Pi}_t + \beta_{\mathcal{ORJ}} \mathcal{ORJ}_t + \varepsilon_{t+1:t+h}, \quad (27)$$

where $\mathcal{ORV}$ and $\mathcal{ORJ}$ are respectively the option realized variance and jump component. $\mathbf{\Pi}$ is the matrix of predictors outlined in equation (25), and $\mathbf{\Lambda}$ is the vector of coefficients.

[31] Our results are qualitatively similar irrespective whether we consider close-to-close or open-to-close returns.

Tables 9 and 10 report in three panels the predictive regression results for SPY and the individual equities. Panels A, B, and C of each table convey the one-day ($h = 1$), one-week ($h = 5$), and one-month ($h = 22$) coefficients and their corresponding robust t-statistics in parentheses. The t-statistics in Table 9 are estimated using Newey-West robust standard errors;[32] for Table 10 the t-statistics are estimated using clustered robust standard errors.

Several conclusions can be drawn from Tables 9 and 10. First, the impact of controls on future excess returns is horizon-dependent. Besides RV, for SPY, and REV and $OptV$ for individual equities, none of the controls are significant across all forecasting horizons. Second, IV shows a very limited predictive power for SPY (individual equities) excess returns at longer (shorter) horizons. By contrast, the option realized variances display a greater predictive power for SPY (individual equities) equity premia at longer (shorter) horizons. Thereby, this finding reaffirms the non-trivial information content of the $\mathcal{ORV}$s, which complements that of low-frequency option implied measures. Third, for SPY, we find that both $\mathcal{ORV}$ significantly predict future excess market return with a negative sign. In addition, we corroborate our previous results suggesting that OTM put $\mathcal{ORV}$ is generally more important than OTM call $\mathcal{ORV}$, as confirmed by a larger and more significant coefficient, e.g. -0.45 (t-stat$= -2.13$) for put $\mathcal{ORV}$ and -0.38 (t-stat$=2.01$) for call $\mathcal{ORV}$ at $h = 22$.

Finally, the negative relationship between future returns and $\mathcal{ORV}$ is in line with the so-called volatility puzzle. For instance, Ang et al. (2006) find that stocks with high sensitivity to volatility lead to lower average returns. The negative relation between volatility and future stock returns first documented by Ang et al. (2006) has also subsequently been called into question by several more recent studies (e.g., Stambaugh et al., 2015; Hou and Loh, 2016). Conversely, some economic theories suggest that volatility should be positively related to expected returns.[33]

[32] We refer to Section 4.1 for more details on the lags for the HAC standard errors.

[33] If investors demand compensation for not being able to diversify risk then agents will demand a premium for holding stocks with high idiosyncratic volatility. For instance, Merton (1987) suggests that in an information-segmented market, firms with larger firm-specific variances require higher average returns to compensate investors for holding imperfectly diversified portfolios. In a behavioral setup, Barberis and Huang (2001) predict that higher idiosyncratic volatility stocks should earn higher expected returns.

Table 9: Predicting SPY Excess Return with Option Realized Measures

		Call ($K/S = 1.10$)		Put ($K/S = 0.90$)			Call ($K/S = 1.10$)		Put ($K/S = 0.90$)			Call ($K/S = 1.10$)		Put ($K/S = 0.90$)	
	Panel A: $h = 1$					Panel B: $h = 5$					Panel C: $h = 22$				
α	−0.006	−0.005	−0.007	−0.004	−0.007	−0.001	0.000	−0.001	0.001	−0.001	0.002	0.003	0.002	0.003	0.001
	(−1.064)	(−0.857)	(−1.147)	(−0.707)	(−1.233)	(−0.187)	(0.024)	(−0.216)	(0.152)	(−0.196)	(0.547)	(0.892)	(0.622)	(1.017)	(0.461)
β_{RV}	−4.831	−4.433	−4.923	−4.224	−5.017	−3.938	−3.598	−3.974	−3.404	−3.952	−1.946	−1.592	−1.892	−1.453	−1.992
	(−2.077)	(−1.897)	(−2.115)	(−1.750)	(−2.153)	(−2.604)	(−2.344)	(−2.630)	(−2.177)	(−2.610)	(−3.177)	(−2.620)	(−3.133)	(−2.347)	(−3.279)
β_{JV}	15.068	15.741	15.070	15.745	15.122	8.994	9.570	8.995	9.590	8.998	−6.505	−5.907	−6.506	−5.956	−6.492
	(0.479)	(0.497)	(0.478)	(0.497)	(0.480)	(0.843)	(0.921)	(0.842)	(0.919)	(0.843)	(−1.543)	(−1.621)	(−1.550)	(−1.588)	(−1.535)
β_{IV}	5.626	5.474	5.714	4.960	5.957	2.006	1.876	2.040	1.420	2.031	1.871	1.736	1.821	1.331	1.954
	(2.079)	(2.036)	(2.104)	(1.737)	(2.153)	(0.760)	(0.718)	(0.775)	(0.534)	(0.760)	(1.600)	(1.524)	(1.569)	(1.123)	(1.642)
β_{REV}	−0.029	−0.030	−0.029	−0.032	−0.028	−0.019	−0.020	−0.019	−0.022	−0.019	−0.002	−0.003	−0.002	−0.005	−0.002
	(−2.205)	(−2.282)	(−2.189)	(−2.417)	(−2.148)	(−2.081)	(−2.181)	(−2.074)	(−2.382)	(−2.096)	(−0.671)	(−1.022)	(−0.702)	(−1.659)	(−0.622)
β_{MoM}	0.002	0.002	0.002	0.002	0.002	0.001	0.000	0.001	0.000	0.001	0.000	0.000	0.000	0.000	0.000
	(1.218)	(1.077)	(1.220)	(1.068)	(1.189)	(0.323)	(0.198)	(0.324)	(0.188)	(0.321)	(0.178)	(−0.013)	(0.177)	(−0.007)	(0.167)
β_{Illiq}	0.681	0.670	0.670	0.763	0.528	1.752	1.742	1.747	1.824	1.740	0.417	0.408	0.424	0.484	0.379
	(0.514)	(0.507)	(0.504)	(0.576)	(0.394)	(1.633)	(1.627)	(1.630)	(1.712)	(1.628)	(0.707)	(0.702)	(0.718)	(0.822)	(0.651)
β_{Size}	0.502	0.402	0.533	0.343	0.580	0.013	−0.073	0.025	−0.127	0.019	−0.190	−0.279	−0.208	−0.319	−0.170
	(1.025)	(0.830)	(1.099)	(0.690)	(1.187)	(0.030)	(−0.170)	(0.057)	(−0.286)	(0.043)	(−0.717)	(−1.043)	(−0.786)	(−1.158)	(−0.632)
β_{OptV}	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(−0.494)	(−0.099)	(−0.553)	(0.008)	(−0.525)	(1.768)	(2.269)	(1.738)	(2.207)	(1.760)	(3.633)	(4.394)	(3.706)	(4.055)	(3.600)
$\beta_{\mathcal{ORV}}$		−0.424		−0.549			−0.363		−0.483			−0.377		−0.445	
		(−1.357)		(−1.154)			(−1.639)		(−1.635)			(−2.009)		(−2.131)	
$\beta_{\mathcal{ORJ}}$			0.753		1.311			0.289		0.099			−0.436		0.327
			(0.640)		(0.899)			(0.495)		(0.138)			(−1.370)		(0.974)
R^2_{adj}	0.458%	0.501%	0.449%	0.485%	0.458%	1.334%	1.487%	1.318%	1.453%	1.311%	4.934%	6.195%	5.024%	5.726%	4.947%

Notes: This table presents the results of the regression models 25, 26, and 27, where the dependent variable is the SPY excess return defined as the SPY (log) excess returns over future horizons with $h \in (1, 5, 22)$ days ahead presented in Panel A, B, and C, respectively. $\mathcal{ORV}$ is the option realized variance for SPY OTM calls ($K/S = 1.10$) and OTM puts ($K/S = 0.90$). $\mathcal{ORJ}$ is the option realized jump component for SPY OTM calls ($K/S = 1.10$) and OTM puts ($K/S = 0.90$). RV, is the daily level of realized variances. JV_t is the jump variation over the last day. RV_t is the past daily realized variance, JV_t is the jump variation over the previous day, IV_t is the ATM 30-day implied volatility (in variance form), REV is the weekly reversal (e.g. Lehmann, 1990; Jegadeesh, 1990), MoM is the medium-term price momentum (see Jegadeesh and Titman, 1993), $Illiq$ is the illiquidity ratio by Amihud (2002), $Size$ is the stock's market value, and $OptV$ is the option (call or put) trading volume (e.g. Pan and Poteshman, 2006). t-stats are reported in parentheses and reflect robust Newey-West standard errors. Adjusted-R^2 are reported in the last row (%). The sample period is from January 11, 2005 to December 31, 2021, at a daily frequency.

Table 10: Predicting Equity Excess Returns with Option Realized Measures

		Call ($K/S = 1.10$)		Put ($K/S = 0.90$)			Call ($K/S = 1.10$)		Put ($K/S = 0.90$)			Call ($K/S = 1.10$)		Put ($K/S = 0.90$)	
	Panel A: $h = 1$					Panel B: $h = 5$					Panel C: $h = 22$				
β_{RV}	−0.127	−0.065	−0.121	−0.025	−0.112	−0.482	−0.454	−0.485	−0.437	−0.481	−0.419	−0.421	−0.425	−0.409	−0.422
	(−0.239)	(−0.120)	(−0.227)	(−0.047)	(−0.211)	(−1.115)	(−1.028)	(−1.116)	(−1.006)	(−1.113)	(−4.978)	(−5.057)	(−4.989)	(−4.908)	(−5.008)
β_{JV}	10.181	10.206	10.190	10.187	10.189	2.919	2.931	2.915	2.922	2.920	−0.006	−0.007	−0.014	−0.005	−0.008
	(2.084)	(2.093)	(2.083)	(2.097)	(2.087)	(1.857)	(1.860)	(1.853)	(1.852)	(1.856)	(−0.014)	(−0.015)	(−0.032)	(−0.012)	(−0.017)
β_{IV}	0.832	0.790	0.826	0.756	0.813	1.454	1.434	1.457	1.420	1.453	0.829	0.831	0.835	0.822	0.833
	(1.294)	(1.222)	(1.286)	(1.179)	(1.271)	(3.411)	(3.322)	(3.400)	(3.309)	(3.406)	(5.044)	(5.018)	(5.045)	(4.905)	(5.040)
β_{REV}	−0.016	−0.016	−0.016	−0.017	−0.016	−0.014	−0.014	−0.014	−0.014	−0.014	−0.004	−0.004	−0.004	−0.004	−0.004
	(−3.267)	(−3.253)	(−3.272)	(−3.365)	(−3.280)	(−4.472)	(−4.462)	(−4.490)	(−4.557)	(−4.470)	(−3.905)	(−3.922)	(−3.936)	(−4.057)	(−3.889)
β_{MoM}	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(−0.298)	(−0.268)	(−0.291)	(−0.234)	(−0.281)	(−0.581)	(−0.570)	(−0.584)	(−0.557)	(−0.579)	(−1.222)	(−1.224)	(−1.233)	(−1.212)	(−1.227)
β_{Illiq}	−0.008	−0.007	−0.008	−0.007	−0.008	−0.008	−0.007	−0.008	−0.007	−0.008	0.007	0.007	0.007	0.008	0.007
	(−0.802)	(−0.772)	(−0.800)	(−0.734)	(−0.778)	(−0.772)	(−0.748)	(−0.778)	(−0.729)	(−0.768)	(1.413)	(1.408)	(1.406)	(1.409)	(1.402)
β_{Size}	−0.010	0.002	−0.006	−0.006	−0.007	−0.082	−0.076	−0.084	−0.080	−0.081	0.018	0.017	0.014	0.018	0.017
	(−0.075)	(0.014)	(−0.044)	(−0.047)	(−0.055)	(−0.490)	(−0.464)	(−0.500)	(−0.483)	(−0.489)	(0.112)	(0.109)	(0.086)	(0.115)	(0.108)
β_{OptV}	−0.001	−0.001	−0.001	−0.001	−0.001	−0.001	−0.001	−0.001	−0.001	−0.001	−0.001	−0.001	−0.001	−0.001	−0.001
	(−1.995)	(−1.991)	(−1.998)	(−1.926)	(−2.002)	(−3.552)	(−3.601)	(−3.539)	(−3.574)	(−3.554)	(−3.328)	(−3.319)	(−3.309)	(−3.306)	(−3.333)
$\beta_{\mathcal{ORV}}$		−0.133		−0.312			−0.061		−0.138			0.005		−0.032	
		(−1.695)		(−2.248)			(−1.392)		(−2.254)			(0.216)		(−0.958)	
$\beta_{\mathcal{ORJ}}$			−0.072		−0.287			0.037		−0.019			0.069		0.062
			(−0.652)		(−1.806)			(0.392)		(−0.154)			(1.429)		(1.389)
R^2_{adj}	0.448%	0.452%	0.446%	0.464%	0.449%	0.761%	0.764%	0.759%	0.771%	0.759%	1.072%	1.071%	1.079%	1.075%	1.074%

Notes: This table presents the results of the regression models 25, 26, and 27, where the dependent variable is the individual equity's excess return defined as the equity (log) excess returns over future horizons with $h \in (1, 5, 22)$ days ahead presented in Panel A, B, and C, respectively. $\mathcal{ORV}$ is the option realized variance for the individual equities OTM calls ($K/S = 1.10$) and OTM puts ($K/S = 0.90$). $\mathcal{ORJ}$ is the option realized jump component for the individual equities OTM calls ($K/S = 1.10$) and OTM puts ($K/S = 0.90$). RV, is the daily level of realized variances. JV_t is the jump variation over the last day. RV_t is the past daily realized variance, JV_t is the jump variation over the previous day, IV_t is the ATM 30-day implied volatility (in variance form), REV is the weekly reversal (e.g. Lehmann, 1990; Jegadeesh, 1990), MoM is the medium-term price momentum (see Jegadeesh and Titman, 1993), $Illiq$ is the illiquidity ratio by Amihud (2002), $Size$ is the stock's market value, and $OptV$ is the option (call or put) trading volume (e.g. Pan and Poteshman, 2006). The models are estimated in a panel framework with firms fixed effect. t-stats are reported in parentheses and reflect robust Newey-West standard errors. Adjusted-R^2 are reported in the last row (%). The sample period is from 11th January 2005 to 31st December 2021, at a daily frequency. The sample period is from January 2, 2004 to December 31, 2021, at a daily frequency.

We are aware of the many papers trying to explain the puzzle, with each paper proposing a different economic mechanism relating volatility to future equity returns (e.g. Hou and Loh, 2016). To explain our findings, we put forward the following possible channel. Time-varying volatility will generate changes in investment opportunities, therefore changes in expected future returns which will eventually change the risk-return trade-off. For instance, risk-averse agents reduce consumptions/investments to increase precautionary savings in the presence of higher uncertainty about the stock market, therefore we observe a decrease in future returns.

6.2 Option Realized Signed Measures

This section exploits the information content of the option realized signed measures. In fact, recent advances in the asset pricing literature have documented richer incremental information sets from decomposed measures of risk (e.g. Ang et al., 2006; Farago and Tédongap, 2018; Bollerslev et al., 2020). Therefore, based on these studies and our previous findings, our prior is that the option signed measures contain enriched information compared to the aggregate measures that may further explain future excess returns.

To assess the predictive ability of the option realized signed measures, we rely on the following models:

$$R_{t+1:t+h} = \alpha + \mathbf{\Lambda}'\mathbf{\Pi}_t + \beta_{\mathcal{ORV}^+}\mathcal{ORV}^+{}_t + \beta_{\mathcal{ORV}^-}\mathcal{ORV}^-{}_t + \varepsilon_{t+1:t+h}, \tag{28}$$

$$R_{t+1:t+h} = \alpha + \mathbf{\Lambda}'\mathbf{\Pi}_t + \beta_{\mathcal{ORJ}^+}\mathcal{ORJ}^+{}_t + \beta_{\mathcal{ORJ}^-}\mathcal{ORJ}^-{}_t + \varepsilon_{t+1:t+h}, \tag{29}$$

where $\mathcal{ORV}^+$ and $\mathcal{ORV}^-$ are respectively the positive and negative option realized semivariance, and the $\mathcal{ORJ}^+$ and $\mathcal{ORJ}^-$ are the positive and negative option realized signed jumps. The remaining variables are defined as in equation (25).

Tables 11 and 12 report the results for SPY and the individual equities respectively. The structure of the tables are identical to that outlined for Tables 9 and 10. The controls display a very similar behavior to that documented in Section 6.1.

Turning our attention to the SPY results (Table 11), we observe that the option realized signed measures are only significant at longer horizons. In particular, the OTM put $\mathcal{ORV}^+$ and $\mathcal{ORJ}^+$ significantly and negatively predict future SPY excess returns both at the weekly and monthly horizons. Similarly, the OTM call $\mathcal{ORV}^-$ and $\mathcal{ORJ}^-$ are also found significant in predicting future SPY excess returns, albeit only at $h = 22$. These findings are consistent with the prevailing view in finance about the evidence for a stronger longer-horizon stock return predictability (e.g. Campbell, 2000). In fact, Stambaugh (1999) and Andersen et al. (2020) argue that at shorter horizons the unpredictable and noisy component of returns dominates, whereas the predictable component emerges as the holding period increases.

Moreover, we confirm the superior information content placed within the put options with respect to the stock market index. Also, the predictability of the option realized measures appears to be flowing through a downside risk channel, namely through the negative (positive) risk components of OTM calls (puts). For the option realized variances the coefficients' sign is found to be negative implying that an increase in the negative (positive) $\mathcal{ORV}$ component of calls (puts) leads to a decrease in the future SPY excess return. Overall this relationship is, again, consistent with a volatility puzzle hypothesis (e.g. Ang et al., 2006), suggesting, as a plausible rationale, that risk-averse agents reduce consumption/investments to increase precautionary savings in the presence of higher uncertainty about the stock market.

With respect to the signed jumps, first of all, we notice that when they are decomposed, they improve their information content becoming significant in explaining the future SPY excess returns at longer horizons. Their predictive power is, again, mostly placed in the $\mathcal{ORJ}^-$ for calls while in the $\mathcal{ORJ}^+$ for puts. For the put options, a positive jump will lead to a decrease in the future SPY excess returns, while for calls we find that an increase, in absolute terms, in $\mathcal{ORJ}^-$ will command a decrease in the future SPY excess return.

The further incremental information uncovered when decomposing the option realized jumps directly translates in a better model fit. To illustrate, we consider the SPY results at the month horizon, where the R^2_{adj} of the baseline model equals 4.93%, while the R^2_{adj} of the models augmented with the option realized signed jumps from OTM calls and puts are equal to 5.86% and 5.82%, respectively. These improvements represent an increase of almost 1% relative to both the baseline model and the models augmented by the $\mathcal{ORJ}$.

Overall, we confirm an incremental information content with respect to the decomposed option realized measures compared to other low- or high-frequency variables. For instance, we detect a strong significant role for the IV and reversal up to the weekly horizon. However, these two variables are not found to be significant at the monthly horizon when the semivariances and signed jumps become significant.

In Table 12, we present the results with respect to the predictability of the individual equities future excess returns. In this case, we detect mixed results in terms of the significance of the option realized semivariances. For instance, we uncover a significant role for the $\mathcal{ORV}^-$ ($\mathcal{ORV}^+$) for calls (puts) at the daily and weekly (weekly and monthly) horizons. Hence, we still confirm the greater information content placed in the negative (positive) semivariance for calls (puts), whenever they emerge to be significant. The coefficient of the semivariance is again, found to be negative in line with the rationale presented for the stock market index. When it comes to signed jumps for individual equities, we notice that the jump component becomes significant in explaining future individual equities' excess returns, especially at the monthly horizon. Also in this case, the significance is placed in the $\mathcal{ORJ}^+$ for puts and $\mathcal{ORJ}^-$ for calls.

Table 11: Predicting SPY Excess Return with Option Realized Signed Measures

		Call ($K/S=1.10$)		Put ($K/S=0.90$)			Call ($K/S=1.10$)		Put ($K/S=0.90$)			Call ($K/S=1.10$)		Put ($K/S=0.90$)	
	Panel A: $h=1$					Panel B: $h=5$					Panel C: $h=22$				
α	-0.006	-0.005	-0.006	-0.004	-0.007	-0.001	0.000	-0.001	0.001	0.001	0.002	0.003	0.002	0.003	0.003
	(-1.064)	(-0.827)	(-1.071)	(-0.617)	(-1.181)	(-0.187)	(0.051)	(-0.106)	(0.150)	(0.103)	(0.547)	(0.942)	(0.707)	(1.036)	(0.912)
β_{RV}	-4.831	-4.501	-4.926	-3.875	-4.905	-3.938	-3.585	-3.828	-3.522	-3.773	-1.946	-1.614	-1.869	-1.504	-1.796
	(-2.077)	(-1.925)	(-2.096)	(-1.611)	(-2.057)	(-2.604)	(-2.323)	(-2.524)	(-2.240)	(-2.460)	(-3.177)	(-2.632)	(-3.168)	(-2.413)	(-2.982)
β_{JV}	15.068	15.601	14.757	15.614	14.767	8.994	9.580	9.418	9.404	9.617	-6.505	-5.961	-6.162	-6.117	-5.983
	(0.479)	(0.492)	(0.466)	(0.498)	(0.465)	(0.843)	(0.924)	(0.894)	(0.902)	(0.917)	(-1.543)	(-1.661)	(-1.585)	(-1.606)	(-1.507)
β_{IV}	5.626	5.527	5.724	4.683	5.796	2.006	1.864	1.878	1.505	1.657	1.871	1.753	1.770	1.364	1.578
	(2.079)	(2.053)	(2.080)	(1.642)	(2.053)	(0.760)	(0.712)	(0.712)	(0.567)	(0.625)	(1.600)	(1.546)	(1.523)	(1.157)	(1.358)
β_{REV}	-0.029	-0.031	-0.029	-0.032	-0.028	-0.019	-0.020	-0.020	-0.023	-0.022	-0.002	-0.004	-0.003	-0.005	-0.004
	(-2.205)	(-2.330)	(-2.223)	(-2.389)	(-2.064)	(-2.081)	(-2.203)	(-2.131)	(-2.437)	(-2.362)	(-0.671)	(-1.260)	(-1.006)	(-1.871)	(-1.315)
β_{MoM}	0.002	0.002	0.002	0.002	0.002	0.001	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(1.218)	(1.065)	(1.232)	(0.992)	(1.231)	(0.323)	(0.186)	(0.266)	(0.200)	(0.281)	(0.178)	(-0.034)	(0.081)	(-0.007)	(0.127)
β_{Illiq}	0.681	0.672	0.634	0.804	0.616	1.752	1.752	1.852	1.821	1.883	0.417	0.413	0.521	0.487	0.526
	(0.514)	(0.508)	(0.481)	(0.605)	(0.464)	(1.633)	(1.638)	(1.734)	(1.713)	(1.769)	(0.707)	(0.709)	(0.886)	(0.829)	(0.886)
β_{Size}	0.502	0.387	0.511	0.304	0.565	0.013	-0.084	-0.021	-0.128	-0.112	-0.190	-0.292	-0.231	-0.325	-0.290
	(1.025)	(0.801)	(1.034)	(0.613)	(1.148)	(0.030)	(-0.196)	(-0.049)	(-0.290)	(-0.255)	(-0.717)	(-1.091)	(-0.874)	(-1.178)	(-1.077)
β_{OptV}	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(-0.494)	(-0.062)	(-0.549)	(0.151)	(-0.668)	(1.768)	(2.295)	(2.020)	(2.240)	(2.079)	(3.633)	(4.389)	(4.192)	(4.144)	(3.994)
$\beta_{\mathcal{ORV}^+}$		-0.129		-0.150			-0.336		-0.852			-0.231		-0.691	
		(-0.220)		(-0.197)			(-1.078)		(-1.738)			(-1.240)		(-2.700)	
$\beta_{\mathcal{ORV}^-}$		-0.758		-1.472			-0.448		-0.082			-0.579		-0.238	
		(-1.199)		(-1.487)			(-1.050)		(-0.163)			(-2.245)		(-0.945)	
$\beta_{\mathcal{ORJ}^+}$			0.449		0.708			-0.617		-1.367			-0.503		-1.060
			(0.487)		(0.665)			(-1.418)		(-1.991)			(-1.822)		(-2.671)
$\beta_{\mathcal{ORJ}^-}$			-0.004		-0.305			0.542		0.695			0.776		0.643
			(-0.005)		(-0.191)			(0.925)		(0.983)			(2.476)		(1.543)
R^2_{adj}	0.458%	0.486%	0.655%	0.522%	0.658%	1.334%	1.474%	1.608%	1.455%	1.690%	4.934%	6.281%	5.862%	5.821%	5.815%

Notes: This table presents the results of the regression models 25, 28, and 29, where the dependent variable is the SPY excess return defined as the SPY (log) excess returns over future horizons with $h \in (1, 5, 22)$ days ahead presented in Panel A, B, and C, respectively. $\mathcal{ORV}^+$and $\mathcal{ORV}^-$are the option realized semivariances for SPY OTM calls ($K/S = 1.10$) and OTM puts ($K/S = 0.90$). $\mathcal{ORJ}^+$and $\mathcal{ORJ}^-$are the option realized signed jumps for SPY OTM calls ($K/S = 1.10$) and OTM puts ($K/S = 0.90$). RV, is the daily level of realized variances. JV_t is the jump variation over the last day. RV_t is the past daily realized variance, JV_t is the jump variation over the previous day, IV_t is the ATM 30-day implied volatility (in variance form), REV is the weekly reversal (e.g. Lehmann, 1990; Jegadeesh, 1990), MoM is the medium-term price momentum (see Jegadeesh and Titman, 1993), $Illiq$ is the illiquidity ratio by Amihud (2002), $Size$ is the stock's market value, and $OptV$ is the option (call or put) trading volume (e.g. Pan and Poteshman, 2006). t-stats are reported in parentheses and reflect robust Newey-West standard errors. Adjusted-R^2 are reported in the last row (%). The sample period is from January 11, 2005 to December 31, 2021, at a daily frequency.

Table 12: Predicting Equity Excess Returns with Option Realized Signed Measures

		Call ($K/S = 1.10$)		Put ($K/S = 0.90$)			Call ($K/S = 1.10$)		Put ($K/S = 0.90$)			Call ($K/S = 1.10$)		Put ($K/S = 0.90$)	
	Panel A: $h = 1$					Panel B: $h = 5$					Panel C: $h = 22$				
β_{RV}	-0.127	-0.077	-0.135	-0.052	-0.129	-0.482	-0.452	-0.487	-0.448	-0.466	-0.419	-0.417	-0.420	-0.416	-0.414
	(-0.239)	(-0.143)	(-0.251)	(-0.096)	(-0.242)	(-1.115)	(-1.025)	(-1.116)	(-1.025)	(-1.076)	(-4.978)	(-4.954)	(-4.948)	(-4.959)	(-4.908)
β_{JV}	10.181	10.181	10.166	10.193	10.186	2.919	2.922	2.912	2.925	2.927	-0.006	-0.007	-0.008	-0.005	-0.002
	(2.084)	(2.090)	(2.082)	(2.093)	(2.085)	(1.857)	(1.856)	(1.856)	(1.856)	(1.860)	(-0.014)	(-0.016)	(-0.019)	(-0.011)	(-0.004)
β_{IV}	0.832	0.800	0.833	0.774	0.835	1.454	1.434	1.457	1.428	1.435	0.829	0.828	0.830	0.827	0.823
	(1.294)	(1.231)	(1.281)	(1.197)	(1.283)	(3.411)	(3.319)	(3.384)	(3.307)	(3.357)	(5.044)	(4.978)	(5.019)	(4.939)	(4.972)
β_{REV}	-0.016	-0.017	-0.017	-0.017	-0.017	-0.014	-0.014	-0.014	-0.014	-0.014	-0.004	-0.004	-0.004	-0.004	-0.004
	(-3.267)	(-3.428)	(-3.451)	(-3.372)	(-3.326)	(-4.472)	(-4.565)	(-4.588)	(-4.566)	(-4.538)	(-3.905)	(-4.034)	(-4.066)	(-4.100)	(-4.083)
β_{MoM}	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(-0.298)	(-0.261)	(-0.294)	(-0.249)	(-0.290)	(-0.581)	(-0.564)	(-0.580)	(-0.559)	(-0.565)	(-1.222)	(-1.220)	(-1.222)	(-1.211)	(-1.209)
β_{Illiq}	-0.008	-0.007	-0.008	-0.007	-0.008	-0.008	-0.007	-0.008	-0.007	-0.008	0.007	0.008	0.007	0.007	0.008
	(-0.802)	(-0.768)	(-0.799)	(-0.750)	(-0.804)	(-0.772)	(-0.742)	(-0.775)	(-0.742)	(-0.752)	(1.413)	(1.411)	(1.413)	(1.401)	(1.415)
β_{Size}	-0.010	-0.001	-0.012	-0.009	-0.009	-0.082	-0.076	-0.083	-0.081	-0.082	0.018	0.018	0.017	0.018	0.018
	(-0.075)	(-0.008)	(-0.089)	(-0.070)	(-0.068)	(-0.490)	(-0.464)	(-0.493)	(-0.491)	(-0.495)	(0.112)	(0.115)	(0.110)	(0.115)	(0.113)
β_{OptV}	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001
	(-1.995)	(-1.995)	(-2.004)	(-1.931)	(-1.989)	(-3.552)	(-3.604)	(-3.552)	(-3.564)	(-3.580)	(-3.328)	(-3.301)	(-3.320)	(-3.307)	(-3.272)
$\beta_{\mathcal{ORV}^+}$		0.148		-0.283			0.043		-0.161			0.025		-0.083	
		(1.052)		(-1.449)			(0.836)		(-1.770)			(1.005)		(-2.610)	
$\beta_{\mathcal{ORV}^-}$		-0.473		-0.182			-0.221		-0.044			-0.045		0.065	
		(-2.306)		(-0.717)			(-2.036)		(-0.405)			(-1.326)		(1.493)	
$\beta_{\mathcal{ORJ}^+}$			0.200		-0.139			0.091		-0.206			0.030		-0.126
			(1.287)		(-0.610)			(1.663)		(-1.694)			(1.239)		(-3.012)
$\beta_{\mathcal{ORJ}^-}$			0.461		-0.205			0.159		0.129			0.062		-0.018
			(2.250)		(-0.628)			(1.446)		(0.953)			(2.202)		(-0.428)
R^2_{adj}	0.448%	0.460%	0.454%	0.456%	0.446%	0.761%	0.770%	0.762%	0.767%	0.763%	1.072%	1.073%	1.074%	1.078%	1.083%

Notes: This table presents the results of the regression models 25, 28, and 29, where the dependent variable is the individual equity's excess return defined as the equity (log) excess returns over future horizons with $h \in (1, 5, 22)$ days ahead presented in Panel A, B, and C, respectively. $\mathcal{ORV}^+$and $\mathcal{ORV}^-$are the option realized semivariances for the individual equities OTM calls ($K/S = 1.10$) and OTM puts ($K/S = 0.90$). $\mathcal{ORJ}^+$and $\mathcal{ORJ}^-$are the option realized signed jumps for individual equities OTM calls ($K/S = 1.10$) and OTM puts ($K/S = 0.90$). RV, is the daily level of realized variances. JV_t is the jump variation over the last day. RV_t is the past daily realized variance, JV_t is the jump variation over the previous day, IV_t is the ATM 30-day implied volatility (in variance form), REV is the weekly reversal (e.g. Lehmann, 1990; Jegadeesh, 1990), MoM is the medium-term price momentum (see Jegadeesh and Titman, 1993), $Illiq$ is the illiquidity ratio by Amihud (2002), $Size$ is the stock's market value, and $OptV$ is the option (call or put) trading volume (e.g. Pan and Poteshman, 2006). t-stats are reported in parentheses and reflect robust Newey-West standard errors. Adjusted-R^2 are reported in the last row (%). The sample period is from January 2, 2004 to December 31, 2021, at a daily frequency.

6.3 Robustness Checks

To further assess the information content of the option realized measures, we perform a robustness analysis that considers various popular equity premium predictors beyond those employed in the equation 25. To this end, we focus on predictors computed from historical returns and option data that are commonly associated with asymmetric behavior of stock prices and option distributions, therefore improving the completeness of our model. We consider the VRP as defined in Section 5 (e.g., Bollerslev et al., 2009; Bekaert and Hoerova, 2014), implied volatility skew (Skew) (Xing et al., 2010), volatility spread (SPRD) (Bali and Hovakimian, 2009), the maximum return (MAX), the minimum return (Min) of Bali et al. (2011),[34] the risk-neutral variance (RNV) and risk-neutral skewness (RNS) of Bakshi et al. (2003), the jump tail index (JTI) of Du and Kapadia (2012), and the left tail variation of Bollerslev et al. (2015).[35] These measures are described in more detail in Appendix A.

Given that, at shorter horizons, equity premia are mainly driven by their noisy component (e.g. Stambaugh, 1999; Andersen et al., 2020), we perform our robustness exercise on monthly predictive regressions. The additional results are reported in Appendix C from Table C5 to C12. Due to the larger number of variables adopted in this robustness exercise, we present separate tables for calls and puts. Starting with the stock market index, we find that the $\mathcal{ORV}$ is still found to be significant for both calls and puts in predicting the SPY future excess return at the monthly horizon (Tables C5 and C6). On the other hand, we confirm the absence of predictive information for the aggregate $\mathcal{ORJ}$. Moreover, among the new adopted controls only the VRP, Min and the LTV are significant predictors of monthly excess returns. It is interesting to note that both the JTI and the LTV predict future returns with the negative sign, albeit the JTI is insignificant. The negative sign in the coefficient of these measures is in line with that found in the option realized measures. A

[34] Since we carry out the robustness exercise focusing on the monthly horizon ($h = 22$), we compute the monthly Max and Min measures. However, our results are robust to the inclusion of weekly Max and Min.

[35] While we compute controls for both SPY and the individual equities, we only consider the left tail variation for the index obtained from www.tailindex.com. We refrain from computing the LTV for individual equities as we identify many days with missing observations due to the lack of available data.

plausible rationale for this finding is related to the fact that the IV is mainly driven by the diffusive component, whereas the JTI, LTV and the $\mathcal{ORV}$ also contain information related to the jump component explaining the common sign.[36] For the individual equities, from Tables C7 and C8, we confirm the finding that the option realized measures show no predictive power for future excess returns at the monthly horizon when considered as aggregates.

On the other hand, Tables C9 and C10 show that despite controlling for additional variables the role of the option realized semivariances, namely $\mathcal{ORV}^-$ for calls and $\mathcal{ORV}^+$ for puts, hold significant for SPY. The role of the stock market index signed jumps also emerges as significant with the information content again placed mostly in the negative (positive) component for calls (puts) consistent with a downside risk channel. Finally, in Tables C11 and C12, we reaffirm the main findings for individual equities even after controlling for additional predictors.

To conclude, we find that our option realized measures contain important information not contained in any other high- or low-frequency common predictors. We generally uncover a strong significant role for the options realized measures at the monthly horizon and when these are decomposed according to the returns' sign. Augmenting our baseline model with additional variables commonly associated with equity predictability (e.g., VRP and LTV) does not affect the predictive power of our measures. Finally, we confirm that the majority of the information content of our measures is included in the negative (positive) risk component of calls (puts).

7 Conclusion

The information enclosed in options markets is widely known to enrich the predictability of the financial markets and to provide a refined understanding of asset prices. In this paper, we exploit the increasing availability of high-frequency option data as well as high-

[36] Bollerslev et al. (2015) find a positive relationship between future excess return and the LTV. Please note that we have a different sample period and we only overlap for about 50% of our sample.

frequency econometric techniques to more accurately understand and measure the real-time information flow regarding investors' preferences and the joint dynamics between the realized and expected asset prices.

We propose option realized measures related to the options variance and jump component, which can be seen as new "observable quantities" that summarize the information of high-frequency option data. In specific, we show that these measures capture jumps that are related to both the underlying asset and underlying risk factor. In addition, we also propose option realized semivariances and signed jumps reflecting investors' preferences and risk appetite enclosed in the sign of the high-frequency option returns. These measures successfully enhance the understanding of the joint dynamics between options and the underlying asset, and are able to capture the downside and upside risk of option contracts.

We show that these measures contain non-trivial information that predicts future RV and VRP of both the stock market index and individual equities. Specifically, the incremental information of the signed option realized measures appears to be placed mainly into the negative (positive) semivariances and jumps of OTM call (put) options. This result is in line with a downside risk channel, as the call (put) option moves in the same (opposite) direction of the underlying asset. Thereby, the downside risk of a call (put) contract is captured by the negative (positive) option realized semivariances or signed jumps.

Finally, we uncover a significant role for the option realized signed measures to predict monthly equity premia. These findings are robust even after controlling for a vast number of common equity predictors. The option realized measures capture the joint variation between the options and underlying returns, which transmit to the predicted quantities through an investors' downside risk channel consistent across options' moneyness.

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Appendices

A Controls Definitions

Our empirical investigations rely on the following explanatory variables and firm characteristics.

- Reversal (REV): following Jegadeesh (1990) and Lehmann (1990), the short-term reversal variable is defined as the weekly return over the previous week from Tuesday to Monday.

- Momentum (MoM): following Jegadeesh and Titman (1993), the momentum variable at the end of day t is defined as the compound gross return from day $t-252$ through day $t-21$, skipping the short-term reversal month.

- Illiquidity (Illiq): following Amihud (2002) the illiquidity for stock i at the end of day t is measured as the average daily ratio of the absolute stock return to the dollar trading volume from day $t-4$ through day t:

$$\text{Illiq}_{i,t} = \frac{1}{N}\sum_{d}\left(\frac{|r_{i,d}|}{\text{volume }_{i,d} \times \text{ price }_{i,d}}\right),$$

  where volume $_{i,d}$ is the daily trading volume, $\text{price}_{i,d}$ is the daily price, and other variables are as previously defined. We further transform the illiquidity measure by its natural logarithm to reduce skewness.

- Firm's market value (Size): following Fama and French (1993), a firm's size is measured by its market value of equity, that is, the product of the closing price and the number of shares outstanding (in millions of dollars). Market equity is updated daily and is used to explain returns over the subsequent week.

- Total Option Volume (OptV): the measure of total option volume as proxy for the total trading activity in the options market for each stock in the previous day (e.g. Pan and Poteshman, 2006).

- Variance Risk Premium (VRP): we compute the variance risk premium as a short position in a variance swap, namely, as the difference between risk neutral and physical expectations of returns (e.g. Bollerslev et al., 2009; Bekaert and Hoerova, 2014).

- Implied Volatility Skew (Skew): following Conrad et al. (2013) and Xing et al. (2010), we define the implied volatility skew as the difference between the out-of-the-money put implied volatility (with delta of 0.20) and the average of the at-the-money call and put implied volatilities (with deltas of 0.50), both using maturities of 30 days.

- Volatility Spread (SPRD): the realized-implied volatility spread is computed as the difference between monthly realized volatility and the average of the at-the-money call and put implied volatilities, using options with a delta of 0.50 and maturity of 30 days as in Goyal and Saretto (2009).

- Maximum daily return (Max): the Max variable is defined as the largest total daily raw return observed over the previous month (see Bali et al., 2011).
- Minimum daily return (Min): the Min variable is defined as the smallest total daily raw return observed over the previous month (see Bali et al., 2011).
- Risk-Neutral Variance (RNV): the RNV is the Bakshi et al. (2003) risk-neutral variance extracted model-free from options by considering a volatility contract that simultaneously involves a long position in out of the money calls and a long position in out of the money puts.
- Risk-Neutral Skewness (RNS): the RNS is the Bakshi et al. (2003) risk-neutral skewness extracted model-free from options by considering a cubic contract that simultaneously involves a long position in out of the money calls and a short position in out of the money puts.
- Jump Tail Index (JTI): the jump tail index proposed by Du and Kapadia (2012) constructed from a portfolio of risk-reversals using 30-day index options and measuring time variations in the intensity of return jumps.
- Left Tail Variation (LTV): the left tail variation proposed by Bollerslev et al. (2015) is an option implied measure of short-horizon downside tail risk obtained from short-dated OTM put options. The measure is obtained from www.tailindex.com.

B Option Quadratic Variation

To derive the option quadratic variation (OQV) outlined in equation (6), we assume that $o_t \equiv \log(O_t)$, where $O_t \equiv O_{t,k,\tau}(S_t, X_t)$ is the option price at time t, is twice continuously differentiable. Thus, Itô's lemma for semimartingale processes can be used to derive the OQV as follows (see, Proposition 8.19 in Cont and Tankov, 2003):

$$
\begin{aligned}
o_t(S_t, X_t) - o_0(S_0, X_0) = & \int_0^t \frac{\partial o_u}{\partial u}(S_u, X_u) du + \int_0^t \frac{\partial o_u}{\partial s}(S_{u-}, X_{u-}) \, dS_u + \int_0^t \frac{\partial o_u}{\partial x}(S_{u-}, X_{u-}) \, dX_u \\
& + \frac{1}{2} \int_0^t \frac{\partial^2 o_u}{\partial s^2}(S_{u-}, X_{u-}) d \left[S, S\right]_u^c + \frac{1}{2} \int_0^t \frac{\partial^2 o_u}{\partial x^2}(S_{u-}, X_{u-}) d \left[X, X\right]_u^c \\
& + \int_0^t \frac{\partial o_u}{\partial sx}(S_{u-}, X_{u-}) d \left[S, X\right]_u^c \\
& + \sum_{0 \le u \le t} \left[o_u(S_u, X_u) - (o_u(S_{u-}, X_{u-}))^+ + o_u(S_u, X_u) - (o_u(S_{u-}, X_{u-}))^- \right] \\
& - \sum_{o \le u \le t} \left[\frac{\partial o_u}{\partial s}(S_{u-}, X_{u-})(S_u - S_{u-})^+ + \frac{\partial o_u}{\partial s}(S_{u-}, X_{u-})(S_u - S_{u-})^- \right] \\
& - \sum_{o \le u \le t} \left[\frac{\partial o_u}{\partial x}(S_{u-}, X_{u-})(X_u - X_{u-})^+ + \frac{\partial o_u}{\partial x}(S_{u-}, X_{u-})(X_u - X_{u-})^- \right],
\end{aligned}
$$

where $(\cdot)^+$ and $(\cdot)^-$ denote respectively the positive and negative jumps.

Replacing equations (1) and (2), we get:

$$
\begin{aligned}
o_t(S_t, X_t) - o_0(S_0, X_0) = & \int_0^t \frac{\partial o_u}{\partial u}(S_{u-}, X_{u-}) du \\
& + \int_0^t \frac{\partial o_u}{\partial s}(S_{u-}, X_{u-}) \left[\mu_S(X_{u-}) du + \sum_{i=1}^m \sigma_{S,i}(X_{u-}) dW_{i,u} + dJ_{S,u}^+ + dJ_{S,u}^- \right] \\
& + \int_0^t \frac{\partial o_u}{\partial x}(S_{u-}, X_{u-}) \left[\mu_X(X_{u-}) du + \sum_{i=1}^m \sigma_{X,i}(X_{u-}) dW_{i,u} + dJ_{X,u}^+ + dJ_{X,u}^- \right] \\
& + \frac{1}{2} \int_0^t \frac{\partial^2 o_u}{\partial s^2}(S_{u-}, X_{u-}) \sum_{i=1}^m \sigma_{S,i}^2(X_{u-}) du + \frac{1}{2} \int_0^t \frac{\partial^2 o_u}{\partial x^2}(S_{u-}, X_{u-}) \sum_{i=1}^m \sigma_{X,i}^2(X_{u-}) du \\
& + \int_0^t \sum_{i=1}^m \frac{\partial o_u}{\partial sx}(S_{u-}, X_{u-}) \sigma_{S,i}(X_{u-}) \sigma_{X,i}(X_{u-}) du \\
& + \sum_{0 \le u \le t} \left(o_u(S_{u-}, X_{u-}) - o_u(S_{u-}, X_{u-})^+ \right) + \sum_{0 \le u \le t} \left(o_u(S_{u-}, X_{u-}) - o_u(S_{u-}, X_{u-})^- \right) \\
& - \int_0^t \frac{\partial o_u}{\partial s}(S_{u-}, X_{u-}) dJ_{S,u}^+ - \int_0^t \frac{\partial o_u}{\partial s}(S_{u-}, X_{u-}) dJ_{S,u}^- \\
& - \int_0^t \frac{\partial o_u}{\partial x}(S_{u-}, X_{u-}) dJ_{X,u}^+ - \int_0^t \frac{\partial o_u}{\partial x}(S_{u-}, X_{u-}) dJ_{X,u}^-.
\end{aligned}
$$

Rearranging terms yields:

$$
\begin{aligned}
&o_t(S_t, X_t) - o_0(S_0, X_0) = \\
&= \int_0^t \left[\begin{array}{c} \dfrac{\partial o_u}{\partial u}(S_u, X_u) + \frac{\partial o_u}{\partial s}(S_{u-}, X_{u-})\mu_S(X_{u-}) + \frac{\partial o_u}{\partial x}(S_{u-}, X_{u-})\mu_X(X_{u-}) \\ + \sum_{i=1}^m \left(\frac{1}{2}\frac{\partial^2 o_u}{\partial s^2}(S_{u-}, X_{u-})\sigma_{S,i}^2(X_{u-}) + \frac{1}{2}\frac{\partial^2 o_u}{\partial x^2}(S_{u-}, X_{u-})\sigma_{X,i}^2(X_{u-}) \right. \\ \left. + \frac{\partial^2 o_u}{\partial sx}(S_u, X_u)\sigma_{S,i}(X_{u-})\sigma_{X,i}(X_{u-}) \right) \end{array} \right] du \\
&+ \sum_{i=1}^m \int_0^t \frac{\partial o_u}{\partial s}(S_{u-}, X_{u-})\sigma_{S,i}(X_{u-}) dW_{i,u} + \sum_{i=1}^m \int_0^t \frac{\partial o_u}{\partial x}(S_{u-}, X_{u-})\sigma_{X,i}(X_{u-}) dW_{i,u} \\
&+ \sum_{0 \le u \le t} \left(o_u(S_u, X_u) - o_u(S_{u-}, X_{u-}) \right)^+ + \sum_{0 \le u \le t} \left(o_u(S_u, X_u) - o_u(S_{u-}, X_{u-}) \right)^- .
\end{aligned}
$$

Finally, the option quadratic variation is given by the following expression:[37]

$$
\begin{aligned}
[o, o]_t = &\sum_{i=1}^m \int_0^t \left(\frac{\partial o_u}{\partial s}(S_u, X_u) \right)^2 \sigma_{S,i}^2(X_{u-}) du + \sum_{i=1}^m \int_0^t \left(\frac{\partial o_u}{\partial x}(S_u, X_u) \right)^2 \sigma_{X,i}^2(X_{u-}) du \\
&+ 2 \sum_{i=1}^m \int_0^t \left(\frac{\partial o_u}{\partial s}(S_u, X_u) \right) \left(\frac{\partial o_u}{\partial x}(S_u, X_u) \right) \sigma_{S,i}(X_{u-}) \sigma_{X,i}(X_{u-}) du \\
&+ \sum_{0 \le u \le t} \left[\left(o_u(S_u, X_u) - o_u(S_{u-}, X_{u-}) \right)^+ \right]^2 + \sum_{0 \le u \le t} \left[\left(o_u(S_u, X_u) - o_u(S_{u-}, X_{u-}) \right)^- \right]^2 .
\end{aligned}
$$

□

[37] We have purposely omitted $\frac{1}{O_u^2(S_{u-}, X_{u-})}$ from the three elements of the diffusive component. This term is obtained by taking the derivative of O_u w.r.t. s and x, and its quadratic form arises because of the quadratic variation.

C Additional Results and Robustness Checks

Table C1: Predicting SPY Variance Risk-Premium with Option Realized Measures

	Call ($K/S = 1.10$)						Put ($K/S = 0.90$)					
	Panel A: $h = 1$											
β_0	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(3.972)	(3.486)	(3.277)	(3.059)	(1.464)	(1.164)	(4.241)	(3.555)	(3.509)	(3.084)	(2.279)	(1.155)
β_{IV}	−0.048	−0.051	−0.056	−0.060	0.281	0.239	−0.035	−0.052	−0.044	−0.061	0.319	0.233
	(−0.610)	(−0.661)	(−0.704)	(−0.764)	(1.130)	(1.081)	(−0.449)	(−0.667)	(−0.560)	(−0.774)	(1.306)	(1.059)
β_{JV}	1.227	1.224	1.212	1.208	1.105	1.106	1.234	1.225	1.216	1.209	1.097	1.108
	(2.728)	(2.725)	(2.700)	(2.695)	(2.441)	(2.421)	(2.784)	(2.721)	(2.754)	(2.690)	(2.496)	(2.415)
β_{VRP}	0.398	0.400	0.393	0.396	0.352	0.365	0.370	0.400	0.365	0.396	0.315	0.367
	(6.848)	(6.755)	(6.733)	(6.658)	(5.348)	(5.925)	(6.159)	(6.731)	(6.030)	(6.615)	(4.500)	(5.920)
β_{RNS}			0.000	0.000					0.000	0.000		
			(1.982)	(1.928)					(2.108)	(1.943)		
β_{JTI}					−0.196	−0.178					−0.213	−0.176
					(−1.724)	(−1.743)					(−1.886)	(−1.725)
β_{ORV}	−0.003		−0.003		−0.011		−0.021		−0.021		−0.031	
	(−0.607)		(−0.784)		(−1.564)		(−2.930)		(−3.011)		(−3.225)	
β_{ORJ}		−0.009		−0.011		−0.019		−0.005		−0.010		−0.010
		(−0.677)		(−0.821)		(−1.528)		(−0.422)		(−0.852)		(−0.798)
R^2_{adj}	13.185%	13.181%	13.294%	13.285%	14.974%	14.768%	13.692%	13.172%	13.829%	13.277%	15.846%	14.727%
	Panel B: $h = 5$											
β_0	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(4.542)	(4.033)	(2.438)	(2.292)	(1.517)	(1.168)	(4.669)	(4.109)	(2.946)	(2.485)	(2.242)	(1.255)
β_{IV}	0.055	0.053	0.049	0.047	0.369	0.330	0.068	0.053	0.062	0.046	0.408	0.330
	(0.626)	(0.616)	(0.566)	(0.550)	(1.317)	(1.313)	(0.793)	(0.616)	(0.717)	(0.539)	(1.525)	(1.321)
β_{JV}	0.761	0.760	0.750	0.749	0.644	0.646	0.768	0.759	0.755	0.746	0.637	0.646
	(1.602)	(1.598)	(1.574)	(1.569)	(1.352)	(1.343)	(1.630)	(1.602)	(1.600)	(1.572)	(1.372)	(1.347)
β_{VRP}	0.429	0.431	0.426	0.429	0.386	0.399	0.403	0.428	0.399	0.424	0.350	0.396
	(5.491)	(5.517)	(5.371)	(5.416)	(3.807)	(4.273)	(5.058)	(5.469)	(4.943)	(5.350)	(3.391)	(4.266)
β_{RNS}			0.000	0.000					0.000	0.000		
			(1.125)	(1.073)					(1.303)	(1.216)		
β_{JTI}					−0.187	−0.170					−0.204	−0.171
					(−1.428)	(−1.433)					(−1.617)	(−1.446)
β_{ORV}	−0.001		−0.002		−0.009		−0.019		−0.019		−0.029	
	(−0.241)		(−0.345)		(−1.134)		(−2.381)		(−2.471)		(−3.206)	
β_{ORJ}		0.004		0.003		−0.005		−0.021		−0.025		−0.026
		(0.364)		(0.250)		(−0.411)		(−1.383)		(−1.660)		(−1.858)
R^2_{adj}	23.614%	23.612%	23.685%	23.677%	25.865%	25.622%	24.206%	23.660%	24.309%	23.747%	26.955%	25.693%
	Panel C: $h = 22$											
β_0	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(4.057)	(3.465)	(0.923)	(0.584)	(1.633)	(1.298)	(3.724)	(3.255)	(1.114)	(0.703)	(1.963)	(1.319)
β_{IV}	0.211	0.202	0.212	0.203	0.339	0.294	0.212	0.201	0.213	0.202	0.339	0.293
	(4.620)	(4.355)	(4.706)	(4.502)	(2.072)	(1.872)	(4.769)	(4.321)	(4.857)	(4.454)	(2.148)	(1.864)
β_{JV}	−0.132	−0.140	−0.131	−0.137	−0.180	−0.178	−0.134	−0.140	−0.132	−0.138	−0.183	−0.178
	(−0.721)	(−0.732)	(−0.728)	(−0.734)	(−0.946)	(−0.904)	(−0.738)	(−0.740)	(−0.746)	(−0.746)	(−0.983)	(−0.910)
β_{VRP}	0.185	0.193	0.185	0.193	0.167	0.182	0.174	0.191	0.174	0.191	0.154	0.180
	(6.124)	(6.024)	(6.094)	(5.962)	(4.560)	(4.993)	(5.639)	(5.899)	(5.642)	(5.825)	(4.295)	(4.975)
β_{RNS}			0.000	0.000					0.000	0.000		
			(−0.147)	(−0.269)					(−0.153)	(−0.201)		
β_{JTI}					−0.076	−0.057					−0.077	−0.057
					(−0.979)	(−0.752)					(−1.004)	(−0.748)
β_{ORV}	−0.007		−0.007		−0.011		−0.013		−0.013		−0.017	
	(−1.167)		(−1.183)		(−1.786)		(−1.890)		(−1.935)		(−2.928)	
β_{ORJ}		−0.005		−0.005		−0.008		−0.018		−0.017		−0.019
		(−0.471)		(−0.470)		(−0.880)		(−1.393)		(−1.541)		(−1.709)
R^2_{adj}	35.090%	34.674%	35.079%	34.673%	35.996%	35.214%	35.404%	34.750%	35.393%	34.743%	36.335%	35.286%

Notes: Everything is defined as in Table 5. The IV is the ATM implied volatility (in variance form), RNS is the risk-neutral skewness of Bakshi et al. (2003), and the JTI is the jump-tail index of Du and Kapadia (2012).

Table C2: Predicting Equity Variance Risk-Premia with Option Realized Measures

	Call ($K/S = 1.10$)						Put ($K/S = 0.90$)					
	Panel A: $h = 1$											
β_{IV}	−0.053	−0.054	−0.052	−0.053	0.166	0.160	−0.052	−0.054	−0.051	−0.053	0.168	0.160
	(−1.244)	(−1.281)	(−1.234)	(−1.269)	(2.242)	(2.181)	(−1.234)	(−1.278)	(−1.219)	(−1.266)	(2.261)	(2.188)
β_{JV}	0.219	0.218	0.217	0.217	0.183	0.183	0.217	0.217	0.216	0.216	0.181	0.182
	(1.172)	(1.171)	(1.165)	(1.164)	(1.033)	(1.034)	(1.165)	(1.162)	(1.157)	(1.155)	(1.022)	(1.024)
β_{VRP}	0.398	0.401	0.397	0.400	0.361	0.366	0.397	0.402	0.396	0.401	0.359	0.367
	(13.480)	(13.967)	(13.392)	(13.855)	(33.451)	(34.159)	(13.539)	(14.079)	(13.377)	(13.934)	(30.589)	(34.565)
β_{RNS}			0.000	0.000					0.000	0.000		
			(1.719)	(1.735)					(1.888)	(1.795)		
β_{JTI}					−0.063	−0.062					−0.063	−0.062
					(−2.667)	(−2.628)					(−2.679)	(−2.633)
β_{ORV}	−0.009		−0.009		−0.013		−0.014		−0.015		−0.022	
	(−2.578)		(−2.670)		(−3.430)		(−2.313)		(−2.345)		(−2.495)	
β_{ORJ}		−0.013		−0.013		−0.014		−0.012		−0.013		−0.015
		(−1.600)		(−1.682)		(−1.970)		(−1.230)		(−1.337)		(−1.572)
R^2_{adj}	15.395%	15.369%	15.413%	15.388%	17.164%	17.086%	15.410%	15.358%	15.434%	15.379%	17.201%	17.076%
	Panel B: $h = 5$											
β_{IV}	0.016	0.015	0.018	0.016	0.087	0.081	0.017	0.015	0.019	0.017	0.088	0.082
	(0.448)	(0.404)	(0.498)	(0.454)	(1.621)	(1.526)	(0.458)	(0.408)	(0.517)	(0.459)	(1.614)	(1.530)
β_{JV}	0.087	0.086	0.084	0.084	0.075	0.075	0.085	0.085	0.082	0.083	0.073	0.074
	(0.781)	(0.767)	(0.759)	(0.746)	(0.702)	(0.689)	(0.767)	(0.757)	(0.746)	(0.737)	(0.684)	(0.678)
β_{VRP}	0.317	0.321	0.316	0.320	0.305	0.310	0.317	0.322	0.315	0.320	0.305	0.311
	(13.715)	(13.911)	(13.508)	(13.682)	(9.575)	(9.918)	(13.452)	(13.932)	(13.148)	(13.663)	(9.341)	(9.925)
β_{RNS}			0.000	0.000					0.000	0.000		
			(2.491)	(2.490)					(2.536)	(2.504)		
β_{JTI}					−0.020	−0.019					−0.020	−0.019
					(−1.737)	(−1.663)					(−1.727)	(−1.667)
β_{ORV}	−0.010		−0.010		−0.012		−0.013		−0.015		−0.016	
	(−3.064)		(−3.250)		(−2.958)		(−2.268)		(−2.308)		(−2.128)	
β_{ORJ}		−0.012		−0.012		−0.013		−0.011		−0.013		−0.011
		(−1.869)		(−2.108)		(−1.940)		(−1.331)		(−1.543)		(−1.417)
R^2_{adj}	14.215%	14.155%	14.331%	14.274%	14.474%	14.391%	14.207%	14.139%	14.341%	14.264%	14.471%	14.375%
	Panel C: $h = 22$											
β_{IV}	0.091	0.090	0.091	0.090	0.090	0.088	0.091	0.090	0.091	0.091	0.091	0.088
	(3.915)	(3.873)	(3.949)	(3.908)	(2.095)	(2.039)	(3.914)	(3.878)	(3.955)	(3.915)	(2.073)	(2.042)
β_{JV}	0.045	0.045	0.045	0.044	0.045	0.045	0.045	0.045	0.044	0.044	0.045	0.045
	(0.537)	(0.531)	(0.527)	(0.521)	(0.544)	(0.541)	(0.527)	(0.525)	(0.516)	(0.515)	(0.534)	(0.534)
β_{VRP}	0.160	0.162	0.160	0.161	0.160	0.162	0.160	0.162	0.160	0.162	0.160	0.162
	(14.337)	(14.710)	(14.102)	(14.428)	(11.598)	(11.901)	(14.345)	(14.835)	(13.984)	(14.487)	(11.384)	(11.948)
β_{RNS}			0.000	0.000					0.000	0.000		
			(1.085)	(1.101)					(1.178)	(1.121)		
β_{JTI}					0.000	0.001					0.000	0.001
					(0.011)	(0.057)					(0.009)	(0.057)
β_{ORV}	−0.005		−0.005		−0.005		−0.006		−0.006		−0.006	
	(−2.233)		(−2.333)		(−2.267)		(−2.165)		(−2.212)		(−1.910)	
β_{ORJ}		−0.006		−0.006		−0.006		−0.005		−0.005		−0.005
		(−1.181)		(−1.243)		(−1.179)		(−0.790)		(−0.898)		(−0.790)
R^2_{adj}	12.979%	12.940%	13.009%	12.971%	12.977%	12.939%	12.965%	12.928%	13.002%	12.962%	12.963%	12.927%

Notes: Everything is defined as in Table 6. The IV is the ATM implied volatility (in variance form), RNS is the risk-neutral skewness of Bakshi et al. (2003), and the JTI is the jump-tail index of Du and Kapadia (2012).

Table C3: Predicting SPY Variance Risk-Premium with Option Realized Signed Measures

	Call ($K/S = 1.10$)						Put ($K/S = 0.90$)					
						Panel A: $h = 1$						
β_0	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(4.025)	(3.780)	(3.308)	(3.297)	(1.513)	(1.415)	(4.254)	(3.840)	(3.402)	(3.335)	(2.305)	(1.677)
β_{IV}	−0.045	−0.042	−0.053	−0.051	0.298	0.287	−0.037	−0.044	−0.045	−0.053	0.313	0.280
	(−0.567)	(−0.551)	(−0.663)	(−0.663)	(1.195)	(1.290)	(−0.471)	(−0.567)	(−0.575)	(−0.679)	(1.285)	(1.244)
β_{JV}	1.208	1.211	1.192	1.194	1.080	1.082	1.219	1.228	1.202	1.212	1.080	1.105
	(2.737)	(2.731)	(2.708)	(2.701)	(2.441)	(2.446)	(2.731)	(2.757)	(2.701)	(2.731)	(2.434)	(2.506)
β_{VRP}	0.400	0.397	0.395	0.393	0.352	0.357	0.378	0.388	0.372	0.383	0.323	0.345
	(6.931)	(6.717)	(6.808)	(6.612)	(5.272)	(5.695)	(6.296)	(6.475)	(6.168)	(6.356)	(4.601)	(5.376)
β_{RNS}			0.000	0.000					0.000	0.000		
			(2.033)	(2.107)					(2.006)	(2.098)		
β_{JTI}					−0.204	−0.201					−0.210	−0.198
					(−1.780)	(−1.931)					(−1.870)	(−1.885)
$\beta_{\mathcal{ORV}^+}$	0.023		0.022		0.016		−0.057		−0.057		−0.066	
	(2.030)		(1.964)		(1.124)		(−3.796)		(−3.808)		(−4.427)	
$\beta_{\mathcal{ORV}^-}$	−0.029		−0.030		−0.041		0.022		0.021		0.008	
	(−2.347)		(−2.438)		(−3.750)		(1.369)		(1.268)		(0.380)	
$\beta_{\mathcal{ORJ}^+}$		0.002		0.001		−0.009		−0.089		−0.091		−0.104
		(0.299)		(0.111)		(−0.844)		(−3.312)		(−3.368)		(−4.089)
$\beta_{\mathcal{ORJ}^-}$		0.050		0.051		0.066		0.005		0.008		0.026
		(2.280)		(2.356)		(3.336)		(0.258)		(0.456)		(1.172)
R^2_{adj}	13.619%	13.807%	13.735%	13.938%	15.527%	15.758%	14.200%	14.477%	14.320%	14.609%	16.299%	16.399%
						Panel B: $h = 5$						
β_0	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(4.567)	(4.540)	(2.469)	(2.653)	(1.557)	(1.408)	(4.543)	(4.471)	(2.785)	(2.589)	(2.262)	(1.624)
β_{IV}	0.058	0.060	0.052	0.053	0.382	0.368	0.067	0.058	0.061	0.052	0.405	0.361
	(0.657)	(0.695)	(0.596)	(0.621)	(1.359)	(1.453)	(0.783)	(0.674)	(0.711)	(0.603)	(1.518)	(1.415)
β_{JV}	0.744	0.746	0.733	0.734	0.623	0.625	0.754	0.756	0.742	0.745	0.620	0.641
	(1.582)	(1.580)	(1.554)	(1.551)	(1.324)	(1.328)	(1.592)	(1.593)	(1.563)	(1.567)	(1.329)	(1.363)
β_{VRP}	0.432	0.429	0.428	0.426	0.386	0.392	0.408	0.424	0.405	0.420	0.356	0.384
	(5.487)	(5.485)	(5.363)	(5.384)	(3.757)	(4.134)	(5.115)	(5.316)	(4.999)	(5.201)	(3.429)	(3.935)
β_{RNS}			0.000	0.000					0.000	0.000		
			(1.160)	(1.237)					(1.219)	(1.190)		
β_{JTI}					−0.193	−0.188					−0.203	−0.185
					(−1.464)	(−1.564)					(−1.610)	(−1.532)
$\beta_{\mathcal{ORV}^+}$	0.020		0.020		0.014		−0.052		−0.052		−0.060	
	(2.359)		(2.257)		(1.126)		(−3.435)		(−3.452)		(−4.365)	
$\beta_{\mathcal{ORV}^-}$	−0.023		−0.024		−0.035		0.018		0.017		0.005	
	(−1.953)		(−2.048)		(−3.212)		(1.764)		(1.610)		(0.283)	
$\beta_{\mathcal{ORJ}^+}$		0.007		0.006		−0.003		−0.065		−0.066		−0.079
		(1.047)		(0.905)		(−0.279)		(−2.964)		(−3.057)		(−4.063)
$\beta_{\mathcal{ORJ}^-}$		0.035		0.036		0.050		−0.011		−0.008		0.009
		(2.005)		(2.119)		(3.621)		(−0.703)		(−0.524)		(0.404)
R^2_{adj}	24.032%	24.085%	24.108%	24.171%	26.399%	26.455%	24.810%	24.660%	24.898%	24.743%	27.520%	26.986%
						Panel C: $h = 22$						
β_0	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(4.047)	(4.108)	(0.994)	(0.834)	(1.664)	(1.556)	(3.723)	(3.523)	(0.995)	(0.800)	(1.982)	(1.548)
β_{IV}	0.213	0.207	0.214	0.208	0.349	0.321	0.211	0.204	0.212	0.206	0.336	0.310
	(4.705)	(4.548)	(4.776)	(4.661)	(2.149)	(2.052)	(4.760)	(4.513)	(4.856)	(4.627)	(2.118)	(2.002)
β_{JV}	−0.142	−0.143	−0.140	−0.141	−0.192	−0.188	−0.143	−0.139	−0.140	−0.137	−0.192	−0.179
	(−0.777)	(−0.770)	(−0.787)	(−0.778)	(−1.020)	(−0.983)	(−0.772)	(−0.750)	(−0.779)	(−0.753)	(−1.021)	(−0.937)
β_{VRP}	0.185	0.190	0.186	0.191	0.166	0.176	0.177	0.188	0.178	0.189	0.158	0.174
	(6.143)	(6.038)	(6.121)	(5.985)	(4.515)	(4.886)	(5.777)	(5.906)	(5.768)	(5.867)	(4.331)	(4.785)
β_{RNS}			0.000	0.000					0.000	0.000		
			(−0.119)	(−0.172)					(−0.201)	(−0.220)		
β_{JTI}					−0.080	−0.070					−0.075	−0.065
					(−1.041)	(−0.921)					(−0.978)	(−0.864)
$\beta_{\mathcal{ORV}^+}$	0.005		0.005		0.002		−0.031		−0.031		−0.034	
	(0.746)		(0.764)		(0.294)		(−2.920)		(−2.930)		(−3.557)	
$\beta_{\mathcal{ORV}^-}$	−0.021		−0.021		−0.026		0.007		0.008		0.002	
	(−2.102)		(−2.141)		(−3.014)		(1.113)		(1.199)		(0.303)	
$\beta_{\mathcal{ORJ}^+}$		−0.005		−0.005		−0.009		−0.038		−0.038		−0.043
		(−0.569)		(−0.569)		(−1.098)		(−2.286)		(−2.338)		(−3.104)
$\beta_{\mathcal{ORJ}^-}$		0.028		0.028		0.034		0.000		0.000		0.007
		(2.274)		(2.325)		(3.250)		(0.026)		(−0.019)		(0.739)
R^2_{adj}	35.473%	35.305%	35.461%	35.296%	36.473%	36.089%	35.778%	35.471%	35.771%	35.465%	36.669%	36.154%

Notes: Everything is defined as in Table 7. The IV is the ATM implied volatility (in variance form), RNS is the risk-neutral skewness of Bakshi et al. (2003), and the JTI is the jump-tail index of Du and Kapadia (2012).

Table C4: Predicting Equity Variance Risk-Premia with Option Realized Signed Measures

	Call ($K/S = 1.10$)						Put ($K/S = 0.90$)					
						Panel A: $h = 1$						
β_{IV}	−0.053	−0.054	−0.052	−0.054	0.165	0.160	−0.053	−0.054	−0.052	−0.053	0.166	0.163
	(−1.246)	(−1.284)	(−1.234)	(−1.272)	(2.238)	(2.189)	(−1.244)	(−1.273)	(−1.230)	(−1.260)	(2.243)	(2.207)
β_{JV}	0.218	0.218	0.217	0.217	0.182	0.182	0.217	0.219	0.216	0.217	0.181	0.183
	(1.169)	(1.167)	(1.162)	(1.160)	(1.029)	(1.028)	(1.168)	(1.177)	(1.160)	(1.169)	(1.027)	(1.038)
β_{VRP}	0.398	0.400	0.398	0.400	0.361	0.365	0.399	0.399	0.398	0.398	0.361	0.363
	(13.503)	(13.834)	(13.411)	(13.722)	(33.318)	(33.871)	(13.619)	(14.050)	(13.456)	(13.888)	(31.043)	(33.418)
β_{RNS}			0.000	0.000					0.000	0.000		
			(1.731)	(1.733)					(1.908)	(1.935)		
β_{JTI}					−0.063	−0.062					−0.063	−0.062
					(−2.665)	(−2.636)					(−2.670)	(−2.651)
$\beta_{\mathcal{ORV}^+}$	−0.007		−0.006		−0.009		−0.031		−0.032		−0.036	
	(−1.189)		(−1.144)		(−1.848)		(−2.750)		(−2.762)		(−2.646)	
$\beta_{\mathcal{ORV}^-}$	−0.010		−0.011		−0.017		0.012		0.012		0.004	
	−1.952		(−1.988)		(−2.423)		(1.451)		(1.413)		(0.725)	
$\beta_{\mathcal{ORJ}^+}$		−0.013		−0.013		−0.015		−0.050		−0.051		−0.057
		(−1.678)		(−1.676)		(−2.100)		(−2.856)		(−2.856)		(−2.725)
$\beta_{\mathcal{ORJ}^-}$		0.019		0.019		0.024		0.003		0.004		0.011
		(2.325)		(2.357)		(2.717)		(0.300)		(0.424)		(1.090)
R^2_{adj}	15.387%	15.378%	15.405%	15.397%	17.151%	17.104%	15.442%	15.471%	15.466%	15.497%	17.217%	17.222%
						Panel B: $h = 5$						
β_{IV}	0.017	0.015	0.018	0.017	0.087	0.082	0.016	0.015	0.018	0.017	0.087	0.083
	(0.451)	(0.404)	(0.503)	(0.456)	(1.623)	(1.538)	(0.449)	(0.415)	(0.507)	(0.469)	(1.597)	(1.545)
β_{JV}	0.086	0.085	0.083	0.083	0.074	0.074	0.085	0.086	0.083	0.083	0.074	0.074
	(0.774)	(0.760)	(0.752)	(0.738)	(0.693)	(0.682)	(0.767)	(0.764)	(0.746)	(0.744)	(0.686)	(0.685)
β_{VRP}	0.317	0.321	0.316	0.319	0.305	0.310	0.318	0.321	0.316	0.319	0.306	0.309
	(13.715)	(13.807)	(13.499)	(13.578)	(9.578)	(9.832)	(13.512)	(13.703)	(13.209)	(13.411)	(9.414)	(9.714)
β_{RNS}			0.000	0.000					0.000	0.000		
			(2.516)	(2.507)					(2.543)	(2.511)		
β_{JTI}					−0.020	−0.019					−0.020	−0.019
					(−1.739)	(−1.674)					(−1.713)	(−1.679)
$\beta_{\mathcal{ORV}^+}$	−0.004		−0.003		−0.005		−0.020		−0.022		−0.022	
	(−1.009)		(−0.835)		(−1.174)		(−2.514)		(−2.519)		(−2.427)	
$\beta_{\mathcal{ORV}^-}$	−0.018		−0.019		−0.020		−0.001		−0.002		−0.004	
	(−2.986)		(−3.082)		(−2.795)		(−0.279)		(−0.415)		(−0.635)	
$\beta_{\mathcal{ORJ}^+}$		−0.007		−0.005		−0.007		−0.026		−0.029		−0.028
		(−1.006)		(−0.911)		(−1.082)		(−2.531)		(−2.519)		(−2.418)
$\beta_{\mathcal{ORJ}^-}$		0.018		0.019		0.020		−0.003		0.000		0.000
		(2.179)		(2.273)		(2.162)		(−0.510)		(−0.075)		(−0.068)
R^2_{adj}	14.221%	14.153%	14.340%	14.275%	14.481%	14.392%	14.211%	14.180%	14.345%	14.310%	14.469%	14.422%
						Panel C: $h = 22$						
β_{IV}	0.091	0.090	0.091	0.091	0.091	0.088	0.091	0.090	0.091	0.091	0.090	0.089
	(3.919)	(3.881)	(3.956)	(3.918)	(2.099)	(2.045)	(3.904)	(3.887)	(3.946)	(3.928)	(2.063)	(2.050)
β_{JV}	0.045	0.044	0.044	0.044	0.045	0.045	0.045	0.045	0.044	0.044	0.045	0.045
	(0.532)	(0.524)	(0.522)	(0.514)	(0.539)	(0.534)	(0.527)	(0.530)	(0.517)	(0.520)	(0.535)	(0.539)
β_{VRP}	0.160	0.162	0.160	0.162	0.160	0.162	0.161	0.162	0.160	0.161	0.161	0.162
	(14.321)	(14.724)	(14.075)	(14.433)	(11.587)	(11.862)	(14.460)	(14.767)	(14.090)	(14.397)	(11.478)	(11.783)
β_{RNS}			0.000	0.000					0.000	0.000		
			(1.115)	(1.121)					(1.190)	(1.175)		
β_{JTI}					0.000	0.000					0.000	0.000
					(0.007)	(0.054)					(0.019)	(0.041)
$\beta_{\mathcal{ORV}^+}$	−0.002		−0.001		−0.002		−0.013		−0.013		−0.013	
	(−0.561)		(−0.479)		(−0.573)		(−2.921)		(−2.943)		(−2.753)	
$\beta_{\mathcal{ORV}^-}$	−0.010		−0.010		−0.010		0.004		0.004		0.004	
	(−2.768)		(−2.847)		(−2.674)		(1.938)		(1.818)		(1.956)	
$\beta_{\mathcal{ORJ}^+}$		−0.001		−0.001		−0.001		−0.016		−0.017		−0.016
		(−0.226)		(−0.146)		(−0.223)		(−3.256)		(−3.266)		(−2.965)
$\beta_{\mathcal{ORJ}^-}$		0.006		0.006		0.006		−0.006		−0.005		−0.006
		(1.565)		(1.659)		(1.477)		(−1.722)		(−1.519)		(−1.696)
R^2_{adj}	12.989%	12.929%	13.021%	12.962%	12.988%	12.928%	12.986%	12.981%	13.024%	13.018%	12.985%	12.980%

Notes: Everything is defined as in Table 8. The IV is the ATM implied volatility (in variance form), RNS is the risk-neutral skewness of Bakshi et al. (2003), and the JTI is the jump-tail index of Du and Kapadia (2012).

Table C5: Predicting SPY Monthly Excess Return with OTM Call Option Realized Measures

	Call ($K/S = 1.10$)																	
α	0.003	0.002	0.003	0.002	0.003	0.002	0.003	0.002	0.003	0.003	0.003	0.002	0.002	0.002	0.002	0.002	0.003	0.003
	(0.919)	(0.629)	(1.000)	(0.774)	(0.943)	(0.686)	(0.904)	(0.647)	(1.057)	(0.875)	(0.920)	(0.650)	(0.733)	(0.491)	(0.700)	(0.579)	(1.079)	(0.767)
β_{RV}			−1.768	−2.098	−1.630	−1.935	−1.619	−1.922	−1.813	−2.083	−1.455	−1.771	−1.547	−1.882	−1.443	−1.873	−1.487	−1.818
			(−3.055)	(−3.743)	(−2.638)	(−3.147)	(−2.577)	(−3.115)	(−3.017)	(−3.523)	(−2.376)	(−2.866)	(−2.579)	(−3.142)	(−2.426)	(−3.187)	(−2.220)	(−2.757)
β_{JV}	−5.602	−6.662	−6.009	−6.600	−6.242	−6.906	−5.896	−6.479	−5.737	−6.185	−6.035	−6.618	−5.980	−6.598	−6.281	−6.573	−5.167	−5.240
	(−1.772)	(−1.906)	(−1.703)	(−1.641)	(−1.741)	(−1.671)	(−1.616)	(−1.545)	(−1.728)	(−1.665)	(−1.655)	(−1.578)	(−1.652)	(−1.574)	(−1.772)	(−1.713)	(−1.219)	(−1.142)
β_{IV}			2.533	2.821	1.794	1.890	2.217	2.461	3.758	4.115			1.678	1.787	3.056	2.031	2.346	2.323
			(1.955)	(2.159)	(1.558)	(1.615)	(1.378)	(1.545)	(2.822)	(2.932)			(1.491)	(1.548)	(1.046)	(0.697)	(1.561)	(1.502)
β_{REV}	−0.003	−0.002	−0.003	−0.002	−0.003	−0.002	−0.002	−0.001	−0.001	0.000	−0.003	−0.002	−0.003	−0.002	−0.003	−0.002	−0.005	−0.004
	(−1.013)	(−0.618)	(−0.876)	(−0.532)	(−0.938)	(−0.595)	(−0.546)	(−0.235)	(−0.395)	(−0.114)	(−1.059)	(−0.742)	(−0.970)	(−0.655)	(−0.972)	(−0.735)	(−1.328)	(−1.032)
β_{MoM}	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(−0.060)	(0.198)	(0.138)	(0.356)	(−0.010)	(0.178)	(−0.068)	(0.093)	(0.087)	(0.249)	(−0.130)	(0.066)	(0.285)	(0.400)	(0.197)	(0.226)	(−0.223)	(−0.025)
β_{Illiq}	0.454	0.401	0.385	0.394	0.397	0.411	0.429	0.452	0.637	0.682	0.439	0.449	0.264	0.326	0.434	0.428	0.458	0.511
	(0.634)	(0.554)	(0.659)	(0.664)	(0.685)	(0.697)	(0.766)	(0.794)	(1.101)	(1.165)	(0.765)	(0.770)	(0.444)	(0.536)	(0.749)	(0.728)	(0.819)	(0.891)
β_{Size}	−0.282	−0.205	−0.295	−0.232	−0.291	−0.223	−0.278	−0.208	−0.315	−0.263	−0.286	−0.215	−0.158	−0.119	−0.240	−0.200	−0.319	−0.244
	(−1.076)	(−0.797)	(−1.103)	(−0.875)	(−1.090)	(−0.846)	(−1.046)	(−0.793)	(−1.180)	(−1.006)	(−1.065)	(−0.809)	(−0.581)	(−0.442)	(−0.876)	(−0.747)	(−1.202)	(−0.906)
β_{OptV}	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(5.046)	(4.473)	(4.619)	(3.986)	(4.366)	(3.689)	(4.410)	(3.748)	(4.494)	(4.168)	(4.383)	(3.674)	(4.470)	(3.711)	(4.061)	(3.526)	(4.840)	(4.262)
β_{VRP}	1.616	1.882																
	(2.706)	(3.182)																
β_{Skew}			−0.007	−0.009														
			(−0.994)	(−1.298)														
β_{SPRD}					0.006	0.007												
					(1.147)	(1.406)												
β_{Max}							−0.007	−0.009										
							(−0.374)	(−0.514)										
β_{Min}									0.030	0.034								
									(1.835)	(2.005)								
β_{RNV}											0.058	0.062						
											(1.275)	(1.346)						
β_{RNS}													0.001	0.000				
													(1.604)	(1.006)				
β_{JTI}															−0.815	−0.129		
															(−0.560)	(−0.087)		
β_{LTV}																	−0.043	−0.041
																	(−2.089)	(−1.917)
$\beta_{\mathcal{ORV}}$	−0.374		−0.360		−0.374		−0.371		−0.307		−0.376		−0.415		−0.408		−0.339	
	(−2.024)		(−1.865)		(−1.990)		(−1.970)		(−1.747)		(−2.008)		(−2.287)		(−2.352)		(−1.845)	
$\beta_{\mathcal{ORJ}}$		−0.437		−0.399		−0.432		−0.432		−0.336		−0.442		−0.464		−0.441		−0.493
		(−1.373)		(−1.199)		(−1.351)		(−1.359)		(−1.095)		(−1.402)		(−1.491)		(−1.481)		(−1.486)
R^2_{adj}	6.210%	5.044%	6.359%	5.299%	6.229%	5.083%	6.231%	5.106%	7.362%	6.607%	6.044%	4.886%	6.578%	5.199%	6.288%	5.004%	6.570%	5.645%

Notes: Everything is defined as in Table 9. VRP is the variance risk-premium as defined in Section 5, $Skew$ is the ex-ante skewness, $SPRD$ is the volatility spread, Max and Min are the Bali et al. (2011) maximum and minimum daily returns, RNV and RNS are the Bakshi et al. (2003) risk-neutral variance and skewness, JTI is the jump-tail risk of Du and Kapadia (2012), and LTV is the left tail variation of Bollerslev et al. (2015). The left tail variation is obtained from www.tailindex.com and the sample size is from January 11, 2005 to December 31, 2019. All these measures are defined in Appendix A.

Table C6: Predicting SPY Monthly Excess Return with OTM Put Option Realized Measures

	Put ($K/S = 0.90$)																	
α	0.003	0.001	0.004	0.002	0.004	0.002	0.003	0.002	0.004	0.002	0.003	0.002	0.003	0.001	0.003	0.001	0.003	0.002
	(1.031)	(0.470)	(1.124)	(0.619)	(1.074)	(0.525)	(1.034)	(0.488)	(1.122)	(0.707)	(1.051)	(0.497)	(0.892)	(0.321)	(0.896)	(0.431)	(0.974)	(0.612)
β_{RV}			−1.655	−2.206	−1.496	−2.035	−1.486	−2.022	−1.748	−2.189	−1.318	−1.866	−1.422	−1.991	−1.369	−1.980	−1.500	−1.917
			(−2.805)	(−3.917)	(−2.378)	(−3.296)	(−2.338)	(−3.263)	(−2.823)	(−3.693)	(−2.129)	(−2.993)	(−2.329)	(−3.311)	(−2.378)	(−3.342)	(−2.256)	(−2.884)
β_{JV}	−6.223	−6.575	−6.068	−6.589	−6.339	−6.899	−5.940	−6.465	−5.816	−6.160	−6.055	−6.607	−6.035	−6.581	−6.169	−6.538	−4.994	−5.178
	(−1.919)	(−1.869)	(−1.677)	(−1.629)	(−1.716)	(−1.659)	(−1.585)	(−1.531)	(−1.697)	(−1.650)	(−1.618)	(−1.565)	(−1.614)	(−1.557)	(−1.741)	(−1.695)	(−1.169)	(−1.126)
β_{IV}			2.225	2.999	1.399	2.024	1.902	2.599	3.535	4.312			1.271	1.934	2.043	2.097	2.042	2.439
			(1.614)	(2.255)	(1.170)	(1.688)	(1.183)	(1.626)	(2.549)	(3.042)			(1.079)	(1.636)	(0.700)	(0.711)	(1.292)	(1.553)
β_{REV}	−0.005	−0.002	−0.004	−0.001	−0.004	−0.002	−0.004	−0.001	−0.002	0.000	−0.005	−0.002	−0.005	−0.002	−0.005	−0.002	−0.006	−0.004
	(−1.459)	(−0.556)	(−1.464)	(−0.442)	(−1.561)	(−0.512)	(−0.971)	(−0.169)	(−0.750)	(−0.021)	(−1.703)	(−0.670)	(−1.633)	(−0.569)	(−1.659)	(−0.658)	(−1.620)	(−0.962)
β_{MoM}	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(0.035)	(0.177)	(0.160)	(0.352)	(−0.005)	(0.168)	(−0.074)	(0.084)	(0.110)	(0.237)	(−0.111)	(0.055)	(0.236)	(0.386)	(0.111)	(0.205)	(−0.093)	(−0.008)
β_{Illiq}	0.445	0.367	0.455	0.345	0.472	0.366	0.508	0.408	0.700	0.633	0.515	0.408	0.375	0.278	0.501	0.382	0.581	0.495
	(0.620)	(0.509)	(0.768)	(0.589)	(0.802)	(0.629)	(0.889)	(0.726)	(1.189)	(1.090)	(0.886)	(0.709)	(0.617)	(0.460)	(0.856)	(0.658)	(1.000)	(0.874)
β_{Size}	−0.315	−0.169	−0.334	−0.195	−0.333	−0.187	−0.318	−0.172	−0.338	−0.225	−0.328	−0.179	−0.223	−0.080	−0.298	−0.165	−0.298	−0.209
	(−1.175)	(−0.647)	(−1.214)	(−0.724)	(−1.210)	(−0.693)	(−1.163)	(−0.640)	(−1.239)	(−0.846)	(−1.187)	(−0.662)	(−0.790)	(−0.291)	(−1.052)	(−0.603)	(−1.106)	(−0.757)
β_{OptV}	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(4.777)	(4.418)	(4.299)	(3.904)	(4.034)	(3.584)	(4.085)	(3.643)	(4.182)	(4.128)	(4.067)	(3.562)	(4.095)	(3.603)	(3.820)	(3.445)	(4.411)	(4.151)
β_{VRP}	1.436	1.987																
	(2.336)	(3.309)																
β_{Skew}			−0.008	−0.009														
			(−1.118)	(−1.371)														
β_{SPRD}					0.006	0.007												
					(1.344)	(1.430)												
β_{Max}							−0.008	−0.009										
							(−0.463)	(−0.521)										
β_{Min}									0.031	0.035								
									(1.877)	(2.045)								
β_{RNV}											0.042	0.067						
											(0.911)	(1.414)						
β_{RNS}													0.001	0.000				
													(1.170)	(0.973)				
β_{JTI}															−0.449	−0.088		
															(−0.310)	(−0.058)		
β_{LTV}																	−0.041	−0.041
																	(−1.889)	(−1.908)
$\beta_{\mathcal{ORV}}$	−0.444		−0.421		−0.443		−0.439		−0.324		−0.456		−0.466		−0.462		−0.329	
	(−2.140)		(−1.974)		(−2.118)		(−2.120)		(−1.784)		(−2.211)		(−2.277)		(−2.480)		(−1.714)	
$\beta_{\mathcal{ORJ}}$		0.332		0.359		0.329		0.325		0.432		0.292		0.367		0.329		0.143
		(1.029)		(1.055)		(0.977)		(0.965)		(1.353)		(0.876)		(1.072)		(0.956)		(0.423)
R^2_{adj}	5.743%	4.969%	5.927%	5.248%	5.778%	5.010%	5.785%	5.031%	6.953%	6.602%	5.624%	4.799%	5.960%	5.117%	5.740%	4.926%	5.974%	5.493%

Notes: Everything is defined as in Table 9. VRP is the variance risk-premium as defined in Section 5, $Skew$ is the ex-ante skewness, $SPRD$ is the volatility spread, Max and Min are the Bali et al. (2011) maximum and minimum daily returns, RNV and RNS are the Bakshi et al. (2003) risk-neutral variance and skewness, JTI is the jump-tail risk of Du and Kapadia (2012), and LTV is the left tail variation of Bollerslev et al. (2015). The left tail variation is obtained from www.tailindex.com and the sample size is from January 11, 2005 to December 31, 2019. All these measures are defined in Appendix A.

Table C7: Predicting Individual Equity Monthly Excess Return with OTM Call Option Realized Measures

	Call ($K/S = 1.10$)															
β_{RV}			-0.421	-0.424	-0.416	-0.420	-0.422	-0.425	-0.420	-0.423	-0.483	-0.486	-0.439	-0.443	-0.510	-0.509
			(-5.136)	(-5.090)	(-4.906)	(-4.847)	(-5.035)	(-4.960)	(-4.973)	(-4.881)	(-5.451)	(-5.424)	(-5.440)	(-5.379)	(-5.451)	(-5.297)
β_{JV}	0.755	0.752	-0.008	-0.016	-0.075	-0.082	-0.010	-0.017	0.001	-0.006	0.030	0.023	0.018	0.011	0.056	0.050
	(1.711)	(1.720)	(-0.018)	(-0.035)	(-0.178)	(-0.194)	(-0.022)	(-0.038)	(0.003)	(-0.013)	(0.065)	(0.051)	(0.040)	(0.023)	(0.124)	(0.110)
β_{IV}			0.833	0.838	0.826	0.831	0.904	0.908	0.913	0.917			0.817	0.822	0.344	0.348
			(4.759)	(4.773)	(4.830)	(4.857)	(4.599)	(4.612)	(5.298)	(5.299)			(5.285)	(5.316)	(1.120)	(1.131)
β_{REV}	-0.004	-0.004	-0.004	-0.004	-0.004	-0.004	-0.003	-0.003	-0.004	-0.004	-0.004	-0.004	-0.004	-0.004	-0.004	-0.004
	(-4.228)	(-4.244)	(-3.923)	(-3.939)	(-3.659)	(-3.676)	(-3.766)	(-3.789)	(-3.984)	(-3.995)	(-3.996)	(-4.004)	(-4.224)	(-4.255)	(-4.019)	(-4.017)
β_{MoM}	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(-1.686)	(-1.695)	(-1.224)	(-1.233)	(-1.235)	(-1.243)	(-1.309)	(-1.316)	(-1.247)	(-1.254)	(-1.278)	(-1.287)	(-1.244)	(-1.253)	(-1.434)	(-1.440)
β_{Illiq}	0.010	0.010	0.007	0.007	0.008	0.008	0.008	0.008	0.008	0.008	0.008	0.008	0.007	0.007	0.009	0.009
	(2.013)	(2.019)	(1.409)	(1.407)	(1.395)	(1.394)	(1.488)	(1.488)	(1.533)	(1.534)	(1.607)	(1.608)	(1.501)	(1.500)	(1.889)	(1.886)
β_{Size}	-0.031	-0.035	0.017	0.014	0.009	0.005	0.014	0.011	0.019	0.015	0.006	0.002	-0.011	-0.014	-0.016	-0.019
	(-0.179)	(-0.194)	(0.110)	(0.087)	(0.057)	(0.035)	(0.090)	(0.068)	(0.119)	(0.097)	(0.035)	(0.014)	(-0.066)	(-0.087)	(-0.098)	(-0.113)
β_{OptV}	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001
	(-1.945)	(-1.912)	(-3.350)	(-3.335)	(-3.363)	(-3.355)	(-3.248)	(-3.230)	(-3.200)	(-3.181)	(-3.127)	(-3.116)	(-3.199)	(-3.161)	(-2.924)	(-2.906)
β_{VRP}	0.445	0.446														
	(5.802)	(5.675)														
β_{Skew}			0.000	0.000												
			(-0.072)	(-0.092)												
β_{SPRD}					0.006	0.005										
					(3.497)	(3.480)										
β_{Max}							-0.002	-0.002								
							(-1.492)	(-1.487)								
β_{Min}									0.003	0.003						
									(1.578)	(1.574)						
β_{RNV}											0.032	0.032				
											(5.945)	(6.004)				
β_{RNS}													0.000	0.000		
													(-2.287)	(-2.285)		
β_{JTI}															0.154	0.153
															(2.422)	(2.419)
$\beta_{\mathcal{ORV}}$	0.011		0.005		0.003		0.007		0.008		0.006		0.002		0.016	
	0.486		(0.228)		(0.156)		(0.337)		(0.363)		(0.295)		(0.082)		(0.763)	
$\beta_{\mathcal{ORJ}}$		0.069		0.070		0.067		0.071		0.071		0.067		0.067		0.075
		(1.382)		(1.433)		(1.389)		(1.440)		(1.473)		(1.384)		(1.547)		(1.528)
R^2_{adj}	0.874%	0.881%	1.069%	1.077%	1.125%	1.133%	1.114%	1.122%	1.141%	1.149%	1.136%	1.143%	1.210%	1.218%	1.222%	1.230%

Notes: Everything is defined as in Table 10. VRP is the variance risk-premium as defined in Section 5, $Skew$ is the ex-ante skewness, $SPRD$ is the volatility spread, Max and Min are the Bali et al. (2011) maximum and minimum daily returns, RNV and RNS are the Bakshi et al. (2003) risk-neutral variance and skewness, and JTI is the jump-tail risk by Du and Kapadia (2012). All these measures are defined in Appendix A.

Table C8: Predicting Individual Equity Monthly Excess Return with OTM Put Option Realized Measures

	Put ($K/S = 0.90$)															
β_{RV}			−0.409	−0.422	−0.403	−0.417	−0.409	−0.422	−0.408	−0.420	−0.471	−0.483	−0.430	−0.442	−0.497	−0.506
			(−5.005)	(−5.116)	(−4.737)	(−4.861)	(−4.891)	(−4.979)	(−4.830)	(−4.897)	(−5.370)	(−5.449)	(−5.359)	(−5.411)	(−5.357)	(−5.304)
β_{JV}	0.766	0.760	−0.006	−0.009	−0.074	−0.075	−0.008	−0.010	0.003	0.001	0.031	0.029	0.019	0.016	0.058	0.056
	(1.758)	(1.740)	(−0.014)	(−0.020)	(−0.179)	(−0.179)	(−0.018)	(−0.023)	(0.007)	(0.002)	(0.069)	(0.064)	(0.041)	(0.036)	(0.130)	(0.126)
β_{IV}			0.823	0.836	0.817	0.829	0.894	0.906	0.903	0.915			0.811	0.822	0.344	0.348
			(4.642)	(4.767)	(4.717)	(4.850)	(4.496)	(4.607)	(5.169)	(5.284)			(5.181)	(5.322)	(1.114)	(1.127)
β_{REV}	−0.004	−0.004	−0.004	−0.004	−0.004	−0.004	−0.003	−0.003	−0.004	−0.004	−0.004	−0.004	−0.004	−0.004	−0.004	−0.004
	(−4.390)	(−4.213)	(−4.067)	(−3.893)	(−3.794)	(−3.634)	(−3.919)	(−3.736)	(−4.104)	(−3.947)	(−4.105)	(−3.958)	(−4.343)	(−4.201)	(−4.094)	(−3.969)
β_{MoM}	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(−1.677)	(−1.689)	(−1.212)	(−1.227)	(−1.223)	(−1.237)	(−1.295)	(−1.310)	(−1.235)	(−1.248)	(−1.264)	(−1.280)	(−1.235)	(−1.250)	(−1.416)	(−1.432)
β_{Illiq}	0.010	0.010	0.008	0.007	0.008	0.008	0.008	0.008	0.008	0.008	0.008	0.008	0.007	0.007	0.009	0.009
	(2.013)	(2.017)	(1.411)	(1.403)	(1.397)	(1.390)	(1.488)	(1.483)	(1.532)	(1.528)	(1.604)	(1.602)	(1.498)	(1.494)	(1.879)	(1.877)
β_{Size}	−0.031	−0.031	0.018	0.017	0.010	0.009	0.015	0.014	0.020	0.019	0.007	0.006	−0.010	−0.012	−0.014	−0.015
	(−0.174)	(−0.177)	(0.115)	(0.109)	(0.062)	(0.056)	(0.097)	(0.090)	(0.126)	(0.120)	(0.041)	(0.035)	(−0.063)	(−0.072)	(−0.086)	(−0.092)
β_{OptV}	−0.001	−0.001	−0.001	−0.001	−0.001	−0.001	−0.001	−0.001	−0.001	−0.001	−0.001	−0.001	−0.001	−0.001	−0.001	−0.001
	(−1.909)	(−1.929)	(−3.340)	(−3.361)	(−3.351)	(−3.379)	(−3.231)	(−3.254)	(−3.189)	(−3.206)	(−3.106)	(−3.139)	(−3.178)	(−3.191)	(−2.908)	(−2.928)
β_{VRP}	0.433	0.443														
	(5.544)	(5.700)														
β_{Skew}			0.000	0.000												
			(−0.042)	(−0.078)												
β_{SPRD}					0.006	0.005										
					(3.477)	(3.470)										
β_{Max}							−0.002	−0.002								
							(−1.473)	(−1.486)								
β_{Min}									0.003	0.003						
									(1.558)	(1.569)						
β_{RNV}											0.032	0.032				
											(5.826)	(6.004)				
β_{RNS}													0.000	0.000		
													(−2.256)	(−2.297)		
β_{JTI}															0.151	0.152
															(2.366)	(2.408)
$\beta_{\mathcal{ORV}}$	−0.025		−0.032		−0.035		−0.029		−0.027		−0.028		−0.022		−0.015	
	(−0.712)		(−0.972)		(−1.038)		(−0.899)		(−0.858)		(−0.904)		(−0.686)		(−0.497)	
$\beta_{\mathcal{ORJ}}$		0.052		0.062		0.054		0.063		0.064		0.057		0.082		0.065
		(1.180)		(1.386)		(1.233)		(1.402)		(1.430)		(1.289)		(1.865)		(1.434)
R^2_{adj}	0.876%	0.875%	1.074%	1.072%	1.131%	1.128%	1.117%	1.116%	1.143%	1.143%	1.139%	1.138%	1.212%	1.215%	1.221%	1.224%

Notes: Everything is defined as in Table 10. VRP is the variance risk-premium as defined in Section 5, $Skew$ is the ex-ante skewness, $SPRD$ is the volatility spread, Max and Min are the Bali et al. (2011) maximum and minimum daily returns, RNV and RNS are the Bakshi et al. (2003) risk-neutral variance and skewness, and JTI is the jump-tail risk by Du and Kapadia (2012). All these measures are defined in Appendix A.

Table C9: Predicting SPY Monthly Excess Return with OTM Call Option Realized Signed Measures

	Call ($K/S = 1.10$)																	
α	0.003	0.002	0.003	0.003	0.003	0.002	0.003	0.002	0.003	0.003	0.003	0.002	0.002	0.002	0.002	0.002	0.004	0.003
	(0.969)	(0.713)	(1.045)	(0.849)	(0.991)	(0.765)	(0.952)	(0.723)	(1.092)	(0.933)	(0.969)	(0.734)	(0.784)	(0.555)	(0.741)	(0.595)	(1.134)	(0.852)
β_{RV}			−1.786	−2.063	−1.652	−1.909	−1.640	−1.894	−1.830	−2.048	−1.475	−1.740	−1.568	−1.853	−1.456	−1.802	−1.530	−1.754
			(−3.057)	(−3.770)	(−2.650)	(−3.187)	(−2.584)	(−3.132)	(−3.008)	(−3.519)	(−2.387)	(−2.891)	(−2.589)	(−3.180)	(−2.414)	(−3.147)	(−2.261)	(−2.666)
β_{JV}	−5.667	−6.377	−6.061	−6.261	−6.290	−6.538	−5.949	−6.145	−5.787	−5.909	−6.088	−6.278	−6.036	−6.241	−6.359	−6.372	−5.250	−5.063
	(−1.809)	(−1.951)	(−1.742)	(−1.679)	(−1.781)	(−1.708)	(−1.655)	(−1.580)	(−1.764)	(−1.700)	(−1.696)	(−1.615)	(−1.695)	(−1.610)	(−1.816)	(−1.744)	(−1.253)	(−1.182)
β_{IV}			2.530	2.721	1.810	1.835	2.216	2.303	3.740	3.941			1.694	1.724	3.152	2.471	2.383	2.366
			(1.958)	(2.086)	(1.579)	(1.564)	(1.375)	(1.441)	(2.823)	(2.868)			(1.512)	(1.492)	(1.085)	(0.857)	(1.594)	(1.566)
β_{REV}	−0.004	−0.003	−0.003	−0.003	−0.003	−0.003	−0.003	−0.002	−0.002	−0.001	−0.004	−0.003	−0.004	−0.003	−0.004	−0.003	−0.006	−0.005
	(−1.239)	(−0.885)	(−1.108)	(−0.832)	(−1.181)	(−0.906)	(−0.738)	(−0.519)	(−0.571)	(−0.349)	(−1.295)	(−1.044)	(−1.216)	(−0.959)	(−1.214)	(−1.010)	(−1.636)	(−1.365)
β_{MoM}	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(−0.079)	(0.113)	(0.114)	(0.254)	(−0.031)	(0.083)	(−0.086)	(0.016)	(0.069)	(0.165)	(−0.152)	(−0.031)	(0.267)	(0.341)	(0.186)	(0.204)	(−0.239)	(−0.111)
β_{Illiq}	0.458	0.490	0.390	0.490	0.403	0.509	0.434	0.543	0.638	0.751	0.445	0.549	0.268	0.411	0.442	0.540	0.463	0.594
	(0.639)	(0.678)	(0.667)	(0.828)	(0.692)	(0.865)	(0.771)	(0.952)	(1.100)	(1.276)	(0.772)	(0.947)	(0.450)	(0.676)	(0.759)	(0.924)	(0.825)	(1.034)
β_{Size}	−0.296	−0.228	−0.308	−0.254	−0.304	−0.246	−0.292	−0.231	−0.325	−0.281	−0.299	−0.238	−0.171	−0.125	−0.252	−0.208	−0.332	−0.265
	(−1.123)	(−0.884)	(−1.147)	(−0.958)	(−1.137)	(−0.929)	(−1.093)	(−0.878)	(−1.215)	(−1.069)	(−1.112)	(−0.896)	(−0.626)	(−0.469)	(−0.916)	(−0.776)	(−1.255)	(−0.992)
β_{OptV}	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(4.997)	(5.014)	(4.631)	(4.459)	(4.360)	(4.172)	(4.405)	(4.215)	(4.480)	(4.455)	(4.384)	(4.160)	(4.473)	(4.224)	(4.073)	(3.906)	(4.855)	(4.701)
β_{VRP}	1.638	1.854																
	(2.725)	(3.175)																
β_{Skew}			−0.007	−0.008														
			(−0.961)	(−1.239)														
β_{SPRD}					0.005	0.006												
					(1.124)	(1.309)												
β_{Max}							−0.007	−0.007										
							(−0.361)	(−0.422)										
β_{Min}									0.030	0.032								
									(1.823)	(1.940)								
β_{RNV}											0.058	0.060						
											(1.293)	(1.289)						
β_{RNS}													0.001	0.001				
													(1.641)	(1.269)				
β_{JTI}															−0.864	−0.432		
															(−0.598)	(−0.296)		
β_{LTV}																	−0.043	−0.043
																	(−2.081)	(−2.068)
$\beta_{\mathcal{ORV}^+}$	−0.227		−0.216		−0.227		−0.229		−0.187		−0.233		−0.265		−0.258		−0.144	
	(−1.261)		(−1.146)		(−1.222)		(−1.223)		(−1.021)		(−1.266)		(−1.453)		(−1.455)		(−0.769)	
$\beta_{\mathcal{ORV}^-}$	−0.576		−0.556		−0.574		−0.568		−0.472		−0.574		−0.627		−0.621		−0.598	
	(−2.239)		(−2.086)		(−2.226)		(−2.225)		(−2.021)		(−2.221)		(−2.514)		(−2.622)		(−2.297)	
$\beta_{\mathcal{ORJ}^+}$		−0.503		−0.489		−0.497		−0.495		−0.430		−0.507		−0.550		−0.525		−0.453
		(−1.819)		(−1.760)		(−1.808)		(−1.777)		(−1.620)		(−1.854)		(−2.092)		(−2.075)		(−1.683)
$\beta_{\mathcal{ORJ}^-}$		0.775		0.751		0.770		0.758		0.643		0.773		0.829		0.803		0.839
		(2.476)		(2.359)		(2.459)		(2.460)		(2.300)		(2.473)		(2.792)		(2.825)		(2.670)
R^2_{adj}	6.296%	5.659%	6.434%	5.888%	6.312%	5.689%	6.312%	5.690%	7.404%	7.036%	6.127%	5.498%	6.676%	5.906%	6.387%	5.652%	6.748%	6.312%

Notes: Everything is defined as in Table 11. VRP is the variance risk-premium as defined in Section 5, $Skew$ is the ex-ante skewness, $SPRD$ is the volatility spread, Max and Min are the Bali et al. (2011) maximum and minimum daily returns, RNV and RNS are the Bakshi et al. (2003) risk-neutral variance and skewness, JTI is the jump-tail risk of Du and Kapadia (2012), and LTV is the left tail variation of Bollerslev et al. (2015). The left tail variation is obtained from www.tailindex.com and the sample size is from January 11, 2005 to December 31, 2019. All these measures are defined in Appendix A.

Table C10: Predicting SPY Monthly Excess Return with OTM Put Option Realized Signed Measures

	Put ($K/S = 0.90$)																	
α	0.003	0.003	0.004	0.003	0.004	0.003	0.003	0.003	0.004	0.004	0.004	0.003	0.003	0.002	0.003	0.003	0.003	0.003
	(1.046)	(0.912)	(1.139)	(1.043)	(1.092)	(0.974)	(1.052)	(0.933)	(1.140)	(1.099)	(1.069)	(0.942)	(0.912)	(0.783)	(0.917)	(0.830)	(0.980)	(0.980)
β_{RV}			−1.707	−1.997	−1.549	−1.839	−1.540	−1.828	−1.819	−2.023	−1.371	−1.673	−1.470	−1.782	−1.420	−1.757	−1.545	−1.706
			(−2.878)	(−3.574)	(−2.445)	(−3.002)	(−2.402)	(−2.957)	(−2.902)	(−3.396)	(−2.190)	(−2.723)	(−2.388)	(−2.986)	(−2.409)	(−3.001)	(−2.294)	(−2.557)
β_{JV}	−6.421	−6.458	−6.219	−6.097	−6.501	−6.386	−6.099	−5.966	−5.925	−5.803	−6.219	−6.081	−6.205	−6.061	−6.334	−6.099	−5.153	−4.666
	(−1.928)	(−1.957)	(−1.691)	(−1.605)	(−1.732)	(−1.631)	(−1.601)	(−1.509)	(−1.715)	(−1.645)	(−1.637)	(−1.533)	(−1.633)	(−1.528)	(−1.772)	(−1.645)	(−1.186)	(−1.082)
β_{IV}			2.252	2.541	1.434	1.648	1.942	2.201	3.601	3.854			1.302	1.538	2.065	1.966	2.066	2.128
			(1.648)	(1.922)	(1.206)	(1.406)	(1.212)	(1.380)	(2.575)	(2.772)			(1.112)	(1.331)	(0.708)	(0.679)	(1.317)	(1.373)
β_{REV}	−0.005	−0.004	−0.005	−0.003	−0.005	−0.004	−0.004	−0.003	−0.003	−0.002	−0.006	−0.004	−0.005	−0.004	−0.005	−0.004	−0.006	−0.005
	(−1.643)	(−1.099)	(−1.678)	(−1.135)	(−1.778)	(−1.208)	(−1.140)	(−0.712)	(−0.946)	(−0.608)	(−1.916)	(−1.358)	(−1.848)	(−1.273)	(−1.876)	(−1.352)	(−1.766)	(−1.498)
β_{MoM}	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(0.041)	(0.196)	(0.160)	(0.302)	(−0.004)	(0.128)	(−0.074)	(0.047)	(0.118)	(0.212)	(−0.111)	(0.021)	(0.237)	(0.357)	(0.109)	(0.202)	(−0.089)	(−0.028)
β_{Illiq}	0.442	0.455	0.457	0.493	0.474	0.512	0.510	0.551	0.703	0.753	0.517	0.554	0.378	0.427	0.504	0.535	0.585	0.627
	(0.619)	(0.630)	(0.774)	(0.826)	(0.809)	(0.865)	(0.896)	(0.958)	(1.197)	(1.273)	(0.892)	(0.946)	(0.623)	(0.696)	(0.863)	(0.908)	(1.005)	(1.073)
β_{Size}	−0.320	−0.282	−0.339	−0.311	−0.339	−0.306	−0.324	−0.290	−0.344	−0.330	−0.334	−0.298	−0.228	−0.200	−0.304	−0.278	−0.300	−0.299
	(−1.192)	(−1.080)	(−1.233)	(−1.151)	(−1.231)	(−1.135)	(−1.183)	(−1.083)	(−1.260)	(−1.233)	(−1.206)	(−1.102)	(−0.810)	(−0.723)	(−1.074)	(−1.002)	(−1.114)	(−1.107)
β_{OptV}	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(4.834)	(4.819)	(4.377)	(4.278)	(4.123)	(3.981)	(4.177)	(4.030)	(4.262)	(4.261)	(4.153)	(3.980)	(4.191)	(4.006)	(3.912)	(3.745)	(4.447)	(4.496)
β_{VRP}	1.483	1.765																
	(2.397)	(3.000)																
β_{Skew}			−0.008	−0.008														
			(−1.110)	(−1.255)														
β_{SPRD}					0.006	0.007												
					(1.360)	(1.424)												
β_{Max}							−0.008	−0.009										
							(−0.468)	(−0.507)										
β_{Min}									0.031	0.033								
									(1.877)	(1.970)								
β_{RNV}											0.044	0.053						
											(0.946)	(1.144)						
β_{RNS}													0.001	0.000				
													(1.179)	(1.050)				
β_{JTI}															−0.441	−0.241		
															(−0.303)	(−0.165)		
β_{LTV}																	−0.040	−0.040
																	(−1.867)	(−1.889)
$\beta_{\mathcal{ORV}^+}$	−0.687		−0.670		−0.692		−0.690		−0.610		−0.701		−0.710		−0.704		−0.510	
	(−2.742)		(−2.584)		(−2.697)		(−2.719)		(−2.655)		(−2.757)		(−2.808)		(−2.956)		(−1.942)	
$\beta_{\mathcal{ORV}^-}$	−0.241		−0.203		−0.229		−0.222		−0.043		−0.251		−0.268		−0.260		−0.178	
	(−0.963)		(−0.795)		(−0.915)		(−0.876)		(−0.179)		(−1.005)		(−1.080)		(−1.097)		(−0.703)	
$\beta_{\mathcal{ORJ}^+}$		−1.044		−1.029		−1.059		−1.055		−0.934		−1.076		−1.079		−1.069		−0.907
		(−2.736)		(−2.571)		(−2.671)		(−2.686)		(−2.646)		(−2.736)		(−2.756)		(−2.881)		(−2.299)
$\beta_{\mathcal{ORJ}^-}$		0.636		0.601		0.637		0.623		0.390		0.662		0.674		0.660		0.666
		(1.532)		(1.425)		(1.534)		(1.490)		(1.037)		(1.608)		(1.647)		(1.727)		(1.576)
R^2_{adj}	5.837%	5.599%	6.017%	5.841%	5.874%	5.653%	5.881%	5.667%	7.067%	7.044%	5.717%	5.475%	6.058%	5.782%	5.834%	5.581%	6.005%	6.080%

Notes: Everything is defined as in Table 11. VRP is the variance risk-premium as defined in Section 5, $Skew$ is the ex-ante skewness, $SPRD$ is the volatility spread, Max and Min are the Bali et al. (2011) maximum and minimum daily returns, RNV and RNS are the Bakshi et al. (2003) risk-neutral variance and skewness, JTI is the jump-tail risk of Du and Kapadia (2012), and LTV is the left tail variation of Bollerslev et al. (2015). The left tail variation is obtained from www.tailindex.com and the sample size is from January 11, 2005 to December 31, 2019. All these measures are defined in Appendix A.

Table C11: Predicting Equity Monthly Excess Return with OTM Call Option Realized Signed Measures

	Call ($K/S = 1.10$)															
β_{RV}			−0.416	−0.419	−0.412	−0.415	−0.420	−0.420	−0.413	−0.412	−0.479	−0.482	−0.435	−0.438	−0.505	−0.504
			(−5.076)	(−5.132)	(−4.805)	(−4.802)	(−4.835)	(−4.817)	(−4.570)	(−4.476)	(−5.348)	(−5.387)	(−5.325)	(−5.313)	(−5.335)	(−5.250)
β_{JV}	0.805	0.803	−0.010	−0.012	−0.076	−0.077	−0.018	−0.018	0.030	0.030	0.029	0.029	0.018	0.017	0.056	0.056
	(1.844)	(1.853)	(−0.024)	(−0.028)	(−0.182)	(−0.184)	(−0.041)	(−0.042)	(0.070)	(0.070)	(0.065)	(0.063)	(0.039)	(0.037)	(0.124)	(0.124)
β_{IV}			0.835	0.837	0.824	0.825	1.121	1.120	1.191	1.189			0.814	0.816	0.346	0.346
			(3.666)	(3.681)	(4.790)	(4.829)	(3.416)	(3.422)	(4.132)	(4.116)			(5.244)	(5.282)	(1.124)	(1.120)
β_{REV}	−0.004	−0.004	−0.004	−0.004	−0.004	−0.004	−0.002	−0.003	−0.004	−0.004	−0.004	−0.004	−0.004	−0.004	−0.004	−0.004
	(−4.379)	(−4.405)	(−3.979)	(−4.009)	(−3.756)	(−3.788)	(−2.205)	(−2.222)	(−4.297)	(−4.324)	(−4.110)	(−4.142)	(−4.332)	(−4.364)	(−4.118)	(−4.145)
β_{MoM}	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(−1.676)	(−1.675)	(−1.218)	(−1.220)	(−1.231)	(−1.233)	(−1.565)	(−1.562)	(−1.319)	(−1.317)	(−1.273)	(−1.275)	(−1.240)	(−1.242)	(−1.427)	(−1.425)
β_{Illiq}	0.010	0.010	0.008	0.008	0.008	0.008	0.008	0.008	0.010	0.010	0.008	0.008	0.007	0.007	0.009	0.009
	(2.017)	(2.026)	(1.414)	(1.416)	(1.397)	(1.400)	(1.731)	(1.737)	(1.924)	(1.928)	(1.609)	(1.612)	(1.504)	(1.506)	(1.885)	(1.887)
β_{Size}	−0.030	−0.030	0.018	0.018	0.010	0.009	0.006	0.006	0.025	0.025	0.006	0.006	−0.010	−0.011	−0.015	−0.015
	(−0.168)	(−0.168)	(0.117)	(0.113)	(0.062)	(0.057)	(0.038)	(0.038)	(0.163)	(0.164)	(0.040)	(0.037)	(−0.061)	(−0.066)	(−0.090)	(−0.090)
β_{OptV}	−0.001	−0.001	−0.001	−0.001	−0.001	−0.001	−0.001	−0.001	−0.001	−0.001	−0.001	−0.001	−0.001	−0.001	−0.001	−0.001
	(−1.929)	(−1.926)	(−3.416)	(−3.425)	(−3.347)	(−3.367)	(−2.985)	(−2.986)	(−2.738)	(−2.730)	(−3.110)	(−3.127)	(−3.182)	(−3.192)	(−2.909)	(−2.917)
β_{VRP}	0.462	0.461														
	(5.922)	(5.877)														
β_{Skew}			0.000	0.000												
			(−0.053)	(−0.060)												
β_{SPRD}					0.006	0.006										
					(3.490)	(3.482)										
β_{Max}							−0.008	−0.008								
							(−1.461)	(−1.460)								
β_{Min}									0.013	0.013						
									(1.518)	(1.513)						
β_{RNV}											0.032	0.032				
											(5.891)	(5.967)				
β_{RNS}													0.000	0.000		
													(−2.281)	(−2.274)		
β_{JTI}															0.152	0.152
															(2.400)	(2.399)
$\beta_{\mathcal{ORV}^+}$	0.031		0.025		0.023		0.030		0.029		0.027		0.018		0.032	
	(1.208)		(1.069)		(0.925)		(1.180)		(1.157)		(1.083)		(0.841)		(1.293)	
$\beta_{\mathcal{ORV}^-}$	−0.037		−0.045		−0.045		−0.029		−0.021		−0.044		−0.042		−0.030	
	(−1.055)		(−1.408)		(−1.327)		(−0.869)		(−0.635)		(−1.291)		(−1.204)		(−0.928)	
$\beta_{\mathcal{ORJ}^+}$		0.028		0.030		0.028		0.034		0.031		0.032		0.022		0.033
		(1.159)		(1.301)		(1.149)		(1.436)		(1.276)		(1.297)		(1.093)		(1.372)
$\beta_{\mathcal{ORJ}^-}$		0.072		0.062		0.062		0.047		0.043		0.063		0.059		0.058
		(2.505)		(2.254)		(2.190)		(1.708)		(1.688)		(2.199)		(1.971)		(2.114)
R^2_{adj}	0.886%	0.888%	1.071%	1.072%	1.128%	1.129%	1.247%	1.249%	1.383%	1.384%	1.137%	1.139%	1.211%	1.212%	1.221%	1.223%

Notes: Everything is defined as in Table 12. VRP is the variance risk-premium as defined in Section 5, $Skew$ is the ex-ante skewness, $SPRD$ is the volatility spread, Max and Min are the Bali et al. (2011) maximum and minimum daily returns, RNV and RNS are the Bakshi et al. (2003) risk-neutral variance and skewness, and JTI is the jump-tail risk by Du and Kapadia (2012). All these measures are defined in Appendix A.

Table C12: Predicting Equity Monthly Excess Return with OTM Put Option Realized Signed Measures

	Put ($K/S = 0.90$)															
β_{RV}			−0.414	−0.412	−0.410	−0.408	−0.417	−0.413	−0.412	−0.406	−0.478	−0.475	−0.437	−0.434	−0.503	−0.497
			(−5.124)	(−5.126)	(−4.791)	(−4.753)	(−4.860)	(−4.779)	(−4.585)	(−4.455)	(−5.386)	(−5.366)	(−5.391)	(−5.309)	(−5.361)	(−5.229)
β_{JV}	0.809	0.809	−0.008	−0.005	−0.074	−0.071	−0.015	−0.011	0.033	0.037	0.032	0.035	0.019	0.022	0.059	0.061
	(1.857)	(1.872)	(−0.018)	(−0.011)	(−0.178)	(−0.172)	(−0.034)	(−0.026)	(0.077)	(0.085)	(0.070)	(0.077)	(0.042)	(0.049)	(0.131)	(0.138)
β_{IV}			0.833	0.829	0.822	0.818	1.118	1.113	1.192	1.184			0.816	0.812	0.346	0.343
			(3.627)	(3.635)	(4.748)	(4.778)	(3.402)	(3.400)	(4.103)	(4.081)			(5.217)	(5.241)	(1.122)	(1.110)
β_{REV}	−0.004	−0.004	−0.004	−0.004	−0.004	−0.004	−0.003	−0.003	−0.004	−0.004	−0.004	−0.004	−0.004	−0.004	−0.004	−0.004
	(−4.441)	(−4.412)	(−4.071)	(−4.044)	(−3.836)	(−3.821)	(−2.260)	(−2.260)	(−4.346)	(−4.354)	(−4.147)	(−4.138)	(−4.371)	(−4.360)	(−4.143)	(−4.146)
β_{MoM}	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(−1.665)	(−1.659)	(−1.208)	(−1.206)	(−1.221)	(−1.219)	(−1.551)	(−1.547)	(−1.309)	(−1.304)	(−1.263)	(−1.260)	(−1.234)	(−1.231)	(−1.415)	(−1.410)
β_{Illiq}	0.010	0.010	0.008	0.008	0.008	0.008	0.008	0.008	0.010	0.010	0.008	0.008	0.007	0.007	0.009	0.009
	(2.005)	(2.029)	(1.405)	(1.419)	(1.388)	(1.402)	(1.719)	(1.739)	(1.914)	(1.927)	(1.597)	(1.612)	(1.489)	(1.504)	(1.874)	(1.887)
β_{Size}	−0.029	−0.029	0.018	0.018	0.009	0.009	0.007	0.007	0.026	0.025	0.007	0.006	−0.010	−0.010	−0.014	−0.014
	(−0.166)	(−0.166)	(0.117)	(0.116)	(0.061)	(0.059)	(0.043)	(0.042)	(0.170)	(0.169)	(0.041)	(0.040)	(−0.063)	(−0.063)	(−0.086)	(−0.086)
β_{OptV}	−0.001	−0.001	−0.001	−0.001	−0.001	−0.001	−0.001	−0.001	−0.001	−0.001	−0.001	−0.001	−0.001	−0.001	−0.001	−0.001
	(−1.917)	(−1.874)	(−3.431)	(−3.379)	(−3.353)	(−3.319)	(−2.977)	(−2.928)	(−2.749)	(−2.692)	(−3.109)	(−3.076)	(−3.177)	(−3.139)	(−2.907)	(−2.868)
β_{VRP}	0.459	0.454														
	(5.838)	(5.809)														
β_{Skew}			0.000	0.000												
			(−0.052)	(−0.052)												
β_{SPRD}					0.006	0.006										
					(3.485)	(3.519)										
β_{Max}							−0.008	−0.008								
							(−1.463)	(−1.461)								
β_{Min}									0.013	0.013						
									(1.521)	(1.513)						
β_{RNV}											0.032	0.032				
											(5.843)	(5.921)				
β_{RNS}													0.000	0.000		
													(−2.257)	(−2.250)		
β_{JTI}															0.152	0.151
															(2.384)	(2.381)
$\beta_{\mathcal{ORV}^+}$	−0.079		−0.083		−0.087		−0.080		−0.074		−0.079		−0.070		−0.067	
	(−2.485)		(−2.713)		(−2.626)		(−2.571)		(−2.697)		(−2.512)		(−2.307)		(−2.227)	
$\beta_{\mathcal{ORV}^-}$	0.076		0.065		0.065		0.079		0.096		0.065		0.070		0.077	
	(1.658)		(1.548)		(1.490)		(1.908)		(2.456)		(1.560)		(1.582)		(1.898)	
$\beta_{\mathcal{ORJ}^+}$		−0.131		−0.126		−0.132		−0.123		−0.113		−0.122		−0.108		−0.112
		(−2.983)		(−3.115)		(−3.043)		(−2.961)		(−3.074)		(−2.936)		(−2.675)		(−2.704)
$\beta_{\mathcal{ORJ}^-}$		−0.008		−0.019		−0.017		−0.028		−0.052		−0.019		−0.031		−0.020
		(−0.186)		(−0.439)		(−0.410)		(−0.674)		(−1.418)		(−0.462)		(−0.713)		(−0.486)
R^2_{adj}	0.892%	0.897%	1.077%	1.081%	1.135%	1.139%	1.254%	1.258%	1.391%	1.393%	1.142%	1.147%	1.216%	1.219%	1.226%	1.229%

Notes: Everything is defined as in Table 12. VRP is the variance risk-premium as defined in Section 5, $Skew$ is the ex-ante skewness, $SPRD$ is the volatility spread, Max and Min are the Bali et al. (2011) maximum and minimum daily returns, RNV and RNS are the Bakshi et al. (2003) risk-neutral variance and skewness, and JTI is the jump-tail risk by Du and Kapadia (2012). All these measures are defined in Appendix A.