Variance Risk: A Bird's Eye View*

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September 6, 2019

Abstract

The literature documents a significantly negative average variance swap payoff (VSP) for the S&P 500 index but generally not for the constituent stocks. We show that this result is affected by biases arising from (i) an intraday momentum effect and (ii) the use of an incoherent measure of return variation. Accounting for these issues, we find stronger evidence of a significant average VSP both at the index level and also for equities. We decompose the index variance risk premium (VRP) into factors related to the VRP of equities and the correlation risk premium (CRP) and assess their predictive power for aggregate stock returns.

JEL classification: G11, G12

Keywords: Correlation Swaps, Return Predictability, Return Variation, Variance Swaps

*We thank Yacine Aït-Sahalia (the editor), the anonymous associate editor and the two anonymous referees for their constructive comments. We are also grateful to Torben Andersen, Tim Bollerslev, Nicole Branger, Arndt Claußen, Mike Clements, Maik Dierkes, Ana González Urteaga, Loriano Mancini, Binh Nguyen, Piotr Orlowski, Marcel Prokopczuk, Rogier Quaedvlieg, Paul Schneider, Tobias Sichert, Michal Svaton, Roméo Tédongap, Viktor Todorov, Fabio Trojani and seminar participants at the 2017 German Finance Association meeting, the 2018 Swiss Finance Conference, the 2018 International French Finance Association meeting, the 2018 Society for Financial Econometrics meeting, the 2018 Spanish Finance Forum, the 2018 Financial Econometrics Conference at the University of Lancaster, the 2018 Econometrics and Financial Data Science meeting, the University of East Anglia, the University of Reading (ICMA Centre) and Leibniz University Hannover for helpful comments and discussions. Part of this research was carried out when Chardin Wese Simen was at the University of Reading.

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1 Introduction

Using daily data, Carr and Wu (2009) and Driessen et al. (2009) document a significantly negative average variance swap payoff (VSP) for the U.S. stock market index. However, they find significant average VSPs only for a small number of individual equities that belong to the stock index. This disconnect between the results observed at the index and individual equities levels is surprising, because the index is a portfolio of its constituent stocks. In addition, this finding is difficult to reconcile with theoretical work on the joint pricing of variance risk for the equity index and constituents stocks. For instance, Buraschi et al. (2014b) propose a structural model that generates a sizable market price of variance risk for both the equity index and the constituent stocks.

This paper investigates the possibility that measurement errors may cause the puzzling differences in the VSP estimates documented in the literature. To understand why measurement errors may be a concern, it is useful to discuss two approaches to estimating the market price of variance risk. The first approach assumes that the researcher observes the time series of prices on a liquid and tradeable variance asset, e.g., a variance swap. She can directly calculate the market price of variance risk by analyzing the ex-post returns on this asset (Dew-Becker et al., 2017; Cheng, 2018; Aït-Sahalia et al., 2019).[1] In this case, the only source of error in the estimate of the market price of variance risk is the price of the variance swap. Unfortunately, this methodology is fraught with issues. To begin with, variance swap data are proprietary. Moreover, conversations with practitioners reveal that the single-stock variance swap

[1] Egloff et al. (2010), Dew-Becker et al. (2017) and Aït-Sahalia et al. (2019) analyze a proprietary dataset of S&P 500 index variance swaps traded over-the-counter (OTC). Cheng (2018) focuses on the exchange-traded VIX futures prices.

market has dried up since 2008, making it difficult to analyze individual equities. Aware of these limitations, the literature has developed an alternative approach that consists in analyzing the realized (ex-post) payoffs of synthetic variance swaps (Carr and Wu, 2009). In this framework, the researcher needs to (i) synthesize the variance swap rate (VSR) using observable option prices and (ii) estimate the realized return variation. Clearly, measurement errors could arise from (i) the (synthetic) VSR and (ii) the computation of the realized return variation. Jiang and Tian (2005) carefully analyze the measurement errors in the computation of the synthetic VSR. Our main focus is thus on the measurement errors in the estimates of the realized return variation and their impact on the variance swap payoff estimates.[2]

Our key finding is that biases in the computation of the return variation, arising from (i) an intraday momentum effect and (ii) the use of a measure of return variation (for the floating leg of the variance swap contract) that is not priced by the Britten-Jones and Neuberger (2000) estimator have contaminated the average VSP estimates of the previous literature. Indeed, the estimates of the VSPs of individual equities change dramatically once we correct for these two biases. For example, when realized variance is computed using daily data and the standard estimator of realized variance, as is done, e.g., in González-Urteaga and Rubio (2016), the average 1-month VSP of individual equities is positive (0.03 %) and statistically indistinguishable from zero. However, when realized variance is measured using high-frequency data and the Andersen et al. (2015) return variation estimator, the average VSP of individual equities becomes

[2] Throughout this paper, we refer to the VSP as the difference between the return variation, computed ex-post, and the risk-neutral expectation of future variance. We also analyze the variance risk premium (VRP), defined as the spread between the physical and risk-neutral expectations of future return variation. Note that, when estimating the VRP, there is a third source of error that stems from the forecasting model used to generate the conditional expectation of the return variation under the physical measure.

negative ($-0.92\,\%$) and statistically significant. Similarly, the average VSP of the S&P 500 index nearly doubles from $-0.68\,\%$ in the benchmark case to $-1.33\,\%$ when making the bias corrections.

Leveraging our finding that there are significant negative VSPs for individual equities, we decompose the index VSP into (i) a factor that depends on the VSPs of the individual equities that make up the index and (ii) a factor that is a function of the correlation swap payoff (CSP). Empirically, the two factors have distinct dynamics and are only weakly correlated. The factor related to the CSP accounts for 70.6 % of the average level of the index VSP while the factor linked to the VSP of individual stocks captures 67.4 % of the variation in the index VSP. We also dissect the index variance risk premium (VRP), modeled as in Bollerslev et al. (2009), into the individual VRP and the correlation risk premium (CRP) factors. Together, the two factors improve the predictability of the S&P 500 excess returns. For instance, the index VRP yields an adjusted R^2 of 10.3 % at the 3-month horizon, whereas a model that combines the two factors achieves an adjusted R^2 equal to 12.8 %. This improvement in forecast accuracy is statistically significant.

We evaluate the robustness of our results to the potential microstructure noise introduced by sampling data at the intraday level. To this end, we use (i) different sampling frequencies and (ii) implement the subsampling and averaging technique of Zhang et al. (2005) when computing the return variation. The key conclusions are similar. One concern may be that the computation of the VSR requires liquid options covering a wide range of strike prices. This requirement may be more problematic for single-stock than index options. Focusing on the stocks with the most active equity options, we find that the average VSP of stocks changes from an insignificant 0.22 % to a significant $-0.89\,\%$ as we switch from the standard to the bias-corrected estimator of return variation. Finally, we check the robustness of the predictability results with respect to the variance forecasting model.

Our research relates to the literature on the differential pricing of individual equity options relative to equity index options. Garleanu et al. (2009) document that investors' demand for index and individual stock options differs substantially. They show that end-users are generally net long index options and net short individual equity options. The authors discuss how this finding can lead to index options that are relatively expensive, whereas individual equity options appear cheaper. Driessen et al. (2009) economically interpret the wedge between the VSP of the market index and that of its constituents as the price to insure against correlation risk. Relative to their work, we analyze a sample period twice as long and cover a broader range of equities. To the best of our knowledge, we are the first to show that biases induced by (i) the intraday momentum effect and (ii) an incoherent definition of the return variation priced by the Britten-Jones and Neuberger (2000) implied variance (IV) materially affect the average VSP estimates. Correcting for the biases, we find that (i) the cost of insuring against stock level variance risk is large and significant and (ii) that of insuring against correlation risk is larger than previously reported.

We connect the bias in the return variation estimates to the growing literature documenting positive intraday momentum. Heston et al. (2010) show that the return on a stock observed at a particular time of a day predicts the return on that stock at the same time over the following days. Gao et al. (2018) show that the sum of the overnight and first half-hour returns of the exchange-traded fund (ETF) tracking the S&P 500 index predicts its last half-hour return. Bogousslavsky (2016) develops a theoretical model with infrequent rebalancing that can rationalize these empirical findings. We show that these intraday patterns have implications that go beyond mere market timing. They make the daily squared return an upward-biased estimate of the sum of squared intraday returns. After correcting for the intraday autocorrelation effects, we find average VSPs for individual equities that are larger in magnitude and more significant.[3]

Our paper contributes to the growing literature that dissects the index VRP. Todorov (2010) and Bollerslev and Todorov (2011) decompose the index VRP into components associated with (i) continuous and (ii) discontinuous movements. Cosemans (2011) decomposes the index VRP into the (value-weighted) average of individual VRP and the CRP. Bollerslev et al. (2015) show that the compensation for the discontinuous movements plays an important role in the predictive power of the index VRP for aggregate excess stock returns. Feunou et al. (2017a) and Kilic and Shaliastovich (2019) decompose the index VRP into upside and downside parts and study their implications for the predictability of aggregate excess returns. Feunou et al. (2017b) extend this analysis to the cross-section of stock returns. To our knowledge, we are the first to correct for the biases in the estimates of the VSP, decompose the index VRP into factors linked to (i) the VRP of constituent stocks and (ii) the CRP in a coherent manner and assess their predictive power for S&P 500 excess returns.[4] Overall, our empirical results suggest that our two-factor structure yields more accurate

[3]The finding of significant average VSPs in stocks is relevant for studies that use IV to directly forecast the return variation of individual stocks: it might be possible to improve the forecast accuracy by accounting for the VRP in the spirit of Prokopczuk and Wese Simen (2014) and Kourtis et al. (2016).

[4]By "coherent decomposition", we mean a decomposition where the factors add up to the index VRP. Feunou et al. (2017a) and Kilic and Shaliastovich (2019) provide a coherent decomposition into upside and downside VRP. However, the decomposition of Cosemans (2011) is not coherent. A coherent decomposition is very useful when it comes to quantifying the contribution of each factor to the average of the index VRP as well as the variations in the index VRP.

return forecasts than the two factors of Cosemans (2011), Feunou et al. (2017a) and Kilic and Shaliastovich (2019).

The remainder of this paper is organized as follows. Section 2 presents the data and empirical methodology. Section 3 analyzes the VSPs. Section 4 focuses on the VRP. Section 5 presents additional results. Finally, Section 6 concludes.

2 Data and Methodology

This section begins with an overview of the dataset. It then introduces our methodology.

2.1 Data

We obtain options data related to the S&P 500 index and its constituents from IvyDB OptionMetrics. The sample period ranges from January 1996 to August 2015.[5] We use the Volatility Surface provided by OptionMetrics. The database contains implied volatilities for different (i) constant time-to-maturity horizons and (ii) levels of delta, where delta is defined as the sensitivity of the option price to a small change in the underlying asset price.[6]

We process the dataset as follows. First, we only retain options that are out-of-the-money (OTM). Essentially, this means that we only keep put and call options with deltas that are higher than -0.5 and lower than 0.5, respectively. Second, we only

[5]The starting date of the sample period is forced upon us as the OptionMetrics dataset is available from 1996 onwards. The end of our sample period reflects the data available at the time we started this study.

[6]The algorithm used by IvyDB to calculate the implied volatility accounts for the early exercise feature of options on single equities. For further information, we refer the interested reader to the IvyDB technical document.

keep options expiring in 1 month. Third, we download the time series of discount rates available from OptionMetrics. We implement a cubic spline interpolation to obtain the discount rate of the same time-to-maturity as the option. We match this time series with our panel data so that, for each option price, there is a discount rate of corresponding maturity.

We also obtain the daily time series of the S&P 500 index, the prices and returns of all individual equities that make up the index. The data come from the Center for Research in Security Prices (CRSP).

2.2 Methodology

Our analysis revolves around the variance swap. A trader with a buy and hold position in the variance swap pays a fixed rate called the variance swap rate at expiration. In return, she receives the return variation ($\sigma^2_{i,t+\tau}$) of the underlying asset computed over the maturity of the variance swap. Thus, the payoff to a long variance swap with a notional amount of \$1 can be computed as follows:

$$VSP_{i,t+\tau} = \sigma^2_{i,t+\tau} - VSR_{i,t} \tag{1}$$

where $VSP_{i,t+\tau}$ is the realized payoff, on day $t+\tau$, of the variance swap written on the underlying asset i. τ is the time-to-maturity of the variance swap, expressed in calendar days. $\sigma^2_{i,t+\tau}$ is the return variation of the underlying asset over the life of the variance swap, i.e., for the period starting at t and ending at $t+\tau$. Notice that the return variation can only be computed ex-post, i.e., at $t+\tau$. $VSR_{i,t}$ is the variance swap rate, which is fixed at inception, i.e., on day t. Because by design no money changes hands at the inception of the variance swap, no-arbitrage implies that the VSR is the risk-neutral expectation of future variance ($E_t^{\mathbb{Q}}(\sigma^2_{i,t+\tau})$).[7] Thus, we can write:

$$VSP_{i,t+\tau} = \sigma^2_{i,t+\tau} - E_t^{\mathbb{Q}}(\sigma^2_{i,t+\tau}) \tag{2}$$

In the market, the term sheets of traded variance swaps typically specify that the floating leg be computed using the (low-frequency) realized variance ($RV^{(LF)}_{i,t+\tau}$):[8]

$$RV^{(LF)}_{i,t+\tau} = \frac{365}{\tau} \sum_{j=t+1}^{t+\tau} r^2_{i,j} \tag{3}$$

where $r_{i,j}$ is the (log) return on security i on day j. Throughout this paper, the factor $\frac{365}{\tau}$ annualizes the variance estimate.

However, as discussed in the Introduction, the variance swap market for individual equities has dried up since 2008. Consequently, we need to synthetically compute the VSR. We follow most of the empirical literature, e.g., Carr and Wu (2009), and fix the VSR to be equal to the Britten-Jones and Neuberger (2000) IV:

$$E_t^{\mathbb{Q}}(\sigma^2_{i,t+\tau}) \;=\; \frac{2e^{\mathrm{rf_t}\frac{\tau}{365}}}{\frac{\tau}{365}} \left(\int_0^{S_t} \frac{P_t(\tau,K)}{K^2} dK + \int_{S_t}^{\infty} \frac{C_t(\tau,K)}{K^2} dK \right) \tag{4}$$

where $\mathrm{rf_t}$ denotes the (annualized) discount rate (of same maturity as that of the option) on day t. $P_t(\tau,K)$ and $C_t(\tau,K)$ denote the price, on day t, of the put and call options with time-to-maturity τ and strike price K, respectively. All options relate to

[7] In this paper, we often refer to the risk-neutral expectation of future total variance as the option-implied variance.

[8] Using demeaned returns when computing the realized variance leads to very similar estimates to those based on the estimator in Equation (3). See also González-Urteaga and Rubio (2016).

the underlying asset i. If the return process is continuous and the sampling frequency fine, the estimator in Equation (4) gives the price of the variance swap contract, where the floating leg is defined as the sum of squared returns.[9] In order to minimize the potential errors in the computation of the synthetic VSR, we broadly follow the numerical scheme of Chang et al. (2012).[10] We begin by computing ex-dividend stock prices. From the Volatility Surface, we interpolate implied volatilities for different levels of moneyness between 0.3 % and 300 % using a cubic spline, where "moneyness" is defined as the ratio of the strike price over the underlying price. In practice, the moneyness range available in the market does not completely span the interval starting at 0.3 % and ending at 300 %, raising the issue of extrapolation. Building on the work of Jiang and Tian (2005), we perform a nearest neighbourhood extrapolation. To be more specific, we assume that the implied volatility remains constant below the lowest and above the highest moneyness points available in the market. We then use the fine grid of interpolated/extrapolated implied volatilities to compute the Black and Scholes (1973) prices of the out-of-the-money (OTM) options. Equipped with these prices, we implement the trapezoidal rule to numerically compute the risk-neutral expectation of future variance (see Equation (4)). We repeat the steps above for each security and observation day.

3 Variance Swap Payoffs

We study the S&P 500 index VSP of maturity 1 month. Each day, we compute the 1-month IV as well as the subsequently realized 1-month return variation. Thus,

[9]Section 3.3 discusses the case of a discontinuous return process.

[10]For a detailed discussion of the errors in the synthetic VSR, we refer the interested reader to Jiang and Tian (2005).

we analyze the daily time series of the 1-month VSPs. We begin by documenting the basic facts. Next, we investigate various factors that could affect these facts.

3.1 Baseline Results

Panel A of Table 1 reports that the average realized variance of the S&P 500 index is 3.85 %, whereas the average S&P 500 index VSR is 4.53 %. Thus, the VSP is negative on average (−0.68 %). The Newey and West (1987) corrected *t*-statistic (*t*-stat=−2.45), computed with 21 lags, indicates that we can reject the null hypothesis that the average index VSP is equal to zero at the 5 % significance level. The positive skewness and the large kurtosis estimates reveal that, while selling variance swaps is generally profitable, it is also prone to crashes. These findings are consistent with those of earlier works, e.g., Carr and Wu (2009).

Given the fat-tailed distribution of the VSP, we conduct a block-bootstrap to make the statistical inference more robust. We split the original sample into overlapping blocks of 22 observations each. From these blocks, we randomly generate 1,000 bootstrap samples of the time series of VSPs. We then compute the test statistic associated with each bootstrap sample. Finally, we use the empirical distribution of the test statistic to obtain the critical values and conduct the statistical inference. We report in **bold** the statistically significant parameter estimates. Generally, the bootstrap-based inference yields similar conclusions as to the asymptotic one.

We now turn our attention to the payoffs of the variance swaps related to the stocks that make up the S&P 500 index. Following Driessen et al. (2009), we compute the equal-weighted average of the fixed and floating legs of the variance swaps of all constituent stocks.[11] Panel A of Table 1 documents that the average realized variance of individual equities is higher than the corresponding IV, implying a marginally positive average VSP (0.03 %). The positive average VSP of individual equities is in contrast to the negative estimate observed for the S&P 500 index. The t-statistic associated with the average VSP of individual stocks reveals that we cannot reject the null hypothesis that the mean is equal to zero. This result is consistent with the finding of Driessen et al. (2013) who also study the S&P 500 index.

It is possible that some stocks have significantly positive VSPs while others have significantly negative VSPs. If this is the case, the positive and negative payoffs might offset each other, making it hard to reject the null hypothesis that the average VSP of stocks is equal to zero. We thus ask the question: how often do we reject the null of a zero average VSP for individual stocks?

The results, presented in Panel B of Table 1, indicate that we cannot reject the null hypothesis of a zero average VSP for 66.9 % of the stocks that make up the S&P 500 index.[12] This finding is congruent with that of Driessen et al. (2009), who document that 77.17 % of the stocks in the S&P 100 index do not exhibit a significant VSP. Similarly, Carr and Wu (2009) show that 85.71 % of the stocks they analyze do not have a significant VSP. The somewhat higher figures reported by these studies are possibly due to the limited power of their test, that results from their shorter sample period and their smaller cross-section of individual stocks.

Summarizing, we confirm the surprising finding of the literature: there is a signif-

[11] In order to minimize the effect of outliers on the average, we winsorize the RV and IV in the cross-section at the 0.5% and 99.5% levels. The results without the winsorization are very similar.

[12] In conducting this analysis, we focus on stocks with at least 300 daily observations. We do this to ensure that stocks with limited data do not bias our empirical results, since the statistical test will not have enough power for these specific securities. 300 observations seems a reasonable sample size in order to perform the statistical inference. This threshold is less stringent than that of Carr and Wu (2009), who use 600 observations.

icantly negative VSP at the index level but generally not for the constituent stocks. Taken together, these results raise the question: what might explain the difference between the results observed at the index and constituent levels?

3.2 Intraday Momentum?

3.2.1 Mechanism

As previously discussed, if the return process is continuous and the sampling frequency high, the IV estimator in Equation (4) gives the risk-neutral expectation of the sum of squared returns. The sum of squared intraday returns may differ from the sum of squared daily returns because of intraday autocovariance effects. To illustrate this effect, recall that the daily log return ($r_{i,j}$) is simply equal to the sum of intraday (log) returns ($r_{i,j,k}$), which implies that:

$$r_{i,j} = \sum_{k=0}^{m} r_{i,j,k} \tag{5}$$

$$r_{i,j}^2 = \sum_{k=0}^{m} r_{i,j,k}^2 + \underbrace{\sum_{k=0}^{m} \sum_{l,l \neq k} r_{i,j,k} r_{i,j,l}}_{\text{Intraday Autocovariance}} \tag{6}$$

$$\underbrace{\frac{365}{\tau} \sum_{j=t+1}^{t+\tau} r_{i,j}^2}_{RV_{i,t+\tau}^{(LF)}} = \underbrace{\frac{365}{\tau} \sum_{j=t+1}^{t+\tau} \sum_{k=0}^{m} r_{i,j,k}^2}_{RV_{i,t+\tau}^{(HF)}} + \underbrace{\frac{365}{\tau} \sum_{j=t+1}^{t+\tau} \sum_{k=0}^{m} \sum_{l,l \neq k} r_{i,j,k} r_{i,j,l}}_{\text{Intraday Autocovariance}} \tag{7}$$

where $RV_{i,t+\tau}^{(LF)}$ and $RV_{i,t+\tau}^{(HF)}$ are the low-frequency and high-frequency estimators of the annualized realized variance of asset i, calculated for the period starting at t and ending at $t + \tau$, respectively.

Equation (7) reveals that the realized variance based on daily data depends on the sum of squared intraday returns as well as the interaction between these intraday returns. In a frictionless world with independent and identically distributed returns, the daily and intraday estimators are both unbiased estimators of the total quadratic variation (McAleer and Medeiros, 2008).[13] However, if there is true autocorrelation in intraday returns, the low-frequency estimator is a biased estimator of the total quadratic variation whereas the high-frequency estimator is unbiased. Consequently, the VSP estimates based on low-frequency realized variance will be inaccurate. The preceding discussion thus raises the question: is there evidence of "true" intraday autocorrelation?[14]

3.2.2 Prior Evidence

Drechsler and Yaron (2011) report the summary statistics of the realized variance of the S&P 500 index calculated separately using (i) daily and (ii) intraday returns. Table 1 of their paper documents an average (annualized) realized variance of 2.48 % and 1.77 % based on daily and intraday data, respectively.[15] These figures are indicative of a positive intraday momentum effect that biases the realized variance estimates based on daily data. As a result, their average index VSP increases by 47 % from −1.51 % when using daily data to −2.23 % when based on high-frequency data.

More recently, Gao et al. (2018) document the intraday momentum effect, namely

[13] Note, however, that the intraday estimator will be more efficient than the daily estimator.

[14] By "true" intraday autocorrelation, we mean autocorrelation patterns that show up after tackling the microstructure noise issue that has been the main focus of the literature on high-frequency financial econometrics. According to that literature, the microstructure noise may arise because of the bid–ask bounce and differences in trade size, to name but a few. In order to minimize the microstructure noise, the standard approach in that literature is to carefully select the sampling frequency of the data.

[15] To be more precise, Table 1 of Drechsler and Yaron (2011) reports the average realized variance estimates equal to 20.69 and 14.74 basis points per month for the daily and 5-minute data, respectively. Since we report annualized quantities, we multiply the figures of the authors by 12. Consequently, we obtain average realized variance estimates of 2.48 % and 1.77 % using daily and intraday data, respectively. Similarly, the annualized IV, which the authors proxy with the squared of the volatility index (VIX), averages 4.00 % for their sample period.

that the sum of the (i) first half-hour and (ii) overnight returns on the S&P 500 index ETF reliably predicts its last half-hour returns. Bogousslavsky (2016) develops a theoretical model with infrequent rebalancing that can rationalize this result. Collectively, these studies present some evidence of positive intraday autocorrelation in equity markets. If this result extends to individual equities, it will introduce a positive bias in (i) the low-frequency realized variance and (ii) the corresponding VSP estimates.

3.2.3 Direct Evidence

We obtain high-frequency data from Thomson Reuters Tick History (TRTH) and implement the data-cleaning steps outlined in Barndorff-Nielsen et al. (2009). First, we use only data with a time stamp falling during the exchange trading hours, i.e., between 9:30 AM and 4:00 PM EST. Second, we remove recording errors in prices. To be more specific, we filter out prices that differ by more than 10 mean absolute deviations from a rolling centered median of 50 observations. Afterwards, we assign prices to every 5-minute interval using the nearest previous entry that occurred at most one day before. We sample observations at the 30-minute frequency exactly as in Gao et al. (2018).[16] Equipped with this data, we use the following high-frequency

[16]The choice of sampling frequency involves a trade-off. On the one hand, pushing the sampling frequency to the highest level introduces microstructure noise in the analysis of liquid stocks. Clearly, using a lower frequency is a good tool to guard against the microstructure noise that occurs at very high frequencies for liquid stocks. On the other, these lower frequencies can increase the contribution of microstructure noise for illiquid stocks due to inactive trading (Andersen et al., 2000). We use the signature plot, which displays the average realized variance estimates as a function of the sampling frequency, to guide our selection of sampling frequency. Our untabulated analysis shows that the plot starts to stabilize around the 30-minute frequency, suggesting that the 30-minute frequency is an appropriate choice for individual stocks. Because we dissect the index VSP into the VSP of constituent stocks and a factor related to correlation terms, it is important to use the same frequency for all assets. We also analyze the impact of the sampling frequency on the average equicorrelation estimate. To do so, we plot the equicorrelation estimate as a function of sampling frequency. The plot stabilizes from 30-minute onwards, confirming that this frequency is overall appropriate. As a robustness check, we also consider an alternative frequency of 75-minute and obtain qualitatively similar results. We also implement the two scale estimator of Zhang et al. (2005) and reach the same conclusion. See Section 5.2 for further details.

estimator for realized variance ($RV^{(HF)}_{i,t+\tau}$):

$$RV^{(HF)}_{i,t+\tau} = \frac{365}{\tau} \sum_{j=t+1}^{t+\tau} \sum_{k=0}^{m} r^2_{i,j,k} \tag{8}$$

where $r_{i,j,k}$ is the (log) return on security i on day j and at time interval k. Note that the case when $k = 0$ corresponds to an overnight return.[17] Overall, we observe $m+1$ intraday returns on each trading day (including the overnight return). All other variables are as previously defined.

S&P 500 Index A comparison of Tables 1 and 2, which are separately based on the low- and high-frequency realized variance estimators, shows that the realized variance of the S&P 500 index based on daily and 30-minute data average 3.85 % and 3.20 %, respectively.[18] The average VSP based on intraday data (−1.33 %) is nearly twice as large in magnitude as that based on the low-frequency data (−0.68 %).

To gauge the contribution of the intraday momentum effect to the difference between the low- and high-frequency realized variance estimates, we introduce the following estimator:

$$RV^{(HF+FL)}_{i,t+\tau} = RV^{(HF)}_{i,t+\tau} + \underbrace{2 \times \frac{365}{\tau} \sum_{j=t+1}^{t+\tau} (r_{i,j,0} + r_{i,j,1}) r_{i,j,m}}_{\text{Autocovariance of First and Last Intraday Returns}} \tag{9}$$

where $RV^{(HF+FL)}_{i,t+\tau}$ is the intraday estimator that accounts for the interaction of the

[17] It is standard in the literature to account for the overnight returns when computing the realized variance with intraday data. See for instance Drechsler and Yaron (2011) and Bekaert and Hoerova (2014). Ignoring the overnight returns would mechanically introduce a bias in the analysis since the identity in Equation (5) would no longer hold. In other words, the close-to-close returns would no longer be equal to the sum of intraday returns (including the overnight returns).

[18] Note that this spread is similar, in terms of magnitude, to that reported in Drechsler and Yaron (2011).

sum of the overnight and first returns with the last intraday returns.

The average index realized variance estimate based on the estimator in Equation (9) is 3.38 %. This result suggests that the intraday momentum effect documented by Gao et al. (2018) alone accounts for 27.02 % of the wedge (0.65 %) between the estimates based on low- and high-frequency data. This observation leaves open the possibility of richer intraday autocorrelation dynamics. To verify this, we regress the time series of intraday returns observed at a particular time of the day on a constant and the time series of 30-minute intraday returns observed at a prior time of the day. Table A.1 of the Online Appendix confirms that the predictability results of Gao et al. (2018) extend to the stock index. The slope estimate is significantly positive and the explanatory power of 2.1 % is similar to the authors' figure of 1.6 %. The table also documents statistically significant slope estimates for various lead–lag pairs, which points to even richer intraday autocorrelation effects than documented previously.

Single Stocks We now extend our analysis to single stocks. We supplement the TRTH database with data on stock splits and distributions from CRSP to adjust the TRTH overnight returns.[19] For every individual stock, we regress the time series of intraday returns observed at a particular time of the day on a constant and the time series of 30-minute intraday returns observed at an earlier time of the day. Tables A.2 and A.3 of the Online Appendix report the fraction of stocks for which we find evidence of a significantly positive and negative slope estimate at the 5 % significance level, respectively. Overall, these tables confirm that there are intraday autocorrelation patterns. For instance, Table A.2 of the Online Appendix shows that the intraday

[19] After matching the two databases, we compare the daily stock prices from CRSP to the end-of-day prices in the TRTH database. We only retain matches with similar end-of-day prices.

momentum effect holds for 45.9 % of stocks. The corresponding average explanatory power is 0.7 %.

The remainder of Table 2 also repeats Table 1 for individual stocks using realized variance estimates based on 30-minute (rather than daily) data. A comparison of the two tables highlights several differences. The average realized variance based on intraday data (14.71 %) is lower than that based on daily data (15.73 %), suggesting that the positive intraday autocorrelation pattern generally dominates. In turn, this result leads to a significantly negative average VSP based on high-frequency data (−1.00 %). This finding is in contrast to the positive average VSP (0.03 %) based on daily data (see Panel A of Table 1). Moreover, the proportion of stocks for which we can reject the null hypothesis of an insignificant VSP rises from about 30 % when using daily returns to more than 40 % when using intraday data.

Summarizing, the estimates of the VSP of individual equities reported in earlier studies are biased by intraday autocorrelation patterns. In order to control for this intraday momentum bias, the rest of this paper proceeds with data sampled at the high-frequency level.

3.3 Inaccurate Measure of Return Variation?

3.3.1 Mechanism

An additional bias arises from the fact that the IV estimator in Equation (4) is the risk-neutral expectation of the sum of the squared returns only if the return process is continuous (Dew-Becker et al., 2017; Schneider and Trojani, 2018). However, the non-parametric evidence presented in Lee and Mykland (2008), among others, indicates that the time series of both the equity index and individual equity prices contain jumps. Given that the assumption of a continuous return process is rejected by the data, a natural question to ask is: what measure of return variation does the IV formula in Equation (4) correctly price?

Andersen et al. (2015) show that the floating leg of the variance swap of which the Britten-Jones and Neuberger (2000) IV is the fixed leg is:

$$RV_{i,t+\tau}^{(HF,BJN)} = \frac{365}{\tau} \sum_{j=t+1}^{t+\tau} \sum_{k=0}^{m} 2\left(e^{r_{i,j,k}} - 1 - r_{i,j,k}\right) \tag{10}$$

where $RV_{i,t+\tau}^{(HF,BJN)}$ is the high-frequency return variation whose risk-neutral expectation is exactly given by the IV estimator presented in Equation (4).

Several points are worth highlighting. First, the IV estimator in Equation (4) prices the return variation given in Equation (10) in a general setup where the return process contains both continuous and discontinuous components. In the case where the return process is continuous, it can be shown that the estimator in Equation (10) reduces to that of Equation (8). Second, the new estimator of return variation relies on intraday data. Using intraday data does not only improve the efficiency of the estimator but also addresses the intraday momentum bias discussed in Section 3.2.[20] Fan et al. (2018)

[20]To understand this, it is worth looking at the extremely good approximation proposed by Andersen et al. (2015):

$$\begin{aligned} RV_{i,t+\tau}^{(HF,BJN)} &\approx \frac{365}{\tau} \sum_{j=t+1}^{t+\tau} \sum_{k=0}^{m} \left(\frac{2}{3} r_{i,j,k}^2 + \frac{1}{3}(e_{i,j,k}^r - 1)^2\right) \\ RV_{i,t+\tau}^{(HF,BJN)} &\approx \frac{2}{3} RV_{i,t+\tau}^{(HF)} + \frac{1}{3}\left[\frac{365}{\tau} \sum_{j=t+1}^{t+\tau} \sum_{k=0}^{m} (e_{i,j,k}^r - 1)^2\right] \end{aligned} \tag{11}$$

Similarly, at the low-frequency, we have:

$$RV_{i,t+\tau}^{(LF,BJN)} \approx \frac{2}{3} RV_{i,t+\tau}^{(LF)} + \frac{1}{3}\left[\frac{365}{\tau} \sum_{j=t+1}^{t+\tau} (e_{i,j}^r - 1)^2\right] \tag{12}$$

document that the total return variation of the S&P 500 index computed using daily return data and the estimator in Equation (12) is equal to 3.81 % per year. When the authors use the estimator in Equation (10) instead of Equation (12), the realized variance estimate drops to 2.93 %. In relative terms, the average VSP of the S&P 500 index moves by 95.60 % from −0.91 % based on daily data to −1.78 %, as the authors move from daily to intraday data. This change is attributable to the intraday momentum effect.

3.3.2 Direct Evidence

Table 3 uses both intraday return data and the Andersen et al. (2015) estimator of return variation (see Equation (10)) to compute the main statistics. Generally, we can see that the figures are quite different from those in our benchmark specification (see Table 1). This difference in results could be due to (i) the change in sampling frequency from daily to 30-minute data and/or (ii) the change in the estimator from that of Equation (3) to Equation (10). To disentangle the two effects, it is instructive to compare Tables 2 and 3. Since both tables are based on the same intraday sampling frequency, any difference in result can only be attributed to the change in estimator. There is very little to distinguish between the two tables suggesting that, at the intraday frequency, the estimator of the return variation does not have a major impact on the main statistics. Table A.4 of the Online Appendix implements the estimator in Equation (12) to compute the return variation. Again, we find that the results are very similar to the benchmark findings of Table 1. At first glance, this result may seem

Because the intraday momentum effect biases the $RV^{(LF)}_{i,t+\tau}$ estimator (see Section 3.2), the corresponding $RV^{(LF,BJN)}_{i,t+\tau}$ will be also affected. It is also worth pointing out that the sum of the squared daily simple returns is likely to be different from the sum of squared intraday simple returns, introducing another disconnect between the estimates based on low- and high-frequency returns.

surprising since one would expect jumps to matter, especially for individual equities. To understand this finding, it is useful to recall that we focus on the unconditional average of the VSP. Accordingly, we aggregate the return variation measures at the (i) time-series and (ii) cross-sectional levels, which essentially lowers the impact of jumps on the main statistics.[21]

Overall, we conclude that the estimates of the earlier literature suffer from two issues. First, they are affected by the intraday momentum effect. Second, they hinge on a measure of return variation (as the floating leg of the swap) that is not priced by the Britten-Jones and Neuberger (2000) formula. Given the preceding discussion, the remainder of this paper addresses these two biases and focuses only on the Andersen et al. (2015) estimator (see Equation (10)) implemented using 30-minute data.

3.4 Dissecting the Market Variance Swap Payoff

Since the VSPs of individual equities are not as small as previously reported, we now ask the question: how large is their contribution to the index VSP? To tackle this question, we start with the identity linking the variance of the equity index returns to the sum of the weighted average of the variance of individual stock returns and

[21] A straightforward analysis of the estimators in Equations (8) and (10) reveals that, at a given point in time, the estimators will yield markedly different estimates if large returns are recorded. To be more precise, the difference between the estimates based on Equations (8) and (10) is positive for large negative returns while it is negative for large positive returns. Thus, on aggregate there is an offsetting effect of these large returns. For instance, on September 29, 2000, the stock price of Apple fell by 51.9 % to end at $25.75. Computing the (annualized) daily return variation on that day, we obtain estimates equal to 111.256 and 94.053 for the estimators in Equations (8) and (10), respectively. However, because we focus on the sample average and price movements such as those observed on September 29, 2000 are relatively rare, the averaging across the time-series dimension helps reduce the gap between the outputs of the two estimators. Indeed, we obtain an unconditional average value of 0.228 and 0.225 for the daily return variation of Apple based on the estimators in Equations (8) and (10), respectively.

covariance terms related to the index constituents:

$$\sigma^2_{I,t+\tau} = \sum_{i=1}^{N} \omega^2_{i,t}\sigma^2_{i,t+\tau} + \sum_{i=1}^{N}\sum_{j,j\neq i} \omega_{i,t}\omega_{j,t}\rho_{t+\tau}\sqrt{\sigma^2_{i,t+\tau}}\sqrt{\sigma^2_{j,t+\tau}} \tag{13}$$

where ${\sigma^2}_{I,t+\tau}$ is the return variation of the index I at time $t+\tau$. $\omega_{i,t}$ is the market capitalization weight of asset i at time t. ${\sigma^2}_{i,t+\tau}$ is the return variation of asset i, computed at time $t+\tau$. $\rho_{t+\tau}$ is the equicorrelation at time $t+\tau$. To be more precise, $\rho_{t+\tau}$ is the correlation that, if used instead of all the pairwise correlations, yields the same index return variation (Skintzi and Refenes, 2005). We follow previous works, e.g., Buraschi et al. (2014b), and extract this term as a residual. That is, given the market capitalization weights, the return variation of the index and that of individual stocks, we can re-arrange Equation (13) to derive the formula for the equicorrelation:[22]

$$\rho_{t+\tau} = \frac{\sigma^2_{I,t+\tau} - \sum_{i=1}^{N}\omega^2_{i,t}\sigma^2_{i,t+\tau}}{\sum_{i=1}^{N}\sum_{j,j\neq i}\omega_{i,t}\omega_{j,t}\sqrt{\sigma^2_{i,t+\tau}}\sqrt{\sigma^2_{j,t+\tau}}} \tag{14}$$

A similar expression holds under the risk-neutral probability measure:

$$E^{\mathbb{Q}}_t(\sigma^2_{I,t+\tau}) = \sum_{i=1}^{N} \omega^2_{i,t}E^{\mathbb{Q}}_t(\sigma^2_{i,t+\tau}) + \sum_{i=1}^{N}\sum_{j,j\neq i} \omega_{i,t}\omega_{j,t}E^{\mathbb{Q}}_t(\rho_{t+\tau})\sqrt{E^{\mathbb{Q}}(\sigma^2_{i,t+\tau})}\sqrt{E^{\mathbb{Q}}(\sigma^2_{j,t+\tau})} \tag{15}$$

where $E^{\mathbb{Q}}_t(\sigma^2_{I,t+\tau})$ is the time-t risk-neutral expectation of the future variance of the index. $E^{\mathbb{Q}}_t(\sigma^2_{i,t+\tau})$ is the time-t risk-neutral expectation of the future variance of asset i. $E^{\mathbb{Q}}_t(\rho_{t+\tau})$ is the time-t risk-neutral expectation of the future equicorrelation. We invert Equation (15) to express the risk-neutral expected correlation as a function of

[22] Throughout this paper, we use the weights computed at time t. This way, the weights are the same for both the realized and option-implied correlations. Driessen et al. (2009) show that time-variations in the weights of the index constituents only marginally affect the estimate of equicorrelation.

observable quantities:

$$E_t^{\mathbb{Q}}(\rho_{t+\tau}) = \frac{E_t^{\mathbb{Q}}(\sigma^2_{I,t+\tau}) - \sum_{i=1}^{N} \omega^2_{i,t} E_t^{\mathbb{Q}}(\sigma^2_{i,t+\tau})}{\sum_{i=1}^{N} \sum_{j,j\neq i} \omega_{i,t}\omega_{j,t} \sqrt{E_t^{\mathbb{Q}}(\sigma^2_{i,t+\tau})}\sqrt{E_t^{\mathbb{Q}}(\sigma^2_{j,t+\tau})}} \tag{16}$$

Using Equations (2), (13) and (15), it is straightforward to show that:

$$\begin{aligned}
VSP_{I,t+\tau} &= \sigma^2{}_{I,t+\tau} - E_t^{\mathbb{Q}}(\sigma^2_{I,t+\tau}) \\
&= \sum_{i=1}^{N} \omega^2_{i,t} VSP_{i,t+\tau} + \sum_{i=1}^{N} \sum_{j,j\neq i} \omega_{i,t}\omega_{j,t} \Big(\rho_{t+\tau} \sqrt{\sigma^2_{i,t+\tau}} \sqrt{\sigma^2_{j,t+\tau}} \\
&\quad - E_t^{\mathbb{Q}}(\rho_{t+\tau}) \sqrt{E_t^{\mathbb{Q}}(\sigma^2_{i,t+\tau})} \sqrt{E_t^{\mathbb{Q}}(\sigma^2_{j,t+\tau})} \Big) \\
&= \underbrace{\sum_{i=1}^{N} \omega^2_{i,t} VSP_{i,t+\tau}}_{Pure\ VSP_{t+\tau}} \\
&\quad + \underbrace{\sum_{i=1}^{N} \sum_{j,j\neq i} \omega_{i,t}\omega_{j,t} E_t^{\mathbb{Q}}(\rho_{t+\tau}) \left(\sqrt{\sigma^2_{i,t+\tau}} \sqrt{\sigma^2_{j,t+\tau}} - \sqrt{E_t^{\mathbb{Q}}(\sigma^2_{i,t+\tau})} \sqrt{E_t^{\mathbb{Q}}(\sigma^2_{j,t+\tau})} \right)}_{Cross\ VSP_{t+\tau}} \\
&\quad + \underbrace{\sum_{i=1}^{N} \sum_{j,j\neq i} \omega_{i,t}\omega_{j,t} \sqrt{\sigma^2_{i,t+\tau}} \sqrt{\sigma^2_{j,t+\tau}} \left(\rho_{t+\tau} - E_t^{\mathbb{Q}}(\rho_{t+\tau}) \right)}_{CSP_{t+\tau}} \\
&= \underbrace{Pure\ VSP_{t+\tau} + Cross\ VSP_{t+\tau}}_{Individual\ VSP_{t+\tau}} + CSP_{t+\tau} \qquad (17) \\
VSP_{I,t+\tau} &= Individual\ VSP_{t+\tau} + CSP_{t+\tau} \qquad (18)
\end{aligned}$$

Equation (18) reveals that the VSP of the equity index can be decomposed into two factors. The first factor (Individual VSP) is a function of the VSP of individual equities.[23] The second factor (CSP) is a function of the correlation swap payoff.[24] We next discuss the implications of this decomposition.

The Level of the Index Variance Swap Payoff Equation (18) shows that, if the VSP of each stock equals 0, then the Individual VSP factor disappears. An upshot of this is that the index VSP is equal to the CSP factor. Conversely, if the CSP is equal to zero, the Individual VSP factor will be equal to the index VSP.

However, if (i) the VSPs of individual equities are generally different from 0 (as Table 3 shows) and (ii) the CSPs are on average negative, as Panel B of Table A.5 in the Online Appendix shows, it is interesting to evaluate the contribution of each factor to the level of the index VSP. We can directly answer this question since Equation (18) implies that the average of the index VSP equals the sum of the average values of the two factors.

The Variance of the Index Variance Swap Payoff It is useful to recall that:

$$\begin{aligned} Var(VSP_{I,t+\tau}) &= Cov(VSP_{I,t+\tau}, VSP_{I,t+\tau}) \\ Var(VSP_{I,t+\tau}) &= Cov(Individual\ VSP_{t+\tau} + CSP_{t+\tau}, VSP_{I,t+\tau}) \end{aligned} \tag{19}$$

[23]This factor comprises two terms: the Pure VSP and the Cross VSP. The Pure VSP provides exposure to the VSPs of individual equities. To be more precise, it is the sum of the VSPs of individual equities multiplied by the squared value of the market capitalization weights. The Cross VSP depends on the interaction between the swaps of different stocks scaled by the market capitalization weights and the risk-neutral expectation of the equicorrelation. In the data, the Pure VSP and the Cross VSP series are strongly related with a correlation coefficient equal to 89.96 %, suggesting that they contain similar information. This finding motivates us to combine the two terms under the label Individual VSP.

[24]The correlation swap is an OTC derivative. The agent who takes a long position in the correlation swap (with notional of \$1) pays the correlation swap rate and receives the realized correlation at maturity. Consistent with the works of Buraschi et al. (2014a) and Faria and Kosowski (2016), among others, Table A.5 of the Online Appendix documents a significantly negative average CSP. This is true irrespective of whether the realized variance is affected by the biases discussed in Sections 3.2 and 3.3 or not. Interestingly, the two panels of the same table show that the average CSP falls by 3.63 percentage points from −7.47 % (Panel A) in the benchmark scenario to −11.10 % (Panel B) after correcting for the biases.

It is straightforward to show that:

$$1 = \frac{Cov(Individual\ VSP_{t+\tau}, VSP_{I,t+\tau})}{Var(VSP_{I,t+\tau})} + \frac{Cov(CSP_{t+\tau}, VSP_{I,t+\tau})}{Var(VSP_{I,t+\tau})} \tag{20}$$

where $Var(\cdot)$ and $Cov(\cdot)$ are the variance and covariance operators, respectively.

Equation (20) shows that we can decompose the variance of the index VSP into two parts. The contribution of each factor corresponds to the slope estimate of a regression of the factor on a constant and the index VSP.

Results Panel A of Table 4 shows that both factors make a positive contribution to the level of the index VSP. The figures reported under "Shr_{var}" reveal that the CSP and individual VSP factors account for 70.6 % and 29.4 % of the average index VSP, respectively.[25]

Turning to the variance decomposition results, the column entitled "Shr_{var}" reveals that both factors make a positive contribution to the variance of the index VSP. The bigger contributor is the Individual VSP factor, which accounts for 67.4 % of the variability.

Taken together, the analysis reveals that the CSP factor captures a large share of the level of the index VSP. This finding is to some extent consistent with the insight of Driessen et al. (2009) regarding the average index VSP. However, when we analyze the variance of the index VSP, we find that the Individual VSP (rather than the CSP) factor is the main driving force.

[25] Note that the sign of the CSP factor is completely determined by that of the CSP. This is because the weights and volatility terms are strictly positive. Thus, the negative average value of the CSP factor indicates that the CSP is negative in general (see Table A.5 of the Online Appendix). This finding is consistent with the works of Buraschi et al. (2014a) and Faria and Kosowski (2016).

4 Variance Risk Premia

Bollerslev et al. (2009) establish the predictive power of the index VRP, which we define as the spread between the physical and risk-neutral expectations of future variance, for future aggregate excess stock returns. This finding raises the following questions: do the decomposition results extend to the index VRP? Which of the two factors is the main driver of this return predictability? Does separating the two factors strengthen the predictability of aggregate excess stock returns?

4.1 Dissecting the Variance Risk Premium

Framework We define the VRP as:

$$VRP_{i,t} = E_t^{\mathbb{P}}(\sigma^2_{i,t+\tau}) - E_t^{\mathbb{Q}}(\sigma^2_{i,t+\tau}) \tag{21}$$

where $VRP_{i,t}$ is the VRP of asset i at time t. $E_t^{\mathbb{P}}(\sigma^2_{i,t+\tau})$ is the physical expectation at time t of the future variance. All other variables are as previously defined.

In order to decompose the VRP of the aggregate index into its factors, it is useful to note the following:

$$E_t^{\mathbb{P}}(\sigma^2_{I,t+\tau}) = \sum_{i=1}^{N} \omega^2_{i,t} E_t^{\mathbb{P}}(\sigma^2_{i,t+\tau}) + \sum_{i=1}^{N} \sum_{j,j\neq i} \omega_{i,t}\omega_{j,t} E_t^{\mathbb{P}}(\rho_{t+\tau}) \sqrt{E_t^{\mathbb{P}}(\sigma^2_{i,t+\tau})} \sqrt{E_t^{\mathbb{P}}(\sigma^2_{j,t+\tau})} \tag{22}$$

Using Equations (15), (21) and (22), we decompose the index VRP as follows:

$$VRP_{I,t} = E_t^{\mathbb{P}}(\sigma^2_{I,t+\tau}) - E_t^{\mathbb{Q}}(\sigma^2_{I,t+\tau})$$

$$
\begin{aligned}
&= \underbrace{\sum_{i=1}^{N} \omega_{i,t}^2 VRP_{i,t}}_{Pure\ VRP_t} \\
&\quad + \underbrace{\sum_{i=1}^{N} \sum_{j,j\neq i} \omega_{i,t}\omega_{j,t} E_t^{\mathbb{Q}}(\rho_{t+\tau}) \Big(\sqrt{E_t^{\mathbb{P}}(\sigma_{i,t+\tau}^2)}\sqrt{E_t^{\mathbb{P}}(\sigma_{j,t+\tau}^2)} - \sqrt{E_t^{\mathbb{Q}}(\sigma_{i,t+\tau}^2)}\sqrt{E_t^{\mathbb{Q}}(\sigma_{j,t+\tau}^2)}\Big)}_{Cross\ VRP_t} \\
&\quad + \underbrace{\sum_{i=1}^{N} \sum_{j,j\neq i} \omega_{i,t}\omega_{j,t} \sqrt{E_t^{\mathbb{P}}(\sigma_{i,t+\tau}^2)}\sqrt{E_t^{\mathbb{P}}(\sigma_{j,t+\tau}^2)} \left(E_t^{\mathbb{P}}(\rho_{t+\tau}) - E_t^{\mathbb{Q}}(\rho_{t+\tau})\right)}_{CRP_t} \\
&= \underbrace{Pure\ VRP_t + Cross\ VRP_t}_{Individual\ VRP_t} + CRP_t \qquad (23) \\
VRP_{I,t} &= Individual\ VRP_t + CRP_t \qquad (24)
\end{aligned}
$$

Two observations are in order. First, the VRP is a conditional expectation of the future VSP. Hence, the ensuing analysis is cast in an ex-ante setting. Second, the VRP involves the physical expectation of the future variance, which is not directly observable. This forces us to specify a model to generate the physical expectation of the future variance. Similar to Bollerslev et al. (2009), we assume a random walk, i.e., the physical expectation for the future variance is equal to its most recent realization. This model is estimation-free, making it useful to bypass sampling errors associated with the realized variance forecasting regressions. Furthermore, it delivers positive variance forecasts at each point in time. This is not always guaranteed for variance forecasting models that need to be estimated; a problem that could be acute for individual equities.[26] Finally, it yields realistic dynamics of the expectation of the future equicorrelation.[27]

[26]The random walk model has the advantage that, in real-time, an investor would have known and therefore considered this model. This is not necessarily the case for recently proposed variance forecasting models such as the HAR–RV model of Corsi (2009) that we analyze in Section 5.4.

[27]This point is important because of the identity linking the variance of the index with that of its constituents (see Equation (22)). Since the expectation of the future realized correlation should lie between −1 and 1, one needs to be careful in the modeling framework to account for this constraint.

Figure 1 summarizes the dynamics of the index VRP, as well as its two factors. The index VRP is generally negative and takes large values during bad economic times, as defined by the National Bureau of Economic Research (NBER). Turning to the two factors, we notice that they exhibit distinct dynamics. The individual VRP factor is more volatile than the CRP factor. Overall, the correlation between the two factors is low and negative ($-40.64\,\%$), suggesting that they contain different information.

Results Panel B of Table 4 reports that the level of the index VRP is significantly negative ($-1.28\,\%$) and comparable to that of the index VSP ($-1.33\,\%$) documented in Panel A of the same table. The decomposition results reveal that the CRP factor accounts for 88.3 % of the level of the index VRP. "Shr_{var}" shows that the Individual VRP factor makes the larger contribution (72.1 %) to the variations of the index VRP.

Overall, these findings are consistent with the insights gleaned by analyzing the VSPs. The CRP factor is important for the level of the index VRP, whereas the Individual VRP factor matters for the variations of the index VRP.

4.2 Implications for Return Predictability

Next, we examine the implications of the two-factor structure for the predictability of aggregate market excess returns. In carrying out the predictability analysis, we follow the literature and sample the VRP at the end of each month. By doing so, we reduce the amount of overlap between consecutive observations, thus facilitating the statistical inference.[28]

[28]We repeated our analysis of the summary statistics using end-of-month data rather than daily observations. Overall, the main findings are not affected by this change. We do not tabulate these results for brevity.

We estimate the following regression:

$$er_{I,t\to t+h} = \alpha + \beta VRP_{I,t} + \epsilon_{I,t+h} \tag{25}$$

where $er_{I,t\to t+h}$ is the (annualized) excess return of the stock market index for the period starting at t and ending at $t+h$ (h is expressed in months). Throughout this paper, the excess return is the difference between the (log) total return and the risk-free rate. We obtain the 1-month U.S. Treasury bill rate data from Kenneth French's website. We examine forecasting horizons of 1, 3, 6, 9, 12, 18 and 24 months. α and β are the intercept and slope parameters, respectively. $\epsilon_{I,t+h}$ is the residual of the regression at time $t+h$.

Panel A of Table 5 reports the results of this analysis. We present the Newey and West (1987) standard errors computed with h lags in parentheses. We also report Hodrick (1992) standard errors in square brackets. To make the statistical inference more robust, we report in **bold** the significant slope estimates based on the empirical p-values from the wild bootstrap of Rapach et al. (2013). Among other things, the procedure is robust to the Stambaugh (1999) bias, preserves the contemporaneous correlations across residuals, and allows for general forms of conditional heteroskedasticity.

The results indicate that the slope parameter is significantly negative (at the 5 % significance level) over horizons of up to 6 months. Thus, the index VRP acts as short-term predictor of S&P 500 excess returns. The adjusted R^2 enables us to gauge the strength of predictability for different forecasting horizons. Consistent with the theoretical model of Bollerslev et al. (2009), we observe a hump-shaped pattern, with the adjusted R^2 peaking at the quarterly horizon (adjusted $R^2 = 10.3\,\%$). Overall, these findings confirm and update the authors' empirical findings to the more recent period.[29]

The decomposition results show that we can express the index VRP as the sum of two factors. To understand which of the two factors is relevant for the predictability of excess returns, we directly use them in the following excess return forecasting regression:

$$er_{I,t\to t+h} = \alpha + \phi Individual\ VRP_t + \gamma CRP_t + \epsilon_{I,t+h} \tag{26}$$

where α, ϕ and γ are parameters to be estimated.

Panel B of Table 5 shows that the slope estimates linked to the two factors are negative. The inference based on the bootstrap experiment suggests that the slope associated with the CRP factor is statistically significant for all horizons, whereas that of the individual VRP factor is significant only for horizons up to 9 months. Viewed as a whole, these patterns indicate that the CRP factor is a reliable predictor of aggregate excess stock returns across all horizons, whereas the individual VRP factor acts as a short-term predictor.

If one starts with the model in Equation (26) and imposes the restriction that $\phi = \gamma$, then this model reduces to that in Equation (25). If the restriction is rejected by the data, then a forecaster who considers the two factors directly could achieve a higher forecasting power. Figure 2 shows that the adjusted R^2 of the unconstrained model (see Equation (26)) is almost always higher than that of the constrained model

[29] In comparing the sign of our parameter estimates to theirs, it is worth remembering that their definition of the VRP is the opposite of ours. Thus, their positive slope estimate is consistent with our negative slope estimate.

(see Equation (25)). We compute the Wald test statistic associated with the null hypothesis that $\phi = \gamma$. The last two rows of Panel B of Table 5 show that the null hypothesis is rejected for nearly all horizons at the 5 % significance level.

We investigate whether the Individual VRP and CRP factors contain information that is independent from that of other established predictors of aggregate excess returns. We consider the following variables: CAY is the consumption-to-wealth ratio. DFSP is the default spread, defined as the difference between BAA- and AAA-rated corporate bond yields. log(P/D) is the logarithm of the level of the S&P 500 index divided by the 12-month trailing sum of dividends paid by S&P 500 firms. log(P/E) is the logarithm of the S&P 500 price index divided by the 12-month trailing sum of earnings. RREL is the stochastically detrended risk-free rate, i.e., the 1-month U.S. T-bill rate minus its 12-month trailing average. TMSP is the term spread, defined as the difference between the U.S. Treasury 10-year yield and the 3-month T-bill rate. We obtain the data on these predictors from Amit Goyal's website.[30] Tables A.6–A.12 of the Online Appendix confirm that the predictability results of the two factors are even stronger following the inclusion of these control variables. In particular, the bootstrap inference shows that the slope estimates associated with the Individual VRP and CRP factors are significant for all horizons. Furthermore, these slope estimates are similar both in terms of sign and magnitude to those obtained by estimating the regression in Equation (26).

[30]The data is available at the following address: http://www.hec.unil.ch/agoyal/.

5 What About ...

This section presents several robustness checks. First, we discuss how our two-factor model compares to alternative decompositions. Second, we assess the robustness of our measure of the return variation to the microstructure noise inherent in high-frequency data. Third, we analyze the impact of the liquidity of option contracts on our results. Fourth, we assess the sensitivity of our results to the choice of the variance forecasting model.

5.1 Alternative VRP Decompositions?

Section 4.1 decomposes the index VRP into an individual VRP factor and a CRP factor. It is, however, interesting to see how this decomposition compares to alternatives proposed in the literature.[31] For example, Cosemans (2011) decomposes the index VRP into an average VRP component (AVRP), defined as the value-weighted average of the VRP of all constituent stocks and the raw CRP (CRP^{RAW}). Although related to our decomposition, there are important conceptual and empirical differences. On the theoretical front, our decomposition highlights that the second factor is the CRP^{RAW} variable interacted with a factor equal to $\sum_{i=1}^{N}\sum_{j,j\neq i}\omega_{i,t}\omega_{j,t}\sqrt{E_t^{\mathbb{Q}}(\sigma^2_{i,t+\tau})}\sqrt{E_t^{\mathbb{Q}}(\sigma^2_{j,t+\tau})}$. In the data, a regression of our CRP factor on a constant and the CRP^{RAW} variable yields an R^2 equal to 0.40. Clearly, this result suggests that CRP and CRP^{RAW} factors are different quantities.

Moreover, the decomposition of Cosemans (2011) is not coherent in the sense that the sum of the proposed two factors does not yield the index VRP. Indeed, the author reports average values of -1.91% and 0.15% for the AVRP and CRP^{RAW}, respec-

[31] We thank an anonymous referee for encouraging us to pursue this analysis.

tively.[32] Clearly, the sum of the two factors ($-1.76\,\%$) does not match the 1.38% figure reported by the author for the average index VRP. In a similar vein, Driessen et al. (2013) argue that the average index VSP is completely determined by the average CSP^{RAW}. Our decomposition highlights that, at the minimum, CSP^{RAW} must be weighed by a term corresponding to $\sum_{i=1}^{N}\sum_{j,j\neq i}\omega_{i,t}\omega_{j,t}\sqrt{\sigma^2_{i,t+\tau}}\sqrt{\sigma^2_{j,t+\tau}}$. Absent this term, there will be a mismatch between the average index VSP and the average CSP^{RAW}. Indeed, the authors find an average CSP^{RAW} of $-6.87\,\%$, more than 6 times the magnitude of the VSP of the S&P 100 index ($-1.05\,\%$). A coherent decomposition is very useful to get a good understanding of the level and variance of the index VSP. Our results suggest that the CSP factor is important to understand the *average* of the index VSP. However, the CSP factor makes a small contribution to the *fluctuations* of the index VSP. It is the individual VSP factor that accounts for most of these time-variations.

Table A.13 of the Online Appendix summarizes the predictability results associated with the AVRP and CRP^{RAW} computed as in Cosemans (2011). In particular, we investigate whether the AVRP and CRP^{RAW} variables contain information that is independent from that of the following predictors of aggregate excess returns: CAY, DFSP, log(P/D), log(P/E), RREL and TMSP. Comparing the result of this table with the corresponding last columns of Tables A.6–A.12 of the Online Appendix, we can see that our decomposition yields more accurate forecasts of excess returns than that

[32] The author presents statistics that are expressed on a per month basis. We annualize the variance estimates by multiplying them by 12. Since the author computes the VRP as the difference between the risk-neutral and physical expectations of future variance, their estimates suggest that the AVRP has the "wrong" sign. This finding arises because the Cosemans (2011) estimates are affected by the use of a measure of return variation (as the floating leg to the swap) that is not priced by the Britten-Jones and Neuberger (2000) IV formula. Moreover, the author uses a sampling frequency of 5 minutes that is likely too high for single stocks, thus introducing microstructure noise in the analysis. Furthermore, the author uses an equal-weighted average to compute the AVRP instead of using the squared of the market capitalization weight, as is done in our decomposition.

of Cosemans (2011), as evidenced by the adjusted R^2. Moreover, our two factors are always associated with significant slope parameters, whereas this is not the case for the two factors of Cosemans (2011). For instance, the AVRP factor of Cosemans (2011) is not significant beyond the 3-month horizon. Overall, this set of findings suggests that our decomposition is different both from a conceptual standpoint as well as empirically from that of Cosemans (2011).

Feunou et al. (2017a) and Kilic and Shaliastovich (2019) propose a coherent dissection of the index VRP into the up VRP (VRP^{UP}) and down VRP (VRP^{DOWN}) and explore the information content of these components for future returns. They report that the VRP^{DOWN} predicts future aggregate stock returns. Feunou et al. (2017a) also document the predictive power of the difference between the up and down VRP (VRP^{UP}–VRP^{DOWN}), which they interpret as a proxy for the skewness risk premium.

We compute these variables as in Feunou et al. (2017a). One might conjecture that the CRP factor merely proxies for the VRP^{DOWN} or VRP^{UP}–VRP^{DOWN} measure. This motivates us to regress the CRP factor on a constant and the VRP^{DOWN}. We obtain an R^2 of 0.16, indicating that the CRP factor and VRP^{DOWN} do not contain the same information. We carry out a similar analysis replacing VRP^{DOWN} by VRP^{UP}–VRP^{DOWN} and obtain an explanatory power of 0.30, leading us to the conclusion that the CRP factor is different from VRP^{UP}–VRP^{DOWN}.

Tables A.14–A.16 of the Online Appendix summarize the predictability results associated with (i) VRP^{UP} and VRP^{DOWN}, (ii) VRP^{UP}–VRP^{DOWN} and (iii) VRP^{DOWN}. Each regression model controls for the effect of the established predictors of stock market excess returns discussed already. Consistent with Feunou et al. (2017a) and Kilic and Shaliastovich (2019), the VRP^{UP} and VRP^{DOWN} predict future aggregate stock excess returns with opposite signs. Looking at the predictive results associated with VRP^{UP}–VRP^{DOWN}, we observe that this variable is generally not associated with a significant slope parameter.[33] This is true for most horizons. Comparing Tables A.6–A.12 and A.14–A.16 of the Online Appendix, we can see that the Individual VRP and CRP factors generally yield the higher explanatory power for most horizons, with both factors being associated with significant slope estimates. This finding suggests that, after controlling for well-documented predictors of excess returns, our two factors are more informative about future aggregate excess returns than the factors independently proposed by Feunou et al. (2017a) and Kilic and Shaliastovich (2019).

5.2 Alternative Sampling Frequencies?

Up to this point, the computation of realized variance and its physical expectation revolves around returns sampled at a frequency of 30 minutes. In order to analyze the sensitivity of our results to the sampling frequency, we repeat the main tests using a sampling frequency of 75 minutes as in Bollerslev et al. (2016). Tables A.17 and A.18 of the Online Appendix point to results that are very similar to those of Tables 3 and 4. The predictability results summarized in Table A.19 of the Online Appendix confirm that explicitly accounting for the two factors strengthens the predictability of aggregate excess returns.

A comparison of Tables 1 and 3 reveals that the biases discussed in Sections 3.2 and 3.3 seem to have a larger effect on the results of the index than those of individual equities. It is likely that a sampling frequency of 30 minutes is too low for the index.

[33] This result is different from that of Feunou et al. (2017a). The difference likely arises from the fact that we control for other established predictors of aggregate stock excess returns, whereas the authors do not. In light of this, we can conclude that the information content of VRP^{UP}–VRP^{DOWN} is already contained in established forecasting variables.

To remedy this issue, we repeat our analysis of the index VSPs using frequencies of 5 and 15 minutes. Table A.20 of the Online Appendix shows the results. Briefly, the magnitude of the average index VSP is $-1.17\,\%$ and $-1.11\,\%$ at the 5- and 15-minute frequency, respectively. This is quite similar to the average of $-1.33\,\%$ based on the 30-minute frequency (see Table 3).

As an additional check, we implement the subsampling and averaging technique of Zhang et al. (2005). Briefly, we create various subgrids of 30-minute spaced returns with different starting times. For each of these subgrids, we estimate the return variation. Next, we average these estimates across all the subgrids and implement the bias-correction of Zhang et al. (2005) to obtain the return variation estimate that we use for the calculation of the VSPs. As Tables A.21–A.23 of the Online Appendix show, the results of this approach are qualitatively similar to those in the main part of the paper.

5.3 The Liquidity of Individual Equity Options?

The implementation of the IV formula in Equation (4) requires liquid options as well as a broad range of strike prices. While this is not a big issue for the S&P 500 index, it could be a concern for individual equity options, potentially introducing a bias in the estimates of the VSR and, thus, the average VSP.

To alleviate this concern, we restrict our focus to the individual equities that satisfy the following two criteria. The first criterion is that the stock belongs to the list of the 80 equity options with the highest average option trading volume. The second criterion is that the stock must be part of the 80 equities with the highest average number of option strike prices per maturity during the sample period. Table A.24 of the Online

Appendix summarizes the results linked to the average VSP of these stocks. Panel A shows the results for the benchmark specification as well as those based on intraday data. To be clear, the benchmark results are based on the low-frequency estimator of realized variance (see Equation (3)). The second set of results obtains when we replace the low-frequency estimator of variance with the Andersen et al. (2015) estimator (see Equation (10)). Since we study very active securities, we implement the subsampling and averaging technique of Zhang et al. (2005). Overall, our main conclusion is the same. By changing the estimator of the return variation and sampling at the intraday level, we observe a meaningful change in the average VSP of stocks from 0.22 % in the benchmark setting to −0.89 %.

5.4 The Physical Expectation of Variance?

An analysis of the VRP involves taking a stance on a model to generate the physical expectation of variance. While our baseline analysis uses the estimation-free random walk model, Bekaert and Hoerova (2014) caution that the predictability results weaken when using alternative models for the realized variance.

To shed light on this, we replace the random walk model with the Heterogeneous Autoregressive Realized Variance (HAR–RV) model of Corsi (2009).[34,35] In this model, the conditional expectation of next-month's realized variance is a function of a constant, the latest observation of the daily realized variance, the most recent weekly

[34] We also considered the HAR–RV–C–J model of Andersen et al. (2007) that decomposes each variance term in the HAR–RV into continuous and discontinuous components. This model underperformed the HAR–RV, with the difference in the mean squared error being statistically significant. As a result, we do not tabulate the corresponding results and focus on the HAR–RV model.

[35] Ideally, one would want to find the best forecasting model for each asset and then use this model to generate the conditional expectation of the realized variance. We caution that this approach is challenging because it may yield implausible forecasts of the equicorrelation. Our experimentation with this approach resulted in correlation forecasts that were often greater than 1 in absolute value. Moreover, these forecasts were too volatile to be plausible.

realized variance, and the most recent monthly realized variance:

$$RV_{i,t+\tau}^{(HF,BJN)} = \alpha + \beta RV_{i,t}^{(HF,BJN,D)} + \gamma RV_{i,t}^{(HF,BJN,W)} + \phi RV_{i,t}^{(HF,BJN)} + \epsilon_{t+\tau} \quad (27)$$

where α is the intercept. β, γ and ϕ are slope parameters. $RV_{i,t}^{(HF,BJN,D)}$ and $RV_{i,t}^{(HF,BJN,W)}$ denote the daily and weekly realized variance, respectively:

$$RV_{i,t}^{(HF,BJN,D)} = 365 \sum_{k=0}^{m} 2(e^{r_{i,t,k}} - 1 - r_{i,t,k}) \quad (28)$$

$$RV_{i,t}^{(HF,BJN,W)} = \frac{365}{7} \sum_{j=t-6}^{t} \sum_{k=0}^{m} 2(e^{r_{i,t,k}} - 1 - r_{i,t,k}) \quad (29)$$

We estimate the model using an expanding window initialized with the first 300 observations. We do this at each point in time, thus yielding the time series of parameter estimates.[36] We then use the time series of the parameter estimates, together with the relevant variables, to generate the expected value of the realized variance and repeat our key analyses. By construction, there is no look-ahead bias since the expectation is computed in real time.

Table 6 confirms that the CRP factor is the main contributor to the average of the index VRP, while the individual VRP captures a sizable part of the variation in the index VRP. Consistent with the results of Bekaert and Hoerova (2014), Table 7 shows that the strength of the predictability observed at the quarterly horizon hinges on the model of expected realized variance. The predictive power of the index VRP drops from 10.3 % when the expected realized variance is modeled as a random walk (Table 5) to 7.9 % when using the HAR–RV model. However, the Wald test reveals

[36]We use daily observations in order to obtain more precise parameter estimates.

that a model that explicitly decomposes the index VRP into the individual VRP and the CRP factors yields superior forecasts compared to a constrained forecasting model that includes only the index VRP. This finding is consistent with our earlier conclusion.

Since we estimate a variance forecasting model to generate the premiums that are then used as forecasting variables in the return predictability regression, the analysis may be subject to sampling error. In order to investigate the impact of the generated regressor problem, we follow the steps of Bekaert and Hoerova (2014). We estimate each HAR–RV model as before. We save the parameter estimates as well as their asymptotic covariance matrix. We draw 500 alternative coefficients from the distribution of these parameters, which we use to generate the relevant return forecasting variables. We do this at the end of each calendar month and thus obtain alternative time series of the return forecasting variable(s). Finally, we estimate the excess return forecasting model using each of the alternative time series of predictive variables. Our untabulated results indicate that the sampling errors do not materially affect the results. This is consistent with the conclusion of Bekaert and Hoerova (2014).

6 Conclusion

We analyze the measurement errors present in the average variance swap payoff estimates documented in the literature. We show that the puzzling conclusion of insignificant VSPs for stocks reported in earlier works (Carr and Wu, 2009; Driessen et al., 2009) is materially affected by measurement errors in the estimates of the return variation. Correcting for these biases, we find significantly negative average VSPs for the constituent stocks.

We decompose the index variance risk premium into two factors and assess their importance. The Individual VRP factor makes a sizable contribution to the variation in the 1-month index VRP, while the CRP factor captures a significant proportion of the level of the index VRP. Jointly accounting for these factors significantly improves the predictability of aggregate excess returns.

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Figure 1: Dissecting the Index Variance Risk Premium

This figure plots the time series of the 1-month index VRP (*blue line*), the individual VRP factor (*orange line*) and the CRP factor (*green line*). The shaded areas indicate business cycle contractions as identified by the NBER.

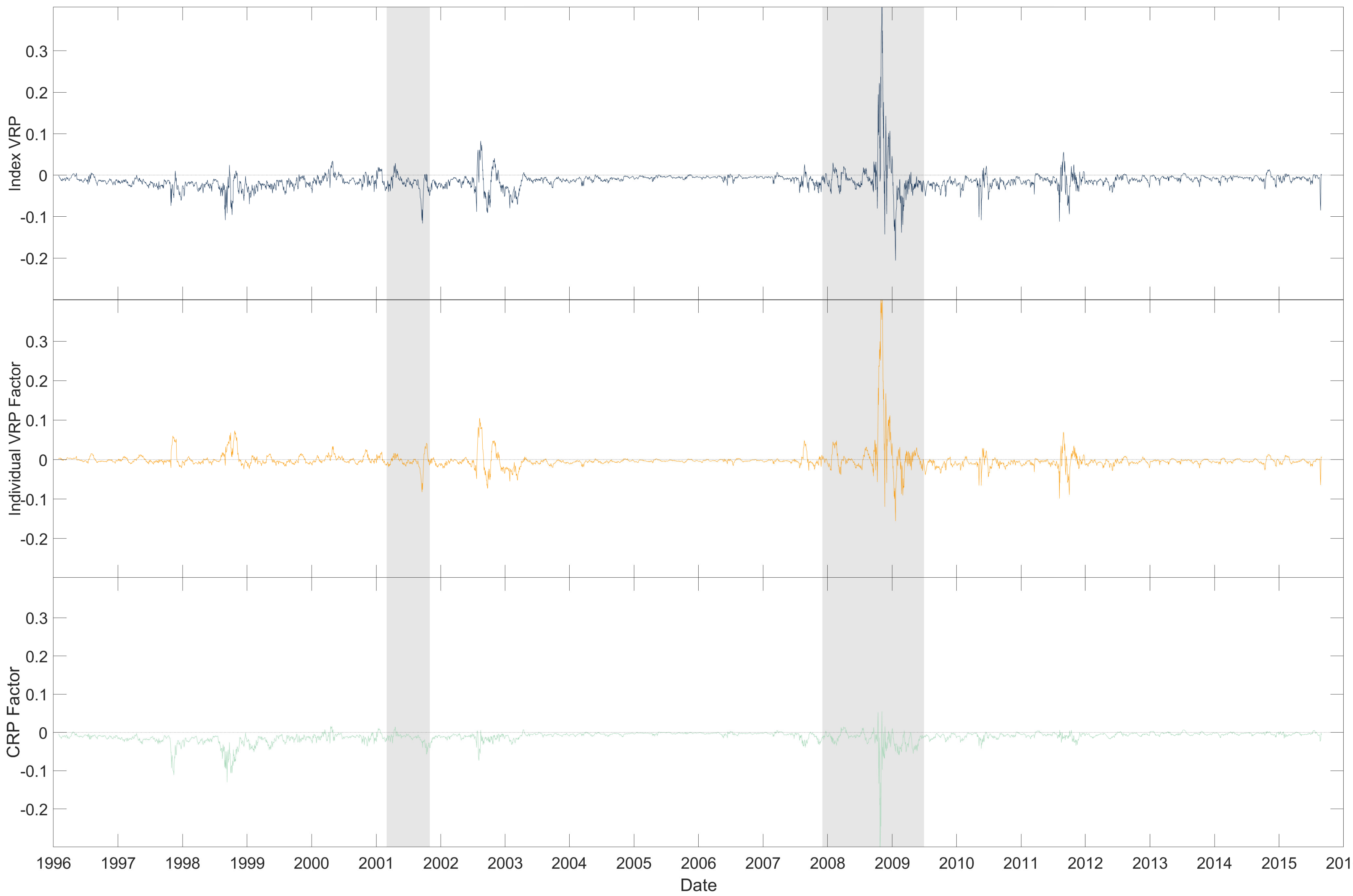

Figure 2: Regression R^2s: Constrained vs. Unconstrained Regressions

This figure plots the adjusted R^2s of the constrained excess return predictability regression (solid line) and unconstrained excess return predictability regression (*dashed line*) for various horizons, ranging from 1 to 24 months. The constrained model involves regressing the h months excess return on the S&P 500 index on a constant and the lagged index VRP. The unconstrained model entails regressing the h months excess return on the index on a constant and the (lagged) two factors that make up the index VRP, namely the CRP and Individual VRP factors.

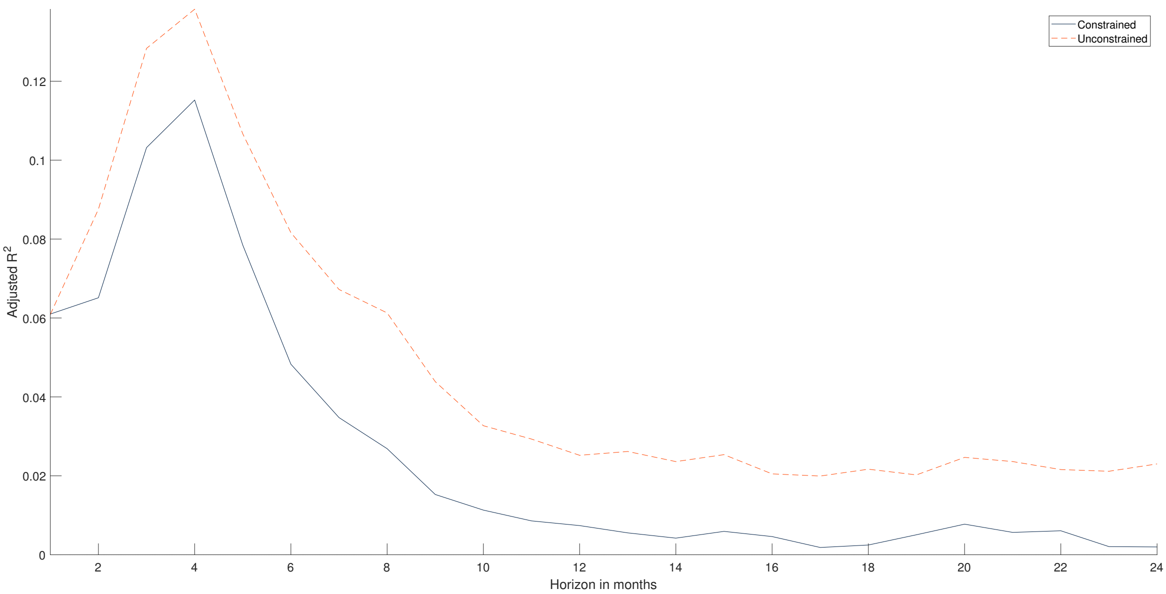

Table 1: Variance Swap Payoffs: Daily RV

This table reports summary statistics on the daily time series of the 1-month VSPs. Panel A presents the results linked to the S&P 500 index, as well as the equal-weighted average of the constituent stocks. RV and IV report the average (annualized) low-frequency realized and Britten-Jones and Neuberger (2000) option-implied variances, respectively. We use daily return data to compute the realized variance (see Equation (3)). VSP shows the average VSP, defined as the spread between RV and IV. *Std Dev*, *Skew*, *Kurt* and $AR(1)$ denote the standard deviation, skewness, kurtosis and first-order autocorrelation of the VSP, respectively. *Median*, $q^{0.05}$ and $q^{0.95}$ are the median, 5 % and 95 % quantiles of the VSP, respectively. *, **, and *** indicate significance at the 10%, 5%, and 1% level based on Newey and West (1987) corrected standard errors (with 21 lags), respectively. We highlight, in **bold**, the significant estimates of the VSP based on a block-bootstrap. The rows in Panel B relate to stocks with insignificant, significantly negative and significantly positive VSPs (at the 5% significance level), respectively. *Share* indicates the fraction of firms for which the VSP satisfies the condition [name in row].

Panel A: Market Variance Swap Payoff

	RV	IV	VSP	*t-stat*	*Std Dev*	*Skew*	*Kurt*	$AR(1)$	*Median*	$q^{0.05}$	$q^{0.95}$
S&P 500	0.0385	0.0453	**-0.0068****	-2.45	0.048	6.26	66.8	0.96	-0.0100	-0.0451	0.0330
Avg. Stocks	0.1573	0.1571	0.0003	0.04	0.109	6.15	55.9	0.98	-0.0172	-0.0756	0.1167

Panel B: Stock Variance Swap Payoff

	Share	RV	IV	VSP	*Std Dev*	*Skew*	*Kurt*	$AR(1)$	*Median*	$q^{0.05}$	$q^{0.95}$
$= 0$ not rejected	0.669	0.2100	0.1868	0.0232	0.340	4.02	42.94	0.94	-0.0251	-0.1766	0.3348
> 0 rejected	0.301	0.1069	0.1363	-0.0295	0.100	1.11	21.85	0.92	-0.0329	-0.1516	0.1077
< 0 rejected	0.030	0.3868	0.2910	0.0959	0.362	3.16	19.23	0.95	-0.0062	-0.1796	0.7802

Table 2: Variance Swap Payoffs: 30-Minute RV

This table reports summary statistics on the daily time series of the 1-month VSPs. Panel A presents the results linked to the S&P 500 index, as well as the equal-weighted average of the constituent stocks. RV and IV are the average (annualized) high-frequency realized and Britten-Jones and Neuberger (2000) option-implied variances, respectively. We use high-frequency return data sampled at the 30-minute frequency to compute the realized variance (see Equation (8)). VSP denotes the average VSP, defined as the spread between RV and IV. *Std Dev*, *Skew*, *Kurt* and $AR(1)$ denote the standard deviation, skewness, kurtosis and first-order autocorrelation of the VSP, respectively. *Median*, $q^{0.05}$ and $q^{0.95}$ are the median, 5 % and 95 % quantiles of the VSP, respectively. *, **, and *** indicate significance at the 10%, 5%, and 1% level based on Newey and West (1987) corrected standard errors (with 21 lags), respectively. We highlight, in **bold**, the significant estimates of the VSP based on a block-bootstrap. The rows in Panels B relate to stocks with insignificant, significantly negative and significantly positive VSPs (at the 5% significance level), respectively. *Share* indicates the fraction of firms for which the VSP satisfies the condition [name in row].

Panel A: Market Variance Swap Payoff

	RV	IV	VSP	*t-stat*	*Std Dev*	*Skew*	*Kurt*	$AR(1)$	*Median*	$q^{0.05}$	$q^{0.95}$
S&P 500	0.0320	0.0453	**-0.0133*** ***	-6.12	0.038	5.16	67.9	0.95	-0.0124	-0.0512	0.0168
Avg. Stocks	0.1471	0.1571	**-0.0100*** *	-1.93	0.089	5.44	56.5	0.97	-0.0202	-0.0847	0.0956

Panel B: Stock Variance Swap Payoff

	Share	RV	IV	VSP	*Std Dev*	*Skew*	*Kurt*	$AR(1)$	*Median*	$q^{0.05}$	$q^{0.95}$
$= 0$ not rejected	0.584	0.2030	0.1922	0.0108	0.291	4.07	48.71	0.94	-0.0256	-0.1797	0.2843
> 0 rejected	0.400	0.1163	0.1461	-0.0298	0.099	1.27	24.61	0.92	-0.0316	-0.1512	0.1001
< 0 rejected	0.016	0.3601	0.2588	0.1013	0.273	2.09	16.45	0.92	0.0248	-0.1588	0.5678

Table 3: Variance Swap Payoffs: 30-Minute Andersen et al. (2015) RV

This table reports summary statistics on the daily time series of the 1-month VSPs. Panel A presents the results linked to the S&P 500 index, as well as the equal-weighted average of the constituent stocks. RV and IV report the average (annualized) realized and Britten-Jones and Neuberger (2000) option-implied variances, respectively. We use high-frequency return data sampled at the 30-minute frequency to compute the Andersen et al. (2015) return variation (see Equation (10)). VSP shows the average VSP, defined as the spread between RV and IV. *Std Dev*, *Skew*, *Kurt* and $AR(1)$ denote the standard deviation, skewness, kurtosis and first-order autocorrelation of the VSP, respectively. $Median$, $q^{0.05}$ and $q^{0.95}$ are the median, 5 % and 95 % quantiles of the VSP, respectively. *, **, and *** indicate significance at the 10%, 5%, and 1% level based on Newey and West (1987) corrected standard errors (with 21 lags), respectively. We highlight, in **bold**, the significant estimates of the VSP based on a block-bootstrap. The rows in Panels B relate to stocks with insignificant, significantly negative and significantly positive VSPs (at the 5% significance level), respectively. *Share* indicates the fraction of firms for which the VSP satisfies the condition [name in row].

Panel A: Market Variance Swap Payoff

	RV	*IV*	*VSP*	*t-stat*	*Std Dev*	*Skew*	*Kurt*	*AR*(1)	*Median*	$q^{0.05}$	$q^{0.95}$
S&P 500	0.0320	0.0453	**-0.0133***	-6.11	0.038	5.19	68.2	0.95	-0.0124	-0.0512	0.0168
Avg. Stocks	0.1479	0.1571	**-0.0092***	-1.77	0.089	5.47	56.9	0.97	-0.0192	-0.0841	0.0976

Panel B: Stock Variance Swap Payoff

	Share	*RV*	*IV*	*VSP*	*Std Dev*	*Skew*	*Kurt*	*AR*(1)	*Median*	$q^{0.05}$	$q^{0.95}$
= 0 not rejected	0.591	0.2007	0.1901	0.0106	0.278	4.07	49.55	0.94	-0.0243	-0.1732	0.2775
> 0 rejected	0.393	0.1170	0.1458	-0.0288	0.097	1.22	25.08	0.92	-0.0303	-0.1477	0.0981
< 0 rejected	0.017	0.4647	0.3104	0.1543	0.331	2.08	14.95	0.93	0.0528	-0.1737	0.7487

Table 4: Decomposition Results: 30-Minute Andersen et al. (2015) RV

This table presents the results of the decomposition of the daily time series of the 1-month index variance swap payoff (Panel A) and variance risk premium (Panel B) into two factors. The variance swap payoff is the difference between the (annualized) Andersen et al. (2015) realized and Britten-Jones and Neuberger (2000) option-implied variance. We use high-frequency return data sampled at the 30-minute frequency to compute the Andersen et al. (2015) return variation (see Equation (10)). The variance risk premium is the difference between the physical expectation of the future variance, using a random walk model (Bollerslev et al., 2009), and the Britten-Jones and Neuberger (2000) option-implied variance. $Mean$ is the average value. *, **, and *** indicate significance at the 10%, 5%, and 1% level based on the Newey and West (1987) corrected standard errors (with 21 lags), respectively. We highlight, in **bold**, the significant estimates of the mean based on a block-bootstrap. Shr$_{mean}$ reports the fraction of the mean of the (i) variance swap payoff (Panel A) or (ii) variance risk premium (Panel B) of the S&P 500 index associated with the factor [name in row]. *Std Dev* is the standard deviation. Shr$_{var}$ reports the share of the variance of the (i) variance swap payoff (Panel A) or (ii) variance risk premium (Panel B) of the S&P 500 index associated with the factor [name in row]. $Skew$, $Kurt$ and $AR(1)$ denote the skewness, kurtosis and first-order autocorrelation, respectively. $Median$, $q^{0.05}$ and $q^{0.95}$ relate to the median, 5% and 95 % of the distribution of the variable [name in row].

Panel A: Variance Swap Payoff

	$Mean$	t-stat	Shr$_{\text{mean}}$	*Std Dev*	Shr$_{\text{var}}$	$Skew$	$Kurt$	$AR(1)$	$Median$	$q^{0.05}$	$q^{0.95}$
Index VSP	**-0.0133*** **	-6.11	1.000	0.038	1.000	5.19	68.2	0.95	-0.0124	-0.0512	0.0168
Individual VSP	**-0.0039** **	-2.28	0.294	0.030	0.674	4.56	61.7	0.96	-0.0046	-0.0321	0.0230
CSP	**-0.0094*** **	-10.2	0.706	0.017	0.326	-1.01	35.2	0.92	-0.0069	-0.0310	0.0021

Panel B: Variance Risk Premium

	$Mean$	t-stat	Shr$_{\text{mean}}$	*Std Dev*	Shr$_{\text{var}}$	$Skew$	$Kurt$	$AR(1)$	$Median$	$q^{0.05}$	$q^{0.95}$
Index VRP	**-0.0128*** **	-10.9	1.000	0.024	1.000	5.99	96.3	0.87	-0.0117	-0.0404	0.0070
Individual VRP	-0.0015	-1.08	0.117	0.026	0.721	8.24	112	0.94	-0.0038	-0.0205	0.0228
CRP	**-0.0113*** **	-14.1	0.883	0.015	0.279	-5.80	76.2	0.88	-0.0078	-0.0341	0.0006

Table 5: Predictability of S&P 500 Excess Returns: 30-Minute Andersen et al. (2015) RV

This table summarizes the results of the regression of S&P 500 (annualized) excess returns measured over a horizon of h months on a constant and the lagged forecasting variable(s). Panel A considers the forecasting power of the market index variance risk premium. The index variance risk premium is the difference between the physical expectation of the future Andersen et al. (2015) variance, computed based on 30-minute data and using a random walk model (Bollerslev et al., 2009), and the Britten-Jones and Neuberger (2000) option-implied variance. Panel B considers the two factors of the index variance risk premium, namely the CRP and Individual VRP factors. We consider forecasting horizons (h) of 1, 3, 6, 9, 12, 18 and 24 months. All the variables are sampled at the end of each month. The entries in parentheses and square brackets indicate Newey and West (1987) corrected standard errors (with h lags) and Hodrick (1992) corrected standard errors, respectively. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively. We highlight, in **bold**, the significant regression coefficient estimates based on the bootstrap of Rapach et al. (2013). Adj. R^2 reports the adjusted R^2. Wald presents the results of a Wald test of the null hypothesis that the two slope parameters are equal. p-value reports the corresponding Newey and West (1987) corrected p-value.

Panel A: Index VRP

Horizon (in Months)	1	3	6	9	12	18	24
Constant	-0.0050	0.0135	0.0317	0.0437	0.0468	0.0477	0.0454
(s.e.) (NW)	(0.037)	(0.029)	(0.032)	(0.035)	(0.036)	(0.038)	(0.039)
[s.e.] (Hod)	[0.038]	[0.037]	[0.038]	[0.037]	[0.037]	[0.036]	[0.037]
Index VRP	**-4.6033**	**-3.5612**	**-1.8849**	-0.9661	-0.6613	-0.4313	-0.3715
(s.e.) (NW)	(1.310)***	(0.814)***	(0.667)***	(0.593)	(0.499)	(0.424)	(0.328)
[s.e.] (Hod)	[1.487]***	[1.090]***	[0.921]**	[0.734]	[0.611]	[0.483]	[0.407]
Adj. R^2	0.061	0.103	0.048	0.015	0.007	0.003	0.002

Panel B: CRP and Individual VRP Factors

Horizon (in Months)	1	3	6	9	12	18	24
Constant	-0.0346	-0.0350	-0.0102	0.0104	0.0224	0.0259	0.0248
(s.e.) (NW)	(0.043)	(0.035)	(0.037)	(0.038)	(0.040)	(0.043)	(0.045)
[s.e.] (Hod)	[0.044]	[0.035]	[0.036]	[0.036]	[0.036]	[0.035]	[0.036]
Individual VRP	**-4.4471**	**-3.3051**	**-1.6661**	**-0.7949**	-0.5378	-0.3266	-0.2777
(s.e.) (NW)	(1.120)***	(0.448)***	(0.336)***	(0.341)**	(0.325)*	(0.267)	(0.191)
[s.e.] (Hod)	[1.266]***	[0.992]***	[0.941]*	[0.746]	[0.611]	[0.469]	[0.390]
CRP	**-6.9035**	**-7.3318**	**-5.1273**	**-3.5232**	**-2.5194**	**-2.0663**	**-1.8879**
(s.e.) (NW)	(2.810)**	(1.313)***	(0.995)***	(0.920)***	(0.887)***	(0.816)**	(1.014)*
[s.e.] (Hod)	[2.976]**	[1.531]***	[1.672]***	[1.588]**	[1.642]	[1.567]	[1.463]
Adj. R^2	0.061	0.128	0.082	0.044	0.025	0.022	0.023
Wald	0.563	**7.446*****	**9.828*****	**7.477*****	**4.454****	**3.931****	**2.408**
p-value	[0.453]	[0.006]	[0.002]	[0.006]	[0.035]	[0.047]	[0.121]

Table 6: Decomposition Results: HAR–RV

This table presents the results of the decomposition of the daily time series of the 1-month index variance risk premium into two factors. The variance risk premium is the difference between the physical expectation of the future variance, using the HAR–RV model (Corsi, 2009), and the Britten-Jones and Neuberger (2000) option-implied variance. We use high-frequency return data sampled at the 30-minute frequency to compute the Andersen et al. (2015) realized variance (see Equation (10)). *Mean* is the average value. *, **, and *** indicate significance at the 10%, 5%, and 1% level based on the Newey and West (1987) corrected standard errors (with 21 lags), respectively. We highlight, in **bold**, the significant estimates of the mean based on a block-bootstrap. Shr_{mean} reports the fraction of the mean of the variance risk premium of the S&P 500 index associated with the factor [name in row]. *Std Dev* is the standard deviation. Shr_{var} reports the share of the variance of the variance risk premium of the S&P 500 index associated with the factor [name in row]. *Skew*, *Kurt* and $AR(1)$ denote the skewness, kurtosis and first-order autocorrelation, respectively. *Median*, $q^{0.05}$ and $q^{0.95}$ relate to the median, 5,% and 95 % of the distribution of the variable [name in row].

	Mean	*t*-stat	Shr_{mean}	*Std Dev*	Shr_{var}	*Skew*	*Kurt*	$AR(1)$	*Median*	$q^{0.05}$	$q^{0.95}$
Index VRP	**-0.0143*****	-11.9	1.000	0.023	1.000	0.31	24.6	0.82	-0.0096	-0.0533	0.0036
Individual VRP	0.0011	1.33	-0.079	0.016	0.384	-2.10	28.0	0.87	0.0053	-0.0225	0.0154
CRP	**-0.0155*****	-21.8	1.079	0.014	0.616	3.63	62.0	0.84	-0.0145	-0.0359	-0.0017

Table 7: Predictability of S&P 500 Excess Returns: HAR–RV

This table summarizes the results of the regression of S&P 500 (annualized) excess returns measured over a horizon of h months on a constant and the lagged forecasting variable(s). Panel A considers the forecasting power of the market index variance risk premium. The index variance risk premium is the difference between the physical expectation of the future variance, computed based on 30-minute data and using the HAR–RV model (Corsi, 2009), and the Britten-Jones and Neuberger (2000) option-implied variance. Panel B considers the two factors of the index variance risk premium, namely the CRP and Individual VRP factors. We consider forecasting horizons (h) of 1, 3, 6, 9, 12, 18 and 24 months. All the variables are sampled at the end of each month. The entries in parentheses and square brackets indicate Newey and West (1987) corrected standard errors (with h lags) and Hodrick (1992) corrected standard errors, respectively. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively. We highlight, in **bold**, the significant regression coefficient estimates based on the bootstrap of Rapach et al. (2013). Adj. R^2 reports the adjusted R^2. Wald presents the results of a Wald test of the null hypothesis that the two slope parameters are equal. p-value reports the corresponding Newey and West (1987) corrected p-value.

Panel A: Index VRP

Horizon (in Months)	1	3	6	9	12	18	24
Constant	-0.0234	-0.0137	0.0012	0.0174	0.0231	0.0255	0.0195
(s.e.) (NW)	(0.036)	(0.033)	(0.034)	(0.035)	(0.037)	(0.040)	(0.042)
[s.e.] (Hod)	[0.033]	[0.034]	[0.035]	[0.034]	[0.034]	[0.034]	[0.036]
Index VRP	**-4.5368**	**-4.1438**	**-2.8509**	**-1.7248**	**-1.2584**	-0.9938	**-1.1684**
(s.e.) (NW)	(1.752)**	(0.837)***	(0.825)***	(0.777)**	(0.685)*	(0.579)*	(0.522)**
[s.e.] (Hod)	[1.772]**	[1.200]***	[0.811]***	[0.704]**	[0.703]*	[0.652]	[0.554]**
Adj. R^2	0.032	0.079	0.065	0.032	0.021	0.017	0.034

Panel B: CRP and Individual VRP Factors

Horizon (in Months)	1	3	6	9	12	18	24
Constant	-0.0739	**-0.1438**	-0.0945	-0.0646	-0.0461	-0.0517	-0.0736
(s.e.) (NW)	(0.086)	(0.060)**	(0.056)*	(0.052)	(0.052)	(0.054)	(0.055)
[s.e.] (Hod)	[0.082]	[0.062]**	[0.061]	[0.057]	[0.056]	[0.051]	[0.053]
Individual VRP	-2.9193	0.0938	0.2739	0.9419	0.9774	1.5273	**1.8280**
(s.e.) (NW)	(3.254)	(1.633)	(1.558)	(1.363)	(1.254)	(1.283)	(1.253)
[s.e.] (Hod)	[3.159]	[2.019]	[1.493]	[1.357]	[1.315]	[1.133]	[1.091]*
CRP	-6.9289	**-10.521**	**-7.6003**	**-5.7823**	**-4.6559**	**-4.8309**	**-5.7745**
(s.e.) (NW)	(4.077)*	(2.100)***	(1.807)***	(1.748)***	(1.827)**	(1.691)***	(1.508)***
[s.e.] (Hod)	[3.830]*	[2.513]***	[2.345]***	[2.205]***	[2.147]**	[1.934]**	[1.746]***
Adj. R^2	0.030	0.131	0.114	0.083	0.067	0.104	0.198
Wald	1.199	**41.616*****	**24.360*****	**17.313*****	**13.436*****	**29.174*****	**60.061*****
p-value	[0.274]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]

Appendix to

"Variance Risk: A Bird's Eye View"

Not Intended for Publication!

Will be Provided as Online Appendix

Table A.1: Intraday S&P 500 Index Autocorrelation

This table summarizes the results of our analysis of intraday return predictability for the S&P 500 index for different half-hour intervals. We regress the time series of the returns observed during the intraday interval ending at *[name in column]* on a constant and the time series of the intraday returns observed during the intraday interval ending at *[name in row]* of the same day. First and Last end at 10:00 and 16:00, respectively. The table presents the regression coefficients. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively. In parentheses, we report the R^2 of the regression.

	10:30	11:00	11:30	12:00	12:30	13:00	13:30	14:00	14:30	15:00	15:30	Last
First+ON	-0.024*	-0.019*	0.037***	-0.005	0.017**	0.011	0.036***	0.002	0.001	0.037***	0.022*	0.136***
	(0.001)	(0.001)	(0.003)	(0.000)	(0.001)	(0.000)	(0.004)	(0.000)	(0.000)	(0.002)	(0.001)	(0.021)
10:30		0.011	-0.024**	-0.008	0.003	-0.024***	-0.004	-0.023**	0.017	-0.002	0.027*	0.070***
		(0.000)	(0.001)	(0.000)	(0.000)	(0.001)	(0.000)	(0.001)	(0.000)	(0.000)	(0.001)	(0.004)
11:00			-0.036***	0.028**	0.004	0.017	-0.015	-0.015	0.001	0.009	-0.017	0.076***
			(0.002)	(0.001)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.004)
11:30				0.061***	-0.011	-0.016	0.005	-0.023*	0.062***	-0.003	0.047**	0.122***
				(0.004)	(0.000)	(0.000)	(0.000)	(0.001)	(0.003)	(0.000)	(0.001)	(0.007)
12:00					-0.020	0.009	-0.076***	-0.043***	-0.015	-0.015	0.044**	0.113***
					(0.001)	(0.000)	(0.006)	(0.002)	(0.000)	(0.000)	(0.001)	(0.005)
12:30						-0.020	-0.010	-0.005	-0.054***	-0.004	-0.000	-0.028
						(0.000)	(0.000)	(0.000)	(0.002)	(0.000)	(0.000)	(0.000)
13:00							-0.084***	0.015	-0.021	0.043**	-0.109***	-0.055**
							(0.006)	(0.000)	(0.000)	(0.001)	(0.004)	(0.001)
13:30								0.018	-0.004	0.049***	0.048**	0.045**
								(0.000)	(0.000)	(0.002)	(0.001)	(0.001)
14:00									0.040**	-0.006	0.002	-0.003
									(0.001)	(0.000)	(0.000)	(0.000)
14:30										0.014	0.027	0.068***
										(0.000)	(0.001)	(0.003)
15:00											0.093***	0.058***
											(0.006)	(0.002)
15:30												0.123***
												(0.014)

Table A.2: Intraday Stock Momentum

This table summarizes the results of our analysis of intraday return predictability for different half-hour intervals. For each stock, we regress the time series of the returns observed during the intraday interval ending at *[name in column]* on a constant and the time series of the intraday returns observed during the intraday interval ending at *[name in row]* of the same days. First and Last end at 10:00 and 16:00, respectively. The table presents the proportion of stocks for which we find a significantly positive slope estimate at the 5 % significance level. In parentheses, we report the average R^2 across stocks.

	10:30	11:00	11:30	12:00	12:30	13:00	13:30	14:00	14:30	15:00	15:30	Last
First+ON	0.209	0.214	0.340	0.212	0.269	0.242	0.365	0.186	0.152	0.281	0.208	0.459
	(0.005)	(0.005)	(0.005)	(0.005)	(0.004)	(0.004)	(0.003)	(0.004)	(0.005)	(0.004)	(0.004)	(0.007)
10:30		0.203	0.141	0.201	0.211	0.152	0.184	0.118	0.179	0.127	0.204	0.253
		(0.005)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.005)	(0.004)	(0.004)
11:00			0.171	0.307	0.264	0.235	0.137	0.134	0.156	0.183	0.118	0.329
			(0.005)	(0.004)	(0.004)	(0.004)	(0.003)	(0.004)	(0.004)	(0.005)	(0.005)	(0.003)
11:30				0.315	0.220	0.179	0.202	0.113	0.312	0.178	0.212	0.335
				(0.005)	(0.004)	(0.004)	(0.003)	(0.005)	(0.003)	(0.003)	(0.004)	(0.004)
12:00					0.130	0.228	0.116	0.129	0.140	0.197	0.227	0.351
					(0.008)	(0.004)	(0.005)	(0.005)	(0.003)	(0.005)	(0.003)	(0.003)
12:30						0.130	0.165	0.192	0.148	0.129	0.112	0.146
						(0.009)	(0.005)	(0.009)	(0.009)	(0.004)	(0.005)	(0.004)
13:00							0.074	0.285	0.184	0.222	0.072	0.108
							(0.006)	(0.005)	(0.005)	(0.003)	(0.004)	(0.004)
13:30								0.198	0.209	0.328	0.210	0.227
								(0.006)	(0.004)	(0.005)	(0.005)	(0.004)
14:00									0.174	0.150	0.159	0.158
									(0.005)	(0.004)	(0.004)	(0.005)
14:30										0.108	0.220	0.347
										(0.004)	(0.004)	(0.004)
15:00											0.217	0.277
											(0.005)	(0.004)
15:30												0.299
												(0.008)

Table A.3: Intraday Stock Reversal

This table summarizes the results of our analysis of intraday return predictability for different half-hour intervals. For each stock, we regress the time series of the returns observed during the intraday interval ending at *[name in column]* on a constant and the time series of the intraday returns observed during the intraday interval ending at *[name in row]* of the same day. First and Last end at 10:00 and 16:00, respectively. The table presents the proportion of stocks for which we find a significantly negative slope estimate at the 5 % significance level. In parentheses, we report the average R^2 across stocks.

	10:30	11:00	11:30	12:00	12:30	13:00	13:30	14:00	14:30	15:00	15:30	Last
First+ON	0.341	0.190	0.114	0.153	0.140	0.150	0.089	0.178	0.181	0.110	0.217	0.103
	(0.007)	(0.004)	(0.004)	(0.004)	(0.006)	(0.005)	(0.004)	(0.004)	(0.004)	(0.005)	(0.003)	(0.005)
10:30		0.347	0.303	0.179	0.155	0.267	0.165	0.245	0.174	0.265	0.213	0.116
		(0.011)	(0.004)	(0.005)	(0.004)	(0.003)	(0.003)	(0.004)	(0.004)	(0.003)	(0.004)	(0.004)
11:00			0.413	0.121	0.128	0.114	0.189	0.234	0.179	0.185	0.280	0.100
			(0.011)	(0.004)	(0.004)	(0.004)	(0.004)	(0.003)	(0.004)	(0.004)	(0.003)	(0.005)
11:30				0.274	0.190	0.199	0.146	0.275	0.100	0.171	0.155	0.109
				(0.016)	(0.006)	(0.004)	(0.004)	(0.003)	(0.004)	(0.004)	(0.004)	(0.005)
12:00					0.471	0.181	0.327	0.266	0.176	0.185	0.140	0.102
					(0.013)	(0.007)	(0.005)	(0.005)	(0.004)	(0.003)	(0.005)	(0.006)
12:30						0.440	0.236	0.211	0.265	0.219	0.258	0.254
						(0.017)	(0.007)	(0.005)	(0.004)	(0.004)	(0.003)	(0.003)
13:00							0.638	0.175	0.224	0.150	0.389	0.314
							(0.014)	(0.009)	(0.004)	(0.005)	(0.003)	(0.004)
13:30								0.451	0.198	0.124	0.175	0.152
								(0.017)	(0.006)	(0.005)	(0.004)	(0.004)
14:00									0.411	0.252	0.249	0.227
									(0.016)	(0.005)	(0.004)	(0.004)
14:30										0.523	0.194	0.117
										(0.014)	(0.005)	(0.005)
15:00											0.357	0.173
											(0.015)	(0.004)
15:30												0.340
												(0.014)

Table A.4: Variance Swap Payoffs: Daily Andersen et al. (2015) RV

This table reports summary statistics on the daily time series of the 1-month VSPs. Panel A presents the results linked to the S&P 500 index, as well as the equal-weighted average of the constituent stocks. *RV* and *IV* report the average (annualized) low-frequency realized and Britten-Jones and Neuberger (2000) option-implied variances, respectively. We use daily return data to compute the return variation based on Equation (12). VSP shows the average VSP, defined as the spread between *RV* and *IV*. *Std Dev*, *Skew*, *Kurt* and *AR*(1) denote the standard deviation, skewness, kurtosis and first-order autocorrelation of the VSP, respectively. *Median*, $q^{0.05}$ and $q^{0.95}$ are the median, 5 % and 95 % quantiles of the VSP, respectively. *, **, and *** indicate significance at the 10%, 5%, and 1% level based on Newey and West (1987) corrected standard errors (with 21 lags), respectively. We highlight, in **bold**, the significant estimates of the VSP based on a block-bootstrap. The rows in Panels B relate to stocks with insignificant, significantly negative and significantly positive VSPs (at the 5% significance level), respectively. *Share* indicates the fraction of firms for which the VSP satisfies the condition [name in row].

Panel A: Market Variance Swap Payoff

	RV	*IV*	*VSP*	*t-stat*	*Std Dev*	*Skew*	*Kurt*	*AR*(1)	*Median*	$q^{0.05}$	$q^{0.95}$
S&P 500	0.0384	0.0453	**-0.0068****	-2.46	0.048	6.26	66.9	0.96	-0.0100	-0.0450	0.0329
Avg. Stocks	0.1568	0.1571	-0.0002	-0.04	0.107	6.11	56.0	0.98	-0.0172	-0.0753	0.1159

Panel B: Stock Variance Swap Payoff

	Share	*RV*	*IV*	*VSP*	*Std Dev*	*Skew*	*Kurt*	*AR*(1)	*Median*	$q^{0.05}$	$q^{0.95}$
= 0 not rejected	0.673	0.2096	0.1883	0.0212	0.320	3.94	41.77	0.94	-0.0250	-0.1765	0.3339
> 0 rejected	0.298	0.1061	0.1355	-0.0294	0.099	1.08	21.73	0.92	-0.0326	-0.1504	0.1071
< 0 rejected	0.029	0.3452	0.2528	0.0924	0.356	3.42	21.23	0.95	-0.0074	-0.1528	0.7051

Table A.5: Correlation Swap Payoffs

This table presents the summary statistics of the daily time series of the 1-month correlation swap payoff (CSP) and correlation risk premium (CRP). CSP is computed by taking the difference between the realized equicorrelation, denoted by RC (see Equation (14)), and the implied equicorrelation (IC), computed as in Equation (15). CRP is the difference between the physical expectation of the future equicorrelation ($E^{\mathbb{P}}$(RC)) and IC. Panels A and B use the low-frequency realized variance (see Equation (3)) and the Andersen et al. (2015) return variation based on the 30-minute frequency (see Equation (10)), respectively. *Mean* denotes the sample average. *t-stat* is the Newey and West (1987) corrected *t*-statistic (with 21 lags). *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively. We highlight, in **bold**, all estimates that are statistically significant based on a block-bootstrap. *Std Dev*, *Skew*, *Kurt* and *AR*(1) denote the standard deviation, skewness, kurtosis and first-order autocorrelation, respectively. *Median*, $q^{0.05}$ and $q^{0.95}$ are the median, 5 % and 95 % quantiles, respectively.

Panel A: Low-Frequency Realized Variation

	Mean	*t*-stat	*Std Dev*	*Skew*	*Kurt*	*AR*(1)	*Median*	$q^{0.05}$	$q^{0.95}$
RC	**0.3218***	36.8	0.141	0.85	3.48	0.98	0.2904	0.1386	0.6126
IC	**0.3965***	48.8	0.131	0.56	3.25	0.96	0.3843	0.1977	0.6371
CSP	**-0.0747***	-11.5	0.121	0.22	4.89	0.93	-0.0729	-0.2668	0.1198
$E^{\mathbb{P}}$(RC)	**0.3233***	36.7	0.142	0.84	3.40	0.98	0.2920	0.1407	0.6058
CRP	**-0.0733***	-13.8	0.101	-0.11	3.22	0.92	-0.0713	-0.2470	0.0884

Panel B: Andersen et al. (2015) Return Variation

	Mean	*t*-stat	*Std Dev*	*Skew*	*Kurt*	*AR*(1)	*Median*	$q^{0.05}$	$q^{0.95}$
RC	**0.2855***	38.1	0.118	0.97	3.75	0.99	0.2597	0.1387	0.5205
IC	**0.3965***	48.8	0.131	0.56	3.25	0.96	0.3843	0.1977	0.6371
CSP	**-0.1110***	-20.5	0.099	-0.26	6.28	0.92	-0.1034	-0.2692	0.0246
$E^{\mathbb{P}}$(RC)	**0.2800***	38.6	0.113	0.97	3.84	0.99	0.2533	0.1363	0.4920
CRP	**-0.1165***	-25.1	0.087	-0.62	4.36	0.90	-0.1051	-0.2631	0.0090

Table A.6: Predictability of S&P 500 Excess Returns: 1-Month Horizon

This table summarizes the results of the regression of S&P 500 (annualized) excess returns measured over a horizon of 1 month on a constant and the lagged forecasting variable(s). VRP is the index variance risk premium, defined as the difference between the physical expectation of the future Andersen et al. (2015) variance, computed based on 30-minute data and using a random walk model (Bollerslev et al., 2009), and the Britten-Jones and Neuberger (2000) option-implied variance. Individual VRP and CRP are the individual variance risk premium and the correlation risk premium factors, respectively. CAY is the consumption-to-wealth ratio. DFSP is the default spread, defined as the difference between BAA- and AAA-rated corporate bond yields. log(P/D) is the logarithm of the level of the S&P 500 over the 12-month trailing sum of dividends paid by S&P 500 firms. log(P/E) is the logarithm of the price over the 12-month trailing sum of earnings. RREL is the stochastically detrended risk-free rate, i.e., the 1-month T-bill rate minus its 12-month trailing average. TMSP is the term spread, defined as the difference between the 10-year yield and the 3-month T-bill rate. All the variables are sampled at the end of each month. The entries in parentheses and square brackets indicate Newey and West (1987) corrected standard errors (with 1 lag) and Hodrick (1992) corrected standard errors, respectively. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively. We highlight, in **bold**, the significant regression coefficient estimates based on the bootstrap of Rapach et al. (2013). Adj. R^2 reports the adjusted R^2.

	(i)	(ii)	(iii)	(iv)	(v)	(vi)	(vii)	(viii)	(ix)	(x)	(xi)	(xii)
Constant	-0.0050	-0.0346	0.0651	0.1429	1.2394	0.2968	0.0676	0.0516	**1.8893**	**1.8211**	**2.8139**	**2.7851**
(s.e.) (NW)	(0.037)	(0.043)	(0.040)	(0.128)	(0.947)	(0.388)	(0.033)**	(0.066)	(0.818)**	(0.817)**	(0.789)***	(0.779)***
[s.e.] (Hod)	[0.038]	[0.044]	[0.038]*	[0.115]	[0.864]	[0.335]	[0.033]**	[0.066]	[0.800]**	[0.798]**	[0.810]***	[0.803]***
VRP	**-4.6033**								**-4.7265**		**-4.3711**	
(s.e.) (NW)	(1.310)***								(1.257)***		(1.417)***	
[s.e.] (Hod)	[1.487]***								[1.440]***		[1.547]***	
Individual VRP		**-4.4471**								**-4.5246**		**-4.1187**
(s.e.) (NW)		(1.120)***								(1.050)***		(1.194)***
[s.e.] (Hod)		[1.266]***								[1.185]***		[1.272]***
CRP		**-6.9035**								**-7.9214**		**-8.5755**
(s.e.) (NW)		(2.810)**								(3.200)**		(3.055)***
[s.e.] (Hod)		[2.976]**								[3.416]**		[3.176]***
CAY			1.6009						1.9754	1.2617	1.8650	1.1139
(s.e.) (NW)			(1.350)						(1.269)	(1.353)	(1.320)	(1.372)
[s.e.] (Hod)			[1.395]						[1.359]	[1.454]	[1.403]	[1.448]
DFSP				-8.9496							-18.364	-19.607
(s.e.) (NW)				(13.69)							(15.27)	(14.96)
[s.e.] (Hod)				[11.96]							[14.63]	[14.34]
log(P/D)					-29.460				**-46.281**	**-45.676**	**-67.096**	**-65.495**
(s.e.) (NW)					(23.26)				(20.27)**	(20.29)**	(19.76)***	(19.84)***
[s.e.] (Hod)					[21.30]				[19.84]**	[19.92]**	[20.00]***	[19.97]***
log(P/E)						-7.7259					3.1940	-0.0735
(s.e.) (NW)						(12.71)					(11.36)	(11.58)
[s.e.] (Hod)						[10.94]					[11.07]	[11.28]
RREL							**120.96**		**141.08**	**158.13**	105.75	122.56
(s.e.) (NW)							(69.80)*		(65.95)**	(69.21)**	(73.81)	(76.95)
[s.e.] (Hod)							[63.08]*		[60.75]**	[63.64]**	[67.96]	[71.15]*
TMSP								0.0637			-0.1895	0.7709
(s.e.) (NW)								(2.671)			(2.736)	(2.784)
[s.e.] (Hod)								[2.561]			[2.574]	[2.605]
Adj. R^2	0.061	0.061	-0.000	0.001	0.010	-0.001	0.013	-0.004	0.099	0.102	0.098	0.104

Table A.7: Predictability of S&P 500 Excess Returns: 3-Month Horizon

This table summarizes the results of the regression of S&P 500 (annualized) excess returns measured over a horizon of 3 months on a constant and the lagged forecasting variable(s). VRP is the index variance risk premium, defined as the difference between the physical expectation of the future Andersen et al. (2015) variance, computed based on 30-minute data and using a random walk model (Bollerslev et al., 2009), and the Britten-Jones and Neuberger (2000) option-implied variance. Individual VRP and CRP are the individual variance risk premium and the correlation risk premium factors, respectively. CAY is the consumption-to-wealth ratio. DFSP is the default spread, defined as the difference between BAA- and AAA-rated corporate bond yields. log(P/D) is the logarithm of the level of the S&P 500 over the 12-month trailing sum of dividends paid by S&P 500 firms. log(P/E) is the logarithm of the price over the 12-month trailing sum of earnings. RREL is the stochastically detrended risk-free rate, i.e., the 1-month T-bill rate minus its 12-month trailing average. TMSP is the term spread, defined as the difference between the 10-year yield and the 3-month T-bill rate. All the variables are sampled at the end of each month. The entries in parentheses and square brackets indicate Newey and West (1987) corrected standard errors (with 3 lags) and Hodrick (1992) corrected standard errors, respectively. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively. We highlight, in **bold**, the significant regression coefficient estimates based on the bootstrap of Rapach et al. (2013). Adj. R^2 reports the adjusted R^2.

	(i)	(ii)	(iii)	(iv)	(v)	(vi)	(vii)	(viii)	(ix)	(x)	(xi)	(xii)
Constant	0.0135	-0.0350	0.0674	0.1004	**1.3504**	0.1871	**0.0708**	0.0444	**1.9911**	**1.8867**	**2.5040**	**2.4650**
(s.e.) (NW)	(0.029)	(0.035)	(0.035)*	(0.112)	(0.822)	(0.354)	(0.029)**	(0.058)	(0.504)***	(0.501)***	(0.664)***	(0.613)***
[s.e.] (Hod)	[0.037]	[0.035]	[0.038]*	[0.116]	[0.821]	[0.297]	[0.033]**	[0.067]	[0.697]***	[0.691]***	[0.822]***	[0.811]***
VRP	**-3.5612**								**-3.6581**		**-3.3116**	
(s.e.) (NW)	(0.814)***								(0.751)***		(0.894)***	
[s.e.] (Hod)	[1.090]***								[1.015]***		[0.999]***	
Individual VRP		**-3.3051**								**-3.3492**		**-2.9686**
(s.e.) (NW)		(0.448)***								(0.385)***		(0.438)***
[s.e.] (Hod)		[0.992]***								[0.900]***		[0.865]***
CRP		**-7.3318**								**-8.5452**		**-9.0241**
(s.e.) (NW)		(1.313)***								(1.278)***		(1.279)***
[s.e.] (Hod)		[1.531]***								[1.468]***		[1.475]***
CAY			**1.7271**						**2.3836**	1.2919	**2.1715**	1.1510
(s.e.) (NW)			(1.119)						(1.048)**	(1.029)	(1.057)**	(1.025)
[s.e.] (Hod)			[1.399]						[1.346]*	[1.337]	[1.394]	[1.358]
DFSP				-4.5230							**-14.006**	**-15.694**
(s.e.) (NW)				(12.48)							(8.709)	(8.359)*
[s.e.] (Hod)				[12.05]							[13.03]	[13.03]
log(P/D)					**-32.153**				**-48.231**	**-47.306**	**-63.070**	**-60.895**
(s.e.) (NW)					(20.06)				(12.58)***	(12.38)***	(15.88)***	(15.00)***
[s.e.] (Hod)					[20.27]				[17.27]***	[17.17]***	[19.59]***	[19.42]***
log(P/E)						-4.1813					6.8361	2.3967
(s.e.) (NW)						(11.64)					(7.535)	(7.711)
[s.e.] (Hod)						[9.710]					[9.664]	[9.809]
RREL							**128.66**		**153.98**	**180.07**	**142.78**	**165.62**
(s.e.) (NW)							(58.49)**		(50.98)***	(51.42)***	(54.88)***	(53.02)***
[s.e.] (Hod)							[61.44]**		[57.07]***	[57.62]***	[63.94]**	[64.49]**
TMSP								0.4583			0.4343	1.7392
(s.e.) (NW)								(2.512)			(2.236)	(2.193)
[s.e.] (Hod)								[2.586]			[2.567]	[2.620]
Adj. R^2	0.103	0.128	0.008	-0.000	0.043	-0.002	0.052	-0.004	0.251	0.289	0.254	0.302

Table A.8: Predictability of S&P 500 Excess Returns: 6-Month Horizon

This table summarizes the results of the regression of S&P 500 (annualized) excess returns measured over a horizon of 6 months on a constant and the lagged forecasting variable(s). VRP is the index variance risk premium, defined as the difference between the physical expectation of the future Andersen et al. (2015) variance, computed based on 30-minute data and using a random walk model (Bollerslev et al., 2009), and the Britten-Jones and Neuberger (2000) option-implied variance. Individual VRP and CRP are the individual variance risk premium and the correlation risk premium factors, respectively. CAY is the consumption-to-wealth ratio. DFSP is the default spread, defined as the difference between BAA- and AAA-rated corporate bond yields. log(P/D) is the logarithm of the level of the S&P 500 over the 12-month trailing sum of dividends paid by S&P 500 firms. log(P/E) is the logarithm of the price over the 12-month trailing sum of earnings. RREL is the stochastically detrended risk-free rate, i.e., the 1-month T-bill rate minus its 12-month trailing average. TMSP is the term spread, defined as the difference between the 10-year yield and the 3-month T-bill rate. All the variables are sampled at the end of each month. The entries in parentheses and square brackets indicate Newey and West (1987) corrected standard errors (with 6 lags) and Hodrick (1992) corrected standard errors, respectively. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively. We highlight, in **bold**, the significant regression coefficient estimates based on the bootstrap of Rapach et al. (2013). Adj. R^2 reports the adjusted R^2.

	(i)	(ii)	(iii)	(iv)	(v)	(vi)	(vii)	(viii)	(ix)	(x)	(xi)	(xii)
Constant	0.0317	-0.0102	**0.0680**	0.0425	**1.4894**	0.1393	**0.0701**	0.0264	**2.0372**	**1.9519**	**2.1345**	**2.1036**
(s.e.) (NW)	(0.032)	(0.037)	(0.033)**	(0.084)	(0.667)**	(0.345)	(0.029)**	(0.058)	(0.446)***	(0.424)***	(0.622)***	(0.558)***
[s.e.] (Hod)	[0.038]	[0.036]	[0.037]*	[0.100]	[0.756]*	[0.259]	[0.033]**	[0.067]	[0.721]***	[0.698]***	[0.851]**	[0.839]**
VRP	**-1.8849**								**-1.9469**		**-1.7200**	
(s.e.) (NW)	(0.667)***								(0.600)***		(0.642)***	
[s.e.] (Hod)	[0.921]**								[0.776]**		[0.666]**	
Individual VRP		**-1.6661**								**-1.6911**		**-1.4413**
(s.e.) (NW)		(0.336)***								(0.276)***		(0.318)***
[s.e.] (Hod)		[0.941]*								[0.787]**		[0.670]**
CRP		**-5.1273**								**-5.9889**		**-6.3551**
(s.e.) (NW)		(0.995)***								(0.824)***		(0.877)***
[s.e.] (Hod)		[1.672]***								[1.637]***		[1.625]***
CAY			**2.0731**						**2.8957**	**1.9829**	**2.7653**	**1.9321**
(s.e.) (NW)			(1.161)*						(1.010)***	(0.934)**	(0.952)***	(0.872)**
[s.e.] (Hod)			[1.370]						[1.368]**	[1.361]	[1.379]**	[1.366]
DFSP				1.2061							**-7.2309**	**-8.6091**
(s.e.) (NW)				(9.430)							(6.802)	(6.042)
[s.e.] (Hod)				[10.29]							[11.77]	[11.23]
log(P/D)					**-35.599**				**-48.813**	**-48.072**	**-54.520**	**-52.780**
(s.e.) (NW)					(16.22)**				(11.13)***	(10.45)***	(13.89)***	(12.58)***
[s.e.] (Hod)					[18.72]*				[17.80]***	[17.29]***	[19.99]***	[19.67]***
log(P/E)						-2.6856					5.6861	2.0942
(s.e.) (NW)						(11.32)					(5.217)	(4.716)
[s.e.] (Hod)						[8.507]					[8.971]	[8.775]
RREL							**126.05**		**160.19**	**181.78**	**166.56**	**185.10**
(s.e.) (NW)							(58.79)**		(55.79)***	(55.73)***	(61.46)***	(59.04)***
[s.e.] (Hod)							[63.79]**		[60.40]***	[61.39]***	[67.48]**	[68.87]***
TMSP								1.1942			1.1920	**2.2487**
(s.e.) (NW)								(2.386)			(1.819)	(1.735)
[s.e.] (Hod)								[2.592]			[2.590]	[2.601]
Adj. R^2	0.048	0.082	0.025	-0.004	0.096	-0.002	0.090	-0.000	0.339	0.385	0.340	0.396

Table A.9: Predictability of S&P 500 Excess Returns: 9-Month Horizon

This table summarizes the results of the regression of S&P 500 (annualized) excess returns measured over a horizon of 9 months on a constant and the lagged forecasting variable(s). VRP is the index variance risk premium, defined as the difference between the physical expectation of the future Andersen et al. (2015) variance, computed based on 30-minute data and using a random walk model (Bollerslev et al., 2009), and the Britten-Jones and Neuberger (2000) option-implied variance. Individual VRP and CRP are the individual variance risk premium and the correlation risk premium factors, respectively. CAY is the consumption-to-wealth ratio. DFSP is the default spread, defined as the difference between BAA- and AAA-rated corporate bond yields. log(P/D) is the logarithm of the level of the S&P 500 over the 12-month trailing sum of dividends paid by S&P 500 firms. log(P/E) is the logarithm of the price over the 12-month trailing sum of earnings. RREL is the stochastically detrended risk-free rate, i.e., the 1-month T-bill rate minus its 12-month trailing average. TMSP is the term spread, defined as the difference between the 10-year yield and the 3-month T-bill rate. All the variables are sampled at the end of each month. The entries in parentheses and square brackets indicate Newey and West (1987) corrected standard errors (with 9 lags) and Hodrick (1992) corrected standard errors, respectively. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively. We highlight, in **bold**, the significant regression coefficient estimates based on the bootstrap of Rapach et al. (2013). Adj. R^2 reports the adjusted R^2.

	(i)	(ii)	(iii)	(iv)	(v)	(vi)	(vii)	(viii)	(ix)	(x)	(xi)	(xii)
Constant	0.0437	0.0104	**0.0680**	0.0247	**1.5633**	0.1747	**0.0714**	0.0074	**2.0409**	**1.9733**	**1.9420**	**1.9167**
(s.e.) (NW)	(0.034)	(0.038)	(0.034)**	(0.073)	(0.568)***	(0.324)	(0.031)**	(0.063)	(0.390)***	(0.379)***	(0.568)***	(0.518)***
[s.e.] (Hod)	[0.037]	[0.036]	[0.037]*	[0.086]	[0.712]**	[0.239]	[0.033]**	[0.067]	[0.696]***	[0.679]***	[0.847]**	[0.840]**
VRP	-0.9661								-1.0226		-0.8663	
(s.e.) (NW)	(0.593)								(0.541)*		(0.542)	
[s.e.] (Hod)	[0.734]								[0.593]*		[0.489]*	
Individual VRP		**-0.7949**								**-0.8191**		**-0.6292**
(s.e.) (NW)		(0.341)**								(0.281)***		(0.257)**
[s.e.] (Hod)		[0.746]								[0.592]		[0.486]
CRP		**-3.5232**								**-4.2557**		**-4.8133**
(s.e.) (NW)		(0.920)***								(0.925)***		(0.875)***
[s.e.] (Hod)		[1.588]**								[1.570]***		[1.499]***
CAY			**2.0818**						**2.9732**	**2.2288**	**3.0102**	**2.2950**
(s.e.) (NW)			(1.333)						(1.033)***	(0.969)**	(0.917)***	(0.848)***
[s.e.] (Hod)			[1.361]						[1.330]**	[1.323]*	[1.302]**	[1.295]*
DFSP				3.1153							-4.3779	-5.5705
(s.e.) (NW)				(7.392)							(6.631)	(5.803)
[s.e.] (Hod)				[8.668]							[9.938]	[9.649]
log(P/D)					**-37.388**				**-48.613**	**-48.036**	**-48.705**	**-47.254**
(s.e.) (NW)					(13.84)***				(9.827)***	(9.388)***	(12.47)***	(11.27)***
[s.e.] (Hod)					[17.65]**				[17.25]***	[16.86]***	[20.08]**	[19.78]**
log(P/E)						-3.7660					3.0434	0.0001
(s.e.) (NW)						(10.57)					(5.510)	(4.410)
[s.e.] (Hod)						[7.872]					[9.044]	[8.635]
RREL							**124.18**		**161.66**	**178.90**	**174.63**	**190.39**
(s.e.) (NW)							(65.74)*		(61.72)***	(61.92)***	(71.75)**	(69.11)***
[s.e.] (Hod)							[65.09]*		[62.81]**	[64.43]***	[70.79]**	[72.44]***
TMSP								**2.0595**			**2.2957**	**3.1939**
(s.e.) (NW)								(2.221)			(1.617)	(1.458)**
[s.e.] (Hod)								[2.527]			[2.581]	[2.571]
Adj. R^2	0.015	0.044	0.034	0.000	0.152	0.001	0.125	0.013	0.435	0.477	0.448	0.506

Table A.10: Predictability of S&P 500 Excess Returns: 12-Month Horizon

This table summarizes the results of the regression of S&P 500 (annualized) excess returns measured over a horizon of 12 months on a constant and the lagged forecasting variable(s). VRP is the index variance risk premium, defined as the difference between the physical expectation of the future Andersen et al. (2015) variance, computed based on 30-minute data and using a random walk model (Bollerslev et al., 2009), and the Britten-Jones and Neuberger (2000) option-implied variance. Individual VRP and CRP are the individual variance risk premium and the correlation risk premium factors, respectively. CAY is the consumption-to-wealth ratio. DFSP is the default spread, defined as the difference between BAA- and AAA-rated corporate bond yields. log(P/D) is the logarithm of the level of the S&P 500 over the 12-month trailing sum of dividends paid by S&P 500 firms. log(P/E) is the logarithm of the price over the 12-month trailing sum of earnings. RREL is the stochastically detrended risk-free rate, i.e., the 1-month T-bill rate minus its 12-month trailing average. TMSP is the term spread, defined as the difference between the 10-year yield and the 3-month T-bill rate. All the variables are sampled at the end of each month. The entries in parentheses and square brackets indicate Newey and West (1987) corrected standard errors (with 12 lags) and Hodrick (1992) corrected standard errors, respectively. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively. We highlight, in **bold**, the significant regression coefficient estimates based on the bootstrap of Rapach et al. (2013). Adj. R^2 reports the adjusted R^2.

	(i)	(ii)	(iii)	(iv)	(v)	(vi)	(vii)	(viii)	(ix)	(x)	(xi)	(xii)
Constant	0.0468	0.0224	0.0666	0.0100	**1.5901**	0.1842	**0.0693**	-0.0161	**2.0052**	**1.9587**	**1.7106**	**1.6926**
(s.e.) (NW)	(0.036)	(0.040)	(0.034)*	(0.066)	(0.509)***	(0.285)	(0.033)**	(0.068)	(0.346)***	(0.349)***	(0.535)***	(0.503)***
[s.e.] (Hod)	[0.037]	[0.036]	[0.037]*	[0.078]	[0.682]**	[0.226]	[0.033]**	[0.067]	[0.669]***	[0.665]***	[0.833]**	[0.830]**
VRP	-0.6613								-0.7371		-0.6676	
(s.e.) (NW)	(0.499)								(0.455)		(0.417)	
[s.e.] (Hod)	[0.611]								[0.490]		[0.398]*	
Individual VRP		-0.5378								**-0.5958**		**-0.4799**
(s.e.) (NW)		(0.325)*								(0.272)**		(0.201)**
[s.e.] (Hod)		[0.611]								[0.481]		[0.387]
CRP		**-2.5194**								**-2.9908**		**-3.7800**
(s.e.) (NW)		(0.887)***								(0.774)***		(0.672)***
[s.e.] (Hod)		[1.642]								[1.577]*		[1.529]**
CAY			**2.1457**						**2.9721**	**2.4356**	**3.2910**	**2.7131**
(s.e.) (NW)			(1.521)						(1.105)***	(1.052)**	(1.014)***	(0.942)***
[s.e.] (Hod)			[1.437]						[1.405]**	[1.374]*	[1.379]**	[1.352]**
DFSP				4.5522							-1.1795	-2.1553
(s.e.) (NW)				(5.390)							(6.360)	(5.585)
[s.e.] (Hod)				[7.577]							[8.827]	[8.683]
log(P/D)					**-38.050**				**-47.728**	**-47.341**	**-41.589**	**-40.507**
(s.e.) (NW)					(12.46)***				(8.769)***	(8.669)***	(11.75)***	(10.88)***
[s.e.] (Hod)					[16.92]**				[16.65]***	[16.49]***	[19.92]**	[19.68]**
log(P/E)						-4.0792					-0.5569	-2.9248
(s.e.) (NW)						(9.213)					(5.720)	(4.702)
[s.e.] (Hod)						[7.472]					[8.908]	[8.505]
RREL							**109.07**		**146.67**	**158.67**	**164.87**	**177.26**
(s.e.) (NW)							(63.00)*		(55.93)***	(55.83)***	(67.56)**	(64.75)***
[s.e.] (Hod)							[64.51]*		[61.75]**	[63.16]**	[69.60]**	[71.26]**
TMSP								**3.0352**			**3.4537**	**4.1567**
(s.e.) (NW)								(1.999)			(1.730)**	(1.555)***
[s.e.] (Hod)								[2.408]			[2.487]	[2.476]*
Adj. R^2	0.007	0.025	0.043	0.008	0.203	0.004	0.124	0.045	0.500	0.526	0.542	0.589

Table A.11: Predictability of S&P 500 Excess Returns: 18-Month Horizon

This table summarizes the results of the regression of S&P 500 (annualized) excess returns measured over a horizon of 18 months on a constant and the lagged forecasting variable(s). VRP is the index variance risk premium, defined as the difference between the physical expectation of the future Andersen et al. (2015) variance, computed based on 30-minute data and using a random walk model (Bollerslev et al., 2009), and the Britten-Jones and Neuberger (2000) option-implied variance. Individual VRP and CRP are the individual variance risk premium and the correlation risk premium factors, respectively. CAY is the consumption-to-wealth ratio. DFSP is the default spread, defined as the difference between BAA- and AAA-rated corporate bond yields. log(P/D) is the logarithm of the level of the S&P 500 over the 12-month trailing sum of dividends paid by S&P 500 firms. log(P/E) is the logarithm of the price over the 12-month trailing sum of earnings. RREL is the stochastically detrended risk-free rate, i.e., the 1-month T-bill rate minus its 12-month trailing average. TMSP is the term spread, defined as the difference between the 10-year yield and the 3-month T-bill rate. All the variables are sampled at the end of each month. The entries in parentheses and square brackets indicate Newey and West (1987) corrected standard errors (with 18 lags) and Hodrick (1992) corrected standard errors, respectively. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively. We highlight, in **bold**, the significant regression coefficient estimates based on the bootstrap of Rapach et al. (2013). Adj. R^2 reports the adjusted R^2.

	(i)	(ii)	(iii)	(iv)	(v)	(vi)	(vii)	(viii)	(ix)	(x)	(xi)	(xii)
Constant	0.0477	0.0259	**0.0631**	-0.0074	**1.6289**	0.1106	0.0606	-0.0497	**1.8971**	**1.8690**	**1.6187**	**1.6091**
(s.e.) (NW)	(0.038)	(0.043)	(0.035)*	(0.068)	(0.452)***	(0.260)	(0.037)	(0.073)	(0.329)***	(0.347)***	(0.409)***	(0.392)***
[s.e.] (Hod)	[0.036]	[0.035]	[0.036]*	[0.070]	[0.651]**	[0.209]	[0.033]*	[0.066]	[0.649]***	[0.648]***	[0.802]**	[0.801]**
VRP	-0.4313								-0.5897		-0.4709	
(s.e.) (NW)	(0.424)								(0.378)		(0.364)	
[s.e.] (Hod)	[0.483]								[0.384]		[0.336]	
Individual VRP		-0.3266								**-0.5037**		**-0.3274**
(s.e.) (NW)		(0.267)								(0.244)**		(0.181)*
[s.e.] (Hod)		[0.469]								[0.371]		[0.320]
CRP		**-2.0663**								**-1.9912**		**-2.8747**
(s.e.) (NW)		(0.816)**								(0.857)**		(0.721)***
[s.e.] (Hod)		[1.567]								[1.502]		[1.476]*
CAY			**2.3206**						**2.8417**	**2.4954**	**3.2418**	**2.7687**
(s.e.) (NW)			(1.787)						(1.276)**	(1.235)**	(1.091)***	(1.019)***
[s.e.] (Hod)			[1.484]						[1.484]*	[1.435]*	[1.410]**	[1.354]**
DFSP				**6.0654**							-3.1834	**-3.9898**
(s.e.) (NW)				(4.027)							(4.109)	(3.849)
[s.e.] (Hod)				[6.625]							[6.540]	[6.528]
log(P/D)					**-39.038**				**-45.286**	**-45.066**	**-39.443**	**-38.727**
(s.e.) (NW)					(11.07)***				(8.288)***	(8.614)***	(8.326)***	(7.898)***
[s.e.] (Hod)					[16.17]**				[16.17]***	[16.09]***	[18.94]**	[18.81]**
log(P/E)						-1.8064					-0.6880	-2.4744
(s.e.) (NW)						(8.154)					(3.926)	(3.458)
[s.e.] (Hod)						[6.874]					[7.689]	[7.463]
RREL							**54.637**		**90.210**	**97.652**	**109.16**	**118.63**
(s.e.) (NW)							(40.59)		(32.38)***	(31.42)***	(39.15)***	(35.85)***
[s.e.] (Hod)							[58.13]		[55.29]	[56.26]*	[62.75]*	[63.98]*
TMSP								**4.3926**			**4.3409**	**4.8731**
(s.e.) (NW)								(1.877)**			(2.018)**	(1.799)***
[s.e.] (Hod)								[2.178]**			[2.408]*	[2.435]**
Adj. R^2	0.003	0.022	0.064	0.026	0.300	-0.002	0.041	0.141	0.509	0.522	0.613	0.651

Table A.12: Predictability of S&P 500 Excess Returns: 24-Month Horizon

This table summarizes the results of the regression of S&P 500 (annualized) excess returns measured over a horizon of 24 months on a constant and the lagged forecasting variable(s). VRP is the index variance risk premium, defined as the difference between the physical expectation of the future Andersen et al. (2015) variance, computed based on 30-minute data and using a random walk model (Bollerslev et al., 2009), and the Britten-Jones and Neuberger (2000) option-implied variance. Individual VRP and CRP are the individual variance risk premium and the correlation risk premium factors, respectively. CAY is the consumption-to-wealth ratio. DFSP is the default spread, defined as the difference between BAA- and AAA-rated corporate bond yields. log(P/D) is the logarithm of the level of the S&P 500 over the 12-month trailing sum of dividends paid by S&P 500 firms. log(P/E) is the logarithm of the price over the 12-month trailing sum of earnings. RREL is the stochastically detrended risk-free rate, i.e., the 1-month T-bill rate minus its 12-month trailing average. TMSP is the term spread, defined as the difference between the 10-year yield and the 3-month T-bill rate. All the variables are sampled at the end of each month. The entries in parentheses and square brackets indicate Newey and West (1987) corrected standard errors (with 24 lags) and Hodrick (1992) corrected standard errors, respectively. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively. We highlight, in **bold**, the significant regression coefficient estimates based on the bootstrap of Rapach et al. (2013). Adj. R^2 reports the adjusted R^2.

	(i)	(ii)	(iii)	(iv)	(v)	(vi)	(vii)	(viii)	(ix)	(x)	(xi)	(xii)
Constant	0.0454	0.0248	**0.0580**	-0.0267	**1.6211**	0.0793	0.0511	-0.0724	**1.7586**	**1.7431**	**1.4678**	**1.4675**
(s.e.) (NW)	(0.038)	(0.045)	(0.035)*	(0.073)	(0.381)***	(0.259)	(0.039)	(0.066)	(0.307)***	(0.324)***	(0.376)***	(0.353)***
[s.e.] (Hod)	[0.037]	[0.036]	[0.036]	[0.068]	[0.620]***	[0.183]	[0.034]	[0.067]	[0.608]***	[0.610]***	[0.783]*	[0.783]*
VRP	-0.3715								**-0.6037**		**-0.5491**	
(s.e.) (NW)	(0.328)								(0.269)**		(0.214)**	
[s.e.] (Hod)	[0.407]								[0.290]**		[0.269]**	
Individual VRP		-0.2777								**-0.5565**		**-0.4314**
(s.e.) (NW)		(0.191)								(0.191)***		(0.113)***
[s.e.] (Hod)		[0.390]								[0.279]**		[0.249]*
CRP		**-1.8879**								**-1.3777**		**-2.4622**
(s.e.) (NW)		(1.014)*								(0.768)*		(0.596)***
[s.e.] (Hod)		[1.463]								[1.344]		[1.362]*
CAY			**2.4398**						**2.6196**	**2.4282**	**3.1203**	**2.7143**
(s.e.) (NW)			(1.891)						(1.321)**	(1.247)*	(1.055)***	(0.952)***
[s.e.] (Hod)			[1.491]						[1.493]*	[1.421]*	[1.381]**	[1.295]**
DFSP				**7.6059**							-1.8489	-2.6544
(s.e.) (NW)				(4.222)*							(4.033)	(3.543)
[s.e.] (Hod)				[6.075]							[5.100]	[5.193]
log(P/D)					**-38.898**				**-42.166**	**-42.046**	**-34.006**	**-33.645**
(s.e.) (NW)					(9.204)***				(7.551)***	(7.901)***	(7.765)***	(7.094)***
[s.e.] (Hod)					[15.42]**				[15.15]***	[15.17]***	[17.95]*	[17.96]*
log(P/E)						-0.9125					**-3.9377**	**-5.2753**
(s.e.) (NW)						(7.927)					(3.534)	(2.946)*
[s.e.] (Hod)						[5.989]					[5.748]	[5.631]
RREL							5.1930		**37.463**	**41.571**	**53.029**	**60.451**
(s.e.) (NW)							(27.84)		(25.92)	(26.28)	(26.25)**	(25.26)**
[s.e.] (Hod)							[45.64]		[44.29]	[45.66]	[49.73]	[51.37]
TMSP								**5.2749**			**4.6974**	**5.1248**
(s.e.) (NW)								(1.724)***			(1.846)**	(1.687)***
[s.e.] (Hod)								[2.088]**			[2.369]**	[2.392]**
Adj. R^2	0.002	0.023	0.080	0.056	0.380	-0.004	-0.004	0.261	0.511	0.514	0.670	0.701

Table A.13: Predictability of S&P 500 Excess Returns: AVRP and CRP

This table summarizes the results of the regression of S&P 500 (annualized) excess returns measured over a horizon (h) of [period in column] on a constant and the lagged forecasting variable(s). AVRP is the (market capitalization weighted) average of the VRP of individual equities. CRP^{RAW} is the raw correlation risk premium. Both variables are computed as in Cosemans (2011). CAY is the consumption-to-wealth ratio. DFSP is the default spread, defined as the difference between BAA- and AAA-rated corporate bond yields. log(P/D) is the logarithm of the level of the S&P 500 over the 12-month trailing sum of dividends paid by S&P 500 firms. log(P/E) is the logarithm of the price over the 12-month trailing sum of earnings. RREL is the stochastically detrended risk-free rate, i.e., the 1-month T-bill rate minus its 12-month trailing average. TMSP is the term spread, defined as the difference between the 10-year yield and the 3-month T-bill rate. All the variables are sampled at the end of each month. The entries in parentheses and square brackets indicate Newey and West (1987) corrected standard errors (with h lags) and Hodrick (1992) corrected standard errors, respectively. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively. We highlight, in **bold**, the significant regression coefficient estimates based on the bootstrap of Rapach et al. (2013). Adj. R^2 reports the adjusted R^2.

	1-Month	3-Month	6-Month	9-Month	12-Month	18-Month	24-Month
Constant	**2.4101**	**2.0090**	**1.7719**	**1.6308**	**1.4409**	**1.4142**	**1.2982**
(s.e.) (NW)	(0.867)***	(0.662)***	(0.612)***	(0.554)***	(0.533)***	(0.391)***	(0.348)***
[s.e.] (Hod)	[0.865]***	[0.819]**	[0.851]**	[0.837]*	[0.823]*	[0.789]*	[0.767]*
AVRP	**-1.1884**	**-0.6981**	-0.2362	0.0562	0.0689	0.0445	0.0010
(s.e.) (NW)	(0.518)**	(0.279)**	(0.207)	(0.179)	(0.131)	(0.100)	(0.105)
[s.e.] (Hod)	[0.506]**	[0.387]*	[0.312]	[0.234]	[0.192]	[0.154]	[0.132]
CRP^{RAW}	-0.6131	**-0.8950**	**-0.6261**	**-0.5301**	**-0.4610**	**-0.3537**	**-0.3097**
(s.e.) (NW)	(0.434)	(0.243)***	(0.195)***	(0.182)***	(0.164)***	(0.159)**	(0.141)**
[s.e.] (Hod)	[0.444]	[0.274]***	[0.276]**	[0.259]**	[0.252]*	[0.231]	[0.226]
CAY	2.1185	**1.7387**	**2.3772**	**2.5499**	**2.8565**	**2.8782**	**2.8025**
(s.e.) (NW)	(1.399)	(1.071)	(0.876)***	(0.858)***	(0.947)***	(1.048)***	(0.960)***
[s.e.] (Hod)	[1.445]	[1.360]	[1.353]*	[1.263]**	[1.325]**	[1.337]**	[1.293]**
DFSP	-15.687	-11.250	-5.2914	-2.9706	0.1034	-2.0441	-1.0993
(s.e.) (NW)	(15.63)	(8.652)	(6.976)	(6.472)	(6.137)	(3.656)	(3.462)
[s.e.] (Hod)	[14.72]	[13.21]	[11.06]	[9.116]	[8.064]	[5.992]	[4.523]
log(P/D)	**-61.825**	**-55.880**	**-48.804**	**-43.520**	**-37.065**	**-35.988**	**-31.322**
(s.e.) (NW)	(21.00)***	(16.07)***	(13.73)***	(11.97)***	(11.46)***	(7.834)***	(6.877)***
[s.e.] (Hod)	[20.70]***	[19.53]***	[19.75]**	[19.47]**	[19.33]*	[18.44]*	[17.53]*
log(P/E)	8.1703	**10.251**	**7.2786**	3.7387	-0.0597	-0.4031	-3.3915
(s.e.) (NW)	(11.36)	(7.925)	(5.025)	(4.864)	(5.171)	(3.592)	(3.172)
[s.e.] (Hod)	[11.08]	[9.756]	[8.971]	[8.596]	[8.531]	[7.525]	[5.715]
RREL	108.24	**149.83**	**175.26**	**185.44**	**174.35**	**115.99**	**58.452**
(s.e.) (NW)	(78.86)	(53.74)***	(58.91)***	(69.30)***	(64.51)***	(35.68)***	(24.62)**
[s.e.] (Hod)	[73.02]	[65.76]**	[69.01]**	[72.13]**	[71.21]**	[64.24]*	[51.56]
TMSP	-0.6988	-0.0544	1.0725	**2.3903**	**3.5401**	**4.3783**	**4.6929**
(s.e.) (NW)	(2.743)	(2.080)	(1.731)	(1.504)	(1.612)**	(1.907)**	(1.737)***
[s.e.] (Hod)	[2.627]	[2.577]	[2.595]	[2.565]	[2.462]	[2.379]*	[2.342]**
Adj. R^2	0.073	0.252	0.353	0.479	0.575	0.640	0.691

Table A.14: Predictability of S&P 500 Excess Returns: UP and DOWN VRP

This table summarizes the results of the regression of S&P 500 (annualized) excess returns measured over a horizon (h) of [period in column] month(s) on a constant and the lagged forecasting variable(s). VRP^{UP} and VRP^{DOWN} denote the up and down variance risk premium, respectively (Feunou et al., 2017a). CAY is the consumption-to-wealth ratio. DFSP is the default spread, defined as the difference between BAA- and AAA-rated corporate bond yields. log(P/D) is the logarithm of the level of the S&P 500 over the 12-month trailing sum of dividends paid by S&P 500 firms. log(P/E) is the logarithm of the price over the 12-month trailing sum of earnings. RREL is the stochastically detrended risk-free rate, i.e., the 1-month T-bill rate minus its 12-month trailing average. TMSP is the term spread, defined as the difference between the 10-year yield and the 3-month T-bill rate. All the variables are sampled at the end of each month. The entries in parentheses and square brackets indicate Newey and West (1987) corrected standard errors (with h lags) and Hodrick (1992) corrected standard errors, respectively. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively. We highlight, in **bold**, the significant regression coefficient estimates based on the bootstrap of Rapach et al. (2013). Adj. R^2 reports the adjusted R^2.

	1-Month	3-Month	6-Month	9-Month	12-Month	18-Month	24-Month
Constant	**2.7145**	**2.4998**	**2.1369**	**1.9479**	**1.7164**	**1.6296**	**1.4846**
(s.e.) (NW)	(0.778)***	(0.615)***	(0.536)***	(0.499)***	(0.489)***	(0.388)***	(0.360)***
[s.e.] (Hod)	[0.808]***	[0.810]***	[0.840]**	[0.846]**	[0.835]**	[0.806]**	[0.786]*
VRP^{UP}	0.9764	1.3248	**3.7370**	**3.6763**	**3.0756**	**1.8629**	**1.0117**
(s.e.) (NW)	(3.188)	(2.548)	(1.940)*	(1.723)**	(1.215)**	(0.989)*	(0.951)
[s.e.] (Hod)	[3.339]	[2.814]	[2.088]*	[1.700]**	[1.496]**	[1.284]	[1.195]
VRP^{DOWN}	**-10.691**	**-9.1956**	**-8.5730**	**-6.5488**	**-5.3372**	**-3.3751**	**-2.4919**
(s.e.) (NW)	(3.984)***	(3.069)***	(2.127)***	(1.943)***	(1.470)***	(1.382)**	(1.309)*
[s.e.] (Hod)	[4.074]***	[2.989]***	[2.400]***	[2.252]***	[2.124]**	[1.926]*	[1.777]
CAY	1.6370	**1.7659**	**2.2889**	**2.5991**	**2.9472**	**2.9878**	**2.9065**
(s.e.) (NW)	(1.322)	(0.967)*	(0.793)***	(0.783)***	(0.898)***	(1.005)***	(0.961)***
[s.e.] (Hod)	[1.376]	[1.341]	[1.362]*	[1.286]**	[1.348]**	[1.365]**	[1.325]**
DFSP	**-27.126**	**-22.839**	**-17.354**	**-12.782**	**-8.1136**	**-7.6357**	**-5.0721**
(s.e.) (NW)	(16.36)*	(9.749)**	(7.931)**	(7.715)*	(6.848)	(4.855)	(5.224)
[s.e.] (Hod)	[15.51]*	[13.48]*	[11.36]	[10.41]	[9.576]	[7.185]	[5.930]
log(P/D)	**-64.798**	**-62.860**	**-54.429**	**-48.741**	**-41.652**	**-39.691**	**-34.451**
(s.e.) (NW)	(19.80)***	(15.16)***	(12.27)***	(11.25)***	(10.85)***	(7.797)***	(7.422)***
[s.e.] (Hod)	[20.02]***	[19.43]***	[19.76]***	[19.96]**	[19.81]**	[18.94]**	[18.07]*
log(P/E)	3.9242	7.4594	**6.3442**	3.6166	-0.0614	-0.2906	-3.5417
(s.e.) (NW)	(11.45)	(7.755)	(4.951)	(5.517)	(5.633)	(3.725)	(3.399)
[s.e.] (Hod)	[10.91]	[9.714]	[8.813]	[8.795]	[8.707]	[7.607]	[5.833]
RREL	120.87	**150.66**	**175.98**	**182.48**	**171.35**	**113.05**	**55.451**
(s.e.) (NW)	(73.12)*	(53.92)***	(58.48)***	(67.67)***	(63.24)***	(35.86)***	(25.01)**
[s.e.] (Hod)	[68.22]*	[64.57]**	[67.99]**	[70.91]**	[69.79]**	[63.69]*	[50.74]
TMSP	-0.1471	0.1546	0.8847	**2.0445**	**3.2463**	**4.2013**	**4.6071**
(s.e.) (NW)	(2.774)	(2.232)	(1.724)	(1.422)	(1.508)**	(1.875)**	(1.709)***
[s.e.] (Hod)	[2.584]	[2.567]	[2.615]	[2.582]	[2.478]	[2.404]*	[2.351]*
Adj. R^2	0.099	0.277	0.398	0.506	0.592	0.639	0.685

Table A.15: Predictability of S&P 500 Excess Returns: UP minus DOWN VRP

This table summarizes the results of the regression of S&P 500 (annualized) excess returns measured over a horizon of [period in column] on a constant and the lagged forecasting variable(s). $\text{VRP}^{UP}-\text{VRP}^{DOWN}$ is the difference between the up and the down index variance risk premium (Feunou et al., 2017a). CAY is the consumption-to-wealth ratio. DFSP is the default spread, defined as the difference between BAA- and AAA-rated corporate bond yields. log(P/D) is the logarithm of the level of the S&P 500 over the 12-month trailing sum of dividends paid by S&P 500 firms. log(P/E) is the logarithm of the price over the 12-month trailing sum of earnings. RREL is the stochastically detrended risk-free rate, i.e., the 1-month T-bill rate minus its 12-month trailing average. TMSP is the term spread, defined as the difference between the 10-year yield and the 3-month T-bill rate. All the variables are sampled at the end of each month. The entries in parentheses and square brackets indicate Newey and West (1987) corrected standard errors (with 24 lags) and Hodrick (1992) corrected standard errors, respectively. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively. We highlight, in **bold**, the significant regression coefficient estimates based on the bootstrap of Rapach et al. (2013). Adj. R^2 reports the adjusted R^2.

	1-Month	3-Month	6-Month	9-Month	12-Month	18-Month	24-Month
Constant	**2.9278**	**2.6726**	**2.2433**	**2.0116**	**1.7682**	**1.6679**	**1.5327**
(s.e.) (NW)	(0.826)***	(0.694)***	(0.592)***	(0.527)***	(0.502)***	(0.393)***	(0.367)***
[s.e.] (Hod)	[0.842]***	[0.838]***	[0.849]***	[0.847]**	[0.836]**	[0.806]**	[0.788]*
$\text{VRP}^{UP}-\text{VRP}^{DOWN}$	1.8108	2.0009	4.1534	**3.9231**	**3.2705**	**1.9959**	1.1586
(s.e.) (NW)	(4.260)	(3.971)	(2.591)	(2.083)*	(1.639)**	(1.351)	(1.348)
[s.e.] (Hod)	[4.383]	[2.974]	[2.215]*	[1.738]**	[1.538]**	[1.330]	[1.245]
CAY	2.0269	**2.0818**	**2.4812**	**2.7070**	**3.0206**	**3.0204**	**2.8922**
(s.e.) (NW)	(1.379)	(1.049)**	(0.826)***	(0.780)***	(0.881)***	(0.984)***	(0.939)***
[s.e.] (Hod)	[1.421]	[1.387]	[1.360]*	[1.282]**	[1.342]**	[1.364]**	[1.330]**
DFSP	**-34.284**	**-28.640**	**-20.922**	**-14.908**	**-9.8186**	**-8.8619**	**-6.5316**
(s.e.) (NW)	(16.35)**	(11.03)**	(9.183)**	(8.622)*	(7.618)	(5.637)	(6.428)
[s.e.] (Hod)	[15.68]**	[14.90]*	[12.05]*	[10.81]	[9.860]	[7.417]	[6.266]
log(P/D)	**-74.490**	**-70.713**	**-59.262**	**-51.628**	**-43.978**	**-41.350**	**-36.377**
(s.e.) (NW)	(20.81)***	(17.20)***	(13.63)***	(11.82)***	(10.94)***	(7.807)***	(7.590)***
[s.e.] (Hod)	[20.95]***	[20.33]***	[19.95]***	[19.82]***	[19.73]**	[18.88]**	[18.03]**
log(P/E)	14.993	**16.428**	**11.858**	6.9044	2.5535	1.5017	-1.6655
(s.e.) (NW)	(12.35)	(9.486)*	(6.569)*	(6.310)	(6.010)	(4.254)	(4.265)
[s.e.] (Hod)	[11.85]	[10.46]	[9.372]	[8.829]	[8.762]	[7.647]	[5.829]
RREL	**127.69**	**156.18**	**179.38**	**184.50**	**172.90**	**114.01**	**56.230**
(s.e.) (NW)	(75.90)*	(57.51)***	(60.36)***	(68.70)***	(64.22)***	(36.51)***	(25.63)**
[s.e.] (Hod)	[69.36]*	[66.29]**	[69.21]**	[72.04]**	[70.73]**	[64.18]*	[51.14]
TMSP	0.1844	0.4232	1.0490	**2.1402**	**3.3172**	**4.2500**	**4.6608**
(s.e.) (NW)	(2.806)	(2.402)	(1.831)	(1.509)	(1.582)**	(1.918)**	(1.778)***
[s.e.] (Hod)	[2.614]	[2.699]	[2.666]	[2.597]	[2.490]	[2.418]*	[2.373]*
Adj. R^2	0.044	0.174	0.330	0.473	0.566	0.624	0.665

Table A.16: Predictability of S&P 500 Excess Returns: DOWN VRP

This table summarizes the results of the regression of S&P 500 (annualized) excess returns measured over a horizon (h) of [period in column] on a constant and the lagged forecasting variable(s). VRP ^{DOWN} is the index down variance risk premium, defined as in Feunou et al. (2017a). CAY is the consumption-to-wealth ratio. DFSP is the default spread, defined as the difference between BAA- and AAA-rated corporate bond yields. log(P/D) is the logarithm of the level of the S&P 500 over the 12-month trailing sum of dividends paid by S&P 500 firms. log(P/E) is the logarithm of the price over the 12-month trailing sum of earnings. RREL is the stochastically detrended risk-free rate, i.e., the 1-month T-bill rate minus its 12-month trailing average. TMSP is the term spread, defined as the difference between the 10-year yield and the 3-month T-bill rate. All the variables are sampled at the end of each month. The entries in parentheses and square brackets indicate Newey and West (1987) corrected standard errors (with h lags) and Hodrick (1992) corrected standard errors, respectively. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively. We highlight, in **bold**, the significant regression coefficient estimates based on the bootstrap of Rapach et al. (2013). Adj. R^2 reports the adjusted R^2.

	1-Month	3-Month	6-Month	9-Month	12-Month	18-Month	24-Month
Constant	**2.7056**	**2.4876**	**2.0998**	**1.9086**	**1.6817**	**1.6016**	**1.4607**
(s.e.) (NW)	(0.778)***	(0.624)***	(0.577)***	(0.541)***	(0.519)***	(0.402)***	(0.369)***
[s.e.] (Hod)	[0.809]***	[0.812]***	[0.843]**	[0.849]**	[0.838]**	[0.808]**	[0.789]*
VRP^{DOWN}	**-9.7630**	**-7.9370**	**-5.0226**	**-3.0557**	**-2.4155**	**-1.6073**	**-1.5379**
(s.e.) (NW)	(2.375)***	(1.554)***	(1.164)***	(1.126)***	(0.946)**	(0.898)*	(0.608)**
[s.e.] (Hod)	[2.628]***	[1.591]***	[1.287]***	[1.117]***	[1.012]**	[0.924]*	[0.797]*
CAY	1.7062	**1.8599**	**2.5717**	**2.8988**	**3.2101**	**3.1844**	**3.0490**
(s.e.) (NW)	(1.305)	(1.004)*	(0.914)***	(0.908)***	(1.007)***	(1.084)***	(1.042)***
[s.e.] (Hod)	[1.388]	[1.362]	[1.373]*	[1.297]**	[1.372]**	[1.397]**	[1.368]**
DFSP	**-25.155**	**-20.165**	**-9.7893**	-5.2871	-1.8148	**-3.6976**	-2.7473
(s.e.) (NW)	(13.63)*	(8.003)**	(6.086)	(6.539)	(6.409)	(3.938)	(3.871)
[s.e.] (Hod)	[13.03]*	[13.27]	[11.92]	[10.16]	[8.924]	[6.511]	[5.121]
log(P/D)	**-64.485**	**-62.436**	**-53.150**	**-47.387**	**-40.465**	**-38.773**	**-33.705**
(s.e.) (NW)	(19.76)***	(15.31)***	(13.02)***	(12.00)***	(11.54)***	(8.254)***	(7.597)***
[s.e.] (Hod)	[20.04]***	[19.54]***	[19.80]***	[20.08]**	[19.98]**	[19.04]**	[18.10]*
log(P/E)	3.4990	6.8824	4.6838	1.9315	-1.4987	-1.2393	**-4.1577**
(s.e.) (NW)	(11.15)	(7.684)	(4.447)	(4.777)	(5.249)	(3.468)	(3.019)
[s.e.] (Hod)	[10.75]	[9.796]	[8.681]	[8.801]	[8.697]	[7.543]	[5.617]
RREL	119.16	**148.33**	**169.40**	**176.05**	**166.01**	**109.96**	**53.926**
(s.e.) (NW)	(72.75)	(52.85)***	(58.12)***	(68.77)**	(65.02)**	(37.51)***	(25.15)**
[s.e.] (Hod)	[67.76]*	[63.60]**	[66.72]**	[69.85]**	[68.92]**	[62.94]*	[50.04]
TMSP	-0.1008	0.2174	1.0696	**2.2313**	**3.4071**	**4.3056**	**4.6589**
(s.e.) (NW)	(2.753)	(2.206)	(1.744)	(1.534)	(1.653)**	(1.963)**	(1.775)***
[s.e.] (Hod)	[2.585]	[2.570]	[2.597]	[2.575]	[2.481]	[2.400]*	[2.353]**
Adj. R^2	0.103	0.279	0.376	0.475	0.564	0.626	0.680

Table A.17: Variance Swap Payoffs: 75-Minute Andersen et al. (2015) RV

This table reports summary statistics on the daily time series of the 1-month VSPs. Panel A presents the results linked to the S&P 500 index, as well as the equal-weighted average of the constituent stocks. *RV* and *IV* report the average (annualized) high-frequency realized and Britten-Jones and Neuberger (2000) option-implied variance, respectively. We use high-frequency return data sampled at the 75-minute frequency to compute the Andersen et al. (2015) realized variance (see Equation (10)). VSP shows the average VSP, defined as the spread between *RV* and IV. *, **, and *** indicate significance at the 10%, 5%, and 1% level based on Newey and West (1987) corrected standard errors (with 21 lags), respectively. We highlight, in **bold**, the significant estimates of the VSP based on a block-bootstrap. *Std Dev*, *Skew*, *Kurt* and $AR(1)$ denote the standard deviation, skewness, kurtosis and first-order autocorrelation of the VSP, respectively. $Median$, $q^{0.05}$ and $q^{0.95}$ are the median, 5 % and 95 % quantiles of the VSP, respectively. The rows in Panel B relate to stocks with insignificant, significantly negative and significantly positive VSPs (at the 5% significance level), respectively. *Share* indicates the fraction of firms for which the VSP satisfies the condition [name in row].

Panel A: Market Variance Swap Payoff

	RV	*IV*	*VSP*	*t-stat*	*Std Dev*	*Skew*	*Kurt*	*AR*(1)	*Median*	$q^{0.05}$	$q^{0.95}$
S&P 500	0.0314	0.0453	**-0.0138*****	-6.55	0.038	4.70	65.4	0.95	-0.0127	-0.0520	0.0171
Avg. Stocks	0.1465	0.1571	**-0.0105****	-2.09	0.087	5.41	58.8	0.97	-0.0196	-0.0844	0.0966

Panel B: Stock Variance Swap Payoff

	Share	*RV*	*IV*	*VSP*	*Std Dev*	*Skew*	*Kurt*	*AR*(1)	*Median*	$q^{0.05}$	$q^{0.95}$
= 0 not rejected	0.557	0.2050	0.1932	0.0118	0.293	4.12	49.69	0.94	-0.0249	-0.1777	0.2823
> 0 rejected	0.427	0.1189	0.1485	-0.0296	0.100	1.13	24.69	0.92	-0.0309	-0.1515	0.1013
< 0 rejected	0.016	0.3606	0.2312	0.1293	0.303	2.24	17.06	0.93	0.0378	-0.1461	0.6798

Table A.18: Decomposition Results: 75-Minute Andersen et al. (2015) RV

This table presents the results of the decomposition of the daily time series of the 1-month index variance swap payoff (Panel A) and variance risk premium (Panel B) into two factors. The VSP is the difference between the (annualized) realized and Britten-Jones and Neuberger (2000) option-implied variance. We use high-frequency return data sampled at the 75-minute frequency to compute the Andersen et al. (2015) realized variance (see Equation (10)). The VRP is the difference between the physical expectation of the future variance, using a random walk model (Bollerslev et al., 2009), and the Britten-Jones and Neuberger (2000) option-implied variance. *Mean* is the average value. *, **, and *** indicate significance at the 10%, 5%, and 1% level based on the Newey and West (1987) corrected standard errors, respectively. We highlight, in **bold**, the significant estimates of the mean based on a block-bootstrap. Shr_{mean} reports the fraction of the mean of the (i) VSP (Panel A) or (ii) VRP (Panel B) of the S&P 500 index associated with the variable [name in row]. *Std Dev* is the standard deviation. Shr_{var} reports the share of the variance of the (i) VSP (Panel A) or (ii) VRP (Panel B) of the S&P 500 index captured by the variable [name in row]. *Skew*, *Kurt* and $AR(1)$ denote the skewness, kurtosis and first-order autocorrelation, respectively. *Median*, $q^{0.05}$ and $q^{0.95}$ relate to the median, 5 % and 95 % quantiles of the distribution of the variable [name in row].

Panel A: Variance Swap Payoff

	Mean	t-stat	Shr_{mean}	*Std Dev*	Shr_{var}	*Skew*	*Kurt*	$AR(1)$	*Median*	$q^{0.05}$	$q^{0.95}$
Index VSP	**-0.0138*** **	-6.55	1.000	0.038	1.000	4.70	65.4	0.95	-0.0127	-0.0520	0.0171
Individual VSP	**-0.0044*** **	-2.69	0.316	0.029	0.660	4.11	62.0	0.95	-0.0049	-0.0322	0.0242
CSP	**-0.0095*** **	-10.4	0.684	0.016	0.341	-0.70	33.9	0.92	-0.0069	-0.0320	0.0018

Panel B: Variance Risk Premium

	Mean	t-stat	Shr_{mean}	*Std Dev*	Shr_{var}	*Skew*	*Kurt*	$AR(1)$	*Median*	$q^{0.05}$	$q^{0.95}$
Index VRP	**-0.0132*** **	-12.0	1.000	0.024	1.000	4.65	75.7	0.87	-0.0118	-0.0414	0.0075
Individual VRP	**-0.0027** **	-2.23	0.205	0.024	0.685	7.21	97.2	0.93	-0.0044	-0.0217	0.0196
CRP	**-0.0105*** **	-14.1	0.795	0.014	0.315	-4.71	58.1	0.87	-0.0073	-0.0333	0.0010

Table A.19: Predictability of S&P 500 Excess Returns: 75-Minute Andersen et al. (2015) RV

This table summarizes the results of the regression of S&P 500 (annualized) excess returns measured over a horizon of h months on a constant and the lagged forecasting variable(s). Panel A considers the forecasting power of the market index VRP. The index VRP is the difference between the physical expectation of the future variance, computed based on 75-minute data and using a random walk model (Bollerslev et al., 2009), and the Britten-Jones and Neuberger (2000) option-implied variance. Panel B considers the two factors of the index VRP, namely the CRP and Individual VRP factors. We examine forecasting horizons (h) of 1, 3, 6, 9, 12, 18 and 24 months. All the variables are sampled at the end of each month. The entries in parentheses and square brackets indicate Newey and West (1987) corrected standard errors (with h lags) and Hodrick (1992) corrected standard errors, respectively. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively. We highlight, in **bold**, the significant regression coefficient estimates based on the bootstrap of Rapach et al. (2013). Adj. R^2 reports the adjusted R^2. Wald presents the results of a Wald test of the null hypothesis that the two slope parameters are equal. p-value reports the corresponding Newey and West (1987) corrected p-value.

Panel A: Index VRP

Horizon (in Months)	1	3	6	9	12	18	24
Constant	-0.0065	0.0136	0.0308	0.0432	0.0457	0.0465	0.0443
(s.e.) (NW)	(0.036)	(0.029)	(0.031)	(0.034)	(0.036)	(0.039)	(0.039)
[s.e.] (Hod)	[0.036]	[0.036]	[0.037]	[0.037]	[0.036]	[0.036]	[0.036]
Index VRP	**-4.5747**	**-3.4378**	**-1.9041**	-0.9792	-0.7304	-0.5121	-0.4423
(s.e.) (NW)	(1.188)***	(0.720)***	(0.655)***	(0.580)*	(0.507)	(0.465)	(0.353)
[s.e.] (Hod)	[1.329]***	[0.940]***	[0.847]**	[0.674]	[0.572]	[0.455]	[0.375]
Adj. R^2	0.053	0.085	0.044	0.014	0.008	0.004	0.004

Panel B: CRP and Individual VRP Factors

Horizon (in Months)	1	3	6	9	12	18	24
Constant	-0.0254	-0.0227	-0.0039	0.0166	0.0254	0.0280	0.0276
(s.e.) (NW)	(0.042)	(0.035)	(0.035)	(0.036)	(0.038)	(0.042)	(0.044)
[s.e.] (Hod)	[0.042]	[0.035]	[0.036]	[0.035]	[0.035]	[0.034]	[0.035]
Individual VRP	**-4.3837**	**-3.0717**	**-1.5547**	-0.7141	-0.5300	-0.3366	-0.2894
(s.e.) (NW)	(1.104)***	(0.468)***	(0.358)***	(0.373)*	(0.362)	(0.324)	(0.241)
[s.e.] (Hod)	[1.183]***	[0.917]***	[0.931]*	[0.730]	[0.595]	[0.450]	[0.364]
CRP	**-6.1631**	**-6.4824**	**-4.8097**	**-3.1897**	**-2.4084**	**-2.0131**	**-1.7761**
(s.e.) (NW)	(2.904)**	(1.791)***	(1.102)***	(0.977)***	(0.886)***	(0.813)**	(0.953)*
[s.e.] (Hod)	[2.973]**	[1.768]***	[1.739]***	[1.627]*	[1.660]	[1.570]	[1.444]
Adj. R^2	0.051	0.099	0.068	0.033	0.022	0.019	0.018
Wald	0.310	**3.482***	**7.152*****	**5.644****	**4.201****	**3.637***	**2.523**
p-value	[0.577]	[0.062]	[0.007]	[0.018]	[0.040]	[0.057]	[0.112]

Table A.20: Index Variance Swap Payoffs: 5- and 15-Minute Andersen et al. (2015) RV

This table reports summary statistics on the daily time series of the 1-month index VSPs. RV and IV report the average (annualized) high-frequency realized and Britten-Jones and Neuberger (2000) option-implied variance, respectively. We separately use high-frequency return data sampled at the 5- and 15-minute frequency to compute the Andersen et al. (2015) realized variance (see Equation (10)). VSP shows the average VSP, defined as the spread between RV and IV. *, **, and *** indicate significance at the 10%, 5%, and 1% level based on Newey and West (1987) corrected standard errors (with 21 lags), respectively. We highlight, in **bold**, the significant estimates of the VSP based on a block-bootstrap. *Std Dev*, *Skew*, *Kurt* and $AR(1)$ denote the standard deviation, skewness, kurtosis and first-order autocorrelation of the VSP, respectively. $Median$, $q^{0.05}$ and $q^{0.95}$ are the median, 5 % and 95 % quantiles of the VSP, respectively.

S&P 500	RV	IV	VSP	*t-stat*	*Std Dev*	*Skew*	*Kurt*	$AR(1)$	$Median$	$q^{0.05}$	$q^{0.95}$
5-Minute	0.0336	0.0453	**-0.0117*****	-5.03	0.041	5.41	64.9	0.95	-0.0120	-0.0495	0.0205
15-Minute	0.0342	0.0453	**-0.0111*****	-4.80	0.040	5.35	63.9	0.95	-0.0115	-0.0487	0.0240

Table A.21: Variance Swap Payoffs: 30-Minute Andersen et al. (2015) RV (Subsampling and Averaging)

This table reports summary statistics on the daily time series of the 1-month VSPs. Panel A presents the results linked to the S&P 500 index, as well as the equal-weighted average of the constituent stocks. *RV* and *IV* report the average (annualized) high-frequency realized and Britten-Jones and Neuberger (2000) option-implied variance, respectively. We use high-frequency return data sampled at the 30-minute frequency to compute the Andersen et al. (2015) realized variance (see Equation (10)). In doing so, we implement the subsampling and averaging technique of Zhang et al. (2005). *VSP* shows the average VSP, defined as the spread between *RV* and *IV*. *, **, and *** indicate significance at the 10%, 5%, and 1% level based on Newey and West (1987) corrected standard errors (with 21 lags), respectively. We highlight, in **bold**, the significant estimates of the VSP based on a block-bootstrap. *Std Dev*, *Skew*, *Kurt* and *AR*(1) denote the standard deviation, skewness, kurtosis and first-order autocorrelation of the VSP, respectively. *Median*, $q^{0.05}$ and $q^{0.95}$ are the median, 5 % and 95 % quantiles of the VSP, respectively. The rows in Panel B relate to stocks with insignificant, significantly negative and significantly positive VSPs (at the 5% significance level), respectively. *Share* indicates the fraction of firms for which the VSP satisfies the condition [name in row].

Panel A: Market Variance Swap Payoff

	RV	*IV*	*VSP*	*t-stat*	*Std Dev*	*Skew*	*Kurt*	*AR*(1)	*Median*	$q^{0.05}$	$q^{0.95}$
S&P 500	0.0324	0.0453	**-0.0129*****	-6.51	0.036	3.55	52.1	0.94	-0.0118	-0.0509	0.0189
Avg. Stocks	0.1469	0.1570	**-0.0101****	-2.14	0.082	4.54	48.8	0.96	-0.0178	-0.0828	0.0906

Panel B: Stock Variance Swap Payoff

	Share	*RV*	*IV*	*VSP*	*Std Dev*	*Skew*	*Kurt*	*AR*(1)	*Median*	$q^{0.05}$	$q^{0.95}$
= 0 not rejected	0.565	0.2000	0.1901	0.0099	0.274	3.86	49.50	0.94	-0.0235	-0.1704	0.2673
> 0 rejected	0.414	0.1183	0.1465	-0.0282	0.098	1.00	26.04	0.92	-0.0288	-0.1476	0.0954
< 0 rejected	0.021	0.4926	0.3130	0.1796	0.336	1.79	11.04	0.93	0.0820	-0.1628	0.8256

Table A.22: Decomposition Results: 30-Minute Andersen et al. (2015) RV (Subsampling and Averaging)

This table presents the results of the decomposition of the daily time-series of the 1-month index VSP (Panel A) and VRP (Panel B) into two factors. The VSP is the difference between the (annualized) realized and Britten-Jones and Neuberger (2000) option-implied variance. We use high-frequency return data sampled at the 30-minute frequency to compute the Andersen et al. (2015) realized variance (see Equation (10)). In doing so, we implement the subsampling and averaging technique of Zhang et al. (2005). The VRP is the difference between the physical expectation of the future variance, using a random walk model (Bollerslev et al., 2009), and the Britten-Jones and Neuberger (2000) option-implied variance. $Mean$ is the average value. *, **, and *** indicate significance at the 10%, 5%, and 1% level based on the Newey and West (1987) corrected standard errors (with 21 lags), respectively. We highlight, in **bold**, the significant estimates of the mean based on a block-bootstrap. Shr_{mean} reports the fraction of the mean of the (i) VSP (Panel A) or (ii) VRP (Panel B) of the S&P 500 index associated with the factor [name in row]. *Std Dev* is the standard deviation. Shr_{var} reports the share of the variance of the (i) VSP (Panel A) or (ii) VRP (Panel B) of the S&P 500 index associated with the factor [name in row]. $Skew$, $Kurt$ and $AR(1)$ denote the skewness, kurtosis and first-order autocorrelation, respectively. $Median$, $q^{0.05}$ and $q^{0.95}$ relate to the median, 5% and 95 % of the distribution of the variable [name in row].

Panel A: Variance Swap Payoff

	$Mean$	t-stat	Shr_{mean}	*Std Dev*	Shr_{var}	$Skew$	$Kurt$	$AR(1)$	$Median$	$q^{0.05}$	$q^{0.95}$
Index VSP	**-0.0129*****	-6.51	1.000	0.036	1.000	3.55	52.1	0.94	-0.0118	-0.0509	0.0189
Individual VSP	**-0.0040****	-2.57	0.310	0.028	0.679	3.29	53.6	0.95	-0.0045	-0.0309	0.0245
CSP	**-0.0089*****	-11.2	0.690	0.015	0.321	-1.11	31.4	0.91	-0.0068	-0.0292	0.0027

Panel B: Variance Risk Premium

	$Mean$	t-stat	Shr_{mean}	*Std Dev*	Shr_{var}	$Skew$	$Kurt$	$AR(1)$	$Median$	$q^{0.05}$	$q^{0.95}$
Index VRP	**-0.0124*****	-13.2	1.000	0.021	1.000	3.36	59.7	0.84	-0.0110	-0.0403	0.0085
Individual VRP	**-0.0024****	-2.16	0.192	0.022	0.674	6.20	81.5	0.92	-0.0041	-0.0213	0.0213
CRP	**-0.0100*****	-14.6	0.808	0.013	0.327	-5.73	77.0	0.87	-0.0072	-0.0299	0.0010

Table A.23: Predictability of S&P 500 Excess Returns: 30-Minute Andersen et al. (2015) RV (Subsampling and Averaging)

This table summarizes the results of the regression of S&P 500 (annualized) excess returns measured over a horizon of h months on a constant and the lagged forecasting variable(s). Panel A considers the forecasting power of the market index VRP. The index VRP is the difference between the physical expectation of the future variance, computed based on 30-minute data and using a random walk model (Bollerslev et al., 2009), and the Britten-Jones and Neuberger (2000) option-implied variance. In computing the return variation, we implement the subsampling and averaging technique of Zhang et al. (2005). Panel B considers the two factors of the index VRP, namely the CRP and Individual VRP factors. We consider forecasting horizons (h) of 1, 3, 6, 9, 12, 18 and 24 months. All the variables are sampled at the end of each month. The entries in parentheses and square brackets indicate Newey and West (1987) corrected standard errors (with h lags) and Hodrick (1992) corrected standard errors, respectively. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively. We highlight, in **bold**, the significant regression coefficient estimates based on the bootstrap of Rapach et al. (2013). Adj. R^2 reports the adjusted R^2. Wald presents the results of a Wald test of the null hypothesis that the two slope parameters are equal. p-value reports the corresponding Newey and West (1987) corrected p-value.

Panel A: Index VRP

Horizon (in Months)	1	3	6	9	12	18	24
Constant	-0.0106	0.0097	0.0287	0.0421	0.0446	0.0452	0.0431
(s.e.) (NW)	(0.036)	(0.030)	(0.031)	(0.034)	(0.036)	(0.039)	(0.039)
[s.e.] (Hod)	[0.037]	[0.037]	[0.038]	[0.037]	[0.037]	[0.036]	[0.037]
Index VRP	**-5.2529**	**-4.0125**	**-2.2066**	-1.1312	-0.8758	-0.6528	-0.5698
(s.e.) (NW)	(1.274)***	(0.601)***	(0.569)***	(0.584)*	(0.555)	(0.508)	(0.395)
[s.e.] (Hod)	[1.521]***	[1.173]***	[0.978]**	[0.794]	[0.671]	[0.535]	[0.447]
Adj. R^2	0.054	0.090	0.045	0.014	0.010	0.007	0.006

Panel B: CRP and Individual VRP Factors

Horizon (in Months)	1	3	6	9	12	18	24
Constant	-0.0243	-0.0280	-0.0081	0.0113	0.0197	0.0210	0.0199
(s.e.) (NW)	(0.047)	(0.034)	(0.035)	(0.037)	(0.039)	(0.043)	(0.045)
[s.e.] (Hod)	[0.048]	[0.035]	[0.036]	[0.035]	[0.035]	[0.035]	[0.036]
Individual VRP	**-5.1483**	**-3.7229**	**-1.9290**	**-0.9011**	**-0.6927**	-0.4816	-0.4142
(s.e.) (NW)	(1.214)***	(0.572)***	(0.316)***	(0.329)***	(0.342)**	(0.294)	(0.196)**
[s.e.] (Hod)	[1.382]***	[1.120]***	[1.037]*	[0.832]	[0.684]	[0.526]	[0.434]
CRP	-6.4336	**-7.2807**	**-5.3801**	**-3.7726**	**-2.9917**	**-2.6919**	**-2.4843**
(s.e.) (NW)	(3.604)*	(1.694)***	(1.222)***	(1.047)***	(0.928)***	(0.880)***	(1.053)**
[s.e.] (Hod)	[3.779]*	[1.879]***	[1.869]***	[1.756]**	[1.800]*	[1.705]	[1.563]
Adj. R^2	0.051	0.104	0.071	0.039	0.029	0.032	0.035
Wald	0.099	**4.295****	**6.582****	**6.165****	**5.169****	**5.017****	**3.566***
p-value	[0.753]	[0.038]	[0.010]	[0.013]	[0.023]	[0.025]	[0.059]

Table A.24: Variance Swap Payoffs: Active Individual Equity Options (Subsampling and Averaging)

This table analyzes the VSPs associated with the individual equities that have a high average trading volume as well as a broad coverage of strike prices per maturity. To be more specific, these equities are found as the intersection of (i) the 80 firms with the highest average option trading volume and (ii) the 80 firms with the highest average number of strikes per maturity during our sample period. Panel A reports summary statistics associated with the equal-weighted average of the selected equities. RV and IV report the average (annualized) realized and Britten-Jones and Neuberger (2000) option-implied variances, respectively. We use 30-minute return data to compute the Andersen et al. (2015) realized variance (see Equation (10)). In doing so, we implement the subsampling and averaging technique of Zhang et al. (2005). VSP shows the average VSP, defined as the spread between RV and IV. $Std\ Dev$, $Skew$, $Kurt$ and $AR(1)$ denote the standard deviation, skewness, kurtosis and first-order autocorrelation of the VSP, respectively. Additionally, $Median$, $q^{0.05}$ and $q^{0.95}$ are the median, 5 % and 95 % quantiles of the VSP, respectively. *, **, and *** indicate significance at the 10%, 5%, and 1% level based on Newey and West (1987) corrected standard errors (with 21 lags), respectively. We highlight, in **bold**, the significant estimates based on a block-bootstrap. The rows in Panel B relate to stocks with insignificant, significantly negative and significantly positive VSPs (at the 5% significance level), respectively. *Share* indicates the fraction of firms for which the VSP satisfies the condition [name in row].

Panel A: Average Variance Swap Payoff

	RV	IV	VSP	*t-stat*	*Std Dev*	*Skew*	*Kurt*	$AR(1)$	*Median*	$q^{0.05}$	$q^{0.95}$
Benchmark Results	0.1725	0.1703	0.0022	0.39	0.105	4.12	34.4	0.96	-0.0134	-0.0906	0.1326
30 Minute Data	0.1614	0.1703	**-0.0089***	-1.75	0.095	2.94	32.6	0.95	-0.0183	-0.1018	0.1186

Panel B: Stock Variance Swap Payoff

	Share	RV	IV	VSP	*Std Dev*	*Skew*	*Kurt*	$AR(1)$	*Median*	$q^{0.05}$	$q^{0.95}$
Benchmark Results											
= 0 not rejected	0.706	0.1896	0.1876	0.0020	0.200	4.26	41.41	0.94	-0.0231	-0.1544	0.2271
> 0 rejected	0.206	0.1008	0.1183	-0.0175	0.098	0.44	23.57	0.94	-0.0195	-0.1067	0.1063
< 0 rejected	0.088	0.2670	0.2136	0.0534	0.338	4.57	31.69	0.94	-0.0130	-0.1515	0.4377
30 Minute Data											
= 0 not rejected	0.559	0.1849	0.1828	0.0020	0.215	4.22	46.09	0.94	-0.0203	-0.1495	0.2175
> 0 rejected	0.441	0.1435	0.1663	-0.0228	0.107	1.59	21.66	0.93	-0.0265	-0.1450	0.1259
< 0 rejected	0.000	0.0000	0.0000	0.0000	0.000	0.00	0.00	0.00	0.0000	0.0000	0.0000