A Forecasting Analysis of Risk-Neutral Equity and Treasury Volatilities

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Abstract

This paper employs equity (VIX) and Treasury (MOVE) risk-neutral volatilities to assess their relative forecasting performance with respect to future real activity, stock and Treasury excess returns, and aggregate risk factors. The in-sample evidence suggests that the square of VIX tends to dominate the square of MOVE. Out-of-sample predictive analysis, performed as a horse race between equity and Treasury risk-neutral volatilities, shows that, contrary to earlier results, the square of VIX and MOVE tend to complement each other.

Keywords: risk-neutral equity volatility, risk-neutral treasury volatility, forecasting real activity, predictability of asset returns

JEL classification: C53, G12, G13

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1. Introduction

The VIX index is the risk-neutral one-month expected stock market volatility for the S&P 500 Index. It is computed by averaging the weighted prices of puts and calls on the S&P 500 Index over a wide range of strike prices. It has become an extremely popular and useful measure of near-term market volatility. It is surprising that the large extant literature on implied volatility focuses almost exclusively on equity markets.[1]

Indeed, by noting the lack of evidence on the relative importance of risk-neutral equity and Treasury volatilities, the main contribution of this paper is to partially fill this gap by analyzing the forecasting performance of both types of risk-neutral volatility. Specifically, we perform an in-sample, and a competing out-of-sample forecasting analysis between VIX and the Treasury risk-neutral volatility regarding future real activity, as well as future financial returns. This may be especially informative given the recent findings of González-Urteaga, Nieto and Rubio (2018). These authors study the connectedness dynamics between both types of risk-neutral volatility, and show that most of the time, but especially during bad economic times, the Treasury risk-neutral volatility is a net sender of volatility to VIX. They also detect that both monetary policy and economic drivers explain the spillover dynamics between the two risk-neutral volatilities.

We use the Merrill Lynch Option Volatility Estimate Index (MOVE), as Treasury implied volatility. This is a term structure index of the normalized implied volatility on one-month Treasury options that are weighted on 2-, 5-, 10-, and 30-year contracts. It is therefore the equivalent of the VIX for Treasury bond returns and reflects

[1] Notable exceptions are Choi, Mueller, and Vedolin (2017) and Mueller, Sabtchevsky, Vedolin, and Whelan (2016), who analyze market variance risk premium in both equity and Treasury markets, and Mele, Obayashi, and Shalen (2015), who study the information contained in the VIX and the interest rate swap rate volatility index known as SRVX.

a market-based measure of uncertainty about the composite future behavior of interest rates across different maturities of the yield curve. Current increases in MOVE suggests that the market is willing to pay more to hedge against unexpected movements in interest rates.

Given the evidence reported by Adrian, Crump, and Vogt (2018) on the importance of nonlinearities, our analysis of forecasting employs the square of VIX and MOVE rather than the volatilities themselves. The in-sample relative forecasting ability of VIX^2 and $MOVE^2$ suggests that VIX^2 tends to dominate $MOVE^2$ in both real activity and financial returns. However, it is important to recall that González-Urteaga et al. (2018) show that MOVE is a net contributor of volatility to VIX. This transmitted information may help VIX improve its forecasting capacity for future output and financial returns.

On the other hand, the out-of-sample forecasting improvement of VIX^2 over $MOVE^2$ and vice versa is mixed when predicting real activity, the stock market, or Treasury bond returns. Both VIX^2 and $MOVE^2$ complement each other in our forecasting exercises. However, VIX^2 tends to outperform $MOVE^2$ when forecasting aggregate risk factors on an out-of-sample basis.

This paper proceeds as follows. Section 2 presents a brief discussion of the behavior of VIX and MOVE and describes the data employed in the analysis. Section 3 describes the decomposition of VIX and MOVE into their uncertainty and risk aversion components. Section 4 describes the in-sample predictive ability of equity and Treasury risk-neutral volatilities, while Section 5 contains the out-of-sample forecasting analysis. Finally, Section 6 presents our conclusions. The online Appendix contains detailed out-of-sample forecasting results.

2. Data and a Preliminary Analysis of VIX and MOVE

We collect daily and monthly data for VIX and MOVE from April 4, 1988 to October 5, 2017, where monthly data refer to the last trading day of each month throughout the sample period.[2]

Figure 1 shows annualized daily behavior of VIX and MOVE. As expected, risk-neutral volatilities are countercyclical, and spikes during economic crises are much larger in equity than in Treasury volatilities. On a daily basis, the minimum (9.2%) and maximum (80.9%) levels for VIX were reached on October 5, 2017 and November 20, 2008, respectively, whereas for MOVE the minimum (4.7%) and maximum (26.5%) were observed on August 7, 2017 and October 10, 2008, respectively. In Figure 2, we show volatility for VIX and MOVE are. This figure displays monthly volatility of both risk-neutral volatilities estimated with daily data within each month in our sample. This is a measure of financial uncertainty in the equity and Treasury bond markets, respectively. As expected, VIX seems to be much more volatile than MOVE with much larger spikes during times of bad economic news.

Table 1 contains summary statistics for VIX and MOVE obtained from monthly data from April 1988 to September 2017 using observations on the last day of each month. Over the full sample period, average risk-neutral volatility for the stock market is 19.5%, whereas the risk-neutral volatility for Treasuries is much lower at 9.7%. VIX is also much more volatile than MOVE, and accordingly, the range between the

[2] VIX was downloaded from www.cboe.com and MOVE from Bloomberg. Since MOVE is available from April 1988, we employ VXO (risk-neutral market volatility for the U.S. S&P 100 Index) from April 1988 to December 1989. Starting January 2003, the CBOE launched the 10-year Treasury Note Volatility Index (TYVIX), which measures a constant 30-day risk-neutral expected volatility on 10-year Treasury Note futures prices. Given that MOVE is available for a much longer sample period, this research employs MOVE rather than TYVIX. The correlation between both series using monthly data (quoted at the last day of each month) from January 2003 to September 2017 is 0.953.

minimum and maximum values is from 9.5% to 59.9% for VIX and 4.8% to 21.4% for MOVE.[3] VIX presents much higher positive skewness and kurtosis than MOVE. Finally, both implied volatilities are highly persistent with autocorrelation coefficients of 0.84 and 0.85 for VIX and MOVE, respectively.

We next describe the data used in our forecasting analysis. All the competing or control variables that we employ together with VIX and MOVE have been shown to be strong predictors in previous literature. We employ two variables regarding the behavior of interest rates. First, the slope of the term structure denoted as *TERM*, which is the difference between the yield on the 10-year government bond and the 3-month Treasury bill rate. *TERM* is one of the most popular forecasting instruments of real activity. Increases in the slope of the term structure have been shown to predict higher future growth rates of economic activity, whereas decreases in the slope tend to predict bad economic times.[4] Moreover, Choi et al. (2017) employ an options panel data set on Treasury futures to show that the term structure of risk-neutral variances is downward sloping and significantly related to economic conditions. Given that MOVE includes data on 2-, 5-, 10-, and 30-year contracts, it seems reasonable to include *TERM* in the regression model. Second, to account for inflation risk, we employ expected inflation for a one-year horizon denoted as *EINF*. Expected inflation is downloaded from the Federal Reserve Bank of Cleveland website. The Cleveland Fed's model employs Treasury yields, inflation rate data, inflation swaps, and survey-based measures of future inflation to estimate expected inflation to alternative horizons. In this research, *EINF* is employed as key variable to obtain the expected (physical) future variance of Treasury bond returns. In other words, it is a variable used to estimate the uncertainty

[3] To be precise, the coefficients of variation are 0.38 and 0.27 for VIX and MOVE, respectively.

[4] Among many others, see Stock and Watson (2003).

component of MOVE rather than serving as a direct predictor of future real activity or financial returns.

Regarding credit risk, Gilchrist and Zakrajsek (2012) show the forecasting power of the term structure of credit spreads for future output growth. These authors argue that there is a pure credit component orthogonal to macroeconomic conditions that accounts for a large part of the predictive capacity of credit spreads. Given that we work with risk-neutral volatilities, it is also important to note that González-Urteaga and Rubio (2016) show that the default premium, denoted as *DEF*, is a key factor explaining the cross-sectional variation of equity volatility risk premia. It seems therefore natural to employ the default spread, calculated as the difference between Moody's yield on Baa corporate bonds and the 10-year government bond yield, as a potentially relevant control variable. Both yields are obtained from the Federal Reserve Statistical Release.

The most popular predictor of future equity returns, is aggregate dividend yield, which we denote as *DY*. As discussed in Cochrane (2011), the time-varying behavior of the expected market risk premium has a clear correlation with the business cycle. Cochrane shows that, indeed, *DY* is a strong forecaster of future market risk premium and, therefore, it may serve as a potential state variable to forecasting real activity.[5] We also employ the Hansen–Jagannathan (1991) volatility bound, denoted as *HJ VOL*, as an additional predictor. Nieto and Rubio (2014) propose a method of extracting future real activity information from optimally combined size-sorted portfolios. Specifically, these authors show that a size-based volatility bound of the stochastic discount factor is a powerful in-sample and out-of-sample predictor of future industrial production growth. Finally, given the discussion of Brunnermeier and Pedersen (2009), we propose *TED* as

[5] The dividend yield in logs is computed from the original series on Robert Shiller's website (http://www.econ.yale.edu/~shiller/).

a proxy for funding liquidity, and as an additional predictor variable. *TED* is the spread between 3-month LIBOR based on U.S. dollars and the 3-month Treasury Bill.

We also collect data on the variables to be predicted. As a measure of real economic activity, we employ monthly data from the Industrial Production Index (*IPI*). These data are downloaded from the Federal Reserve, with series identifier G17/IP Major Industry Groups. We obtain data on the excess return of the composite index of 5-, 10-, and 30-year horizons of Treasury bonds, denoted as *TRYRET*, from https://fred.stlouisfed.org/.

In addition, we study the forecasting ability of VIX and MOVE with respect to the aggregate risk factors from the Fama and French (2015) five-factor model, which expands their popular three-factor model with profitability (robust minus weak, *RMW*) and investment (aggressive minus conservative, *CMA*) factors. We denote excess market portfolio return as *EXCMKET*, and the size and value factors as *SMB* and *HML*, respectively. Moreover, given that these factors are not able to explain the cross-sectional variability of momentum portfolios unless the Carhart's (1997) momentum factor (*MOM*) is included in the cross section, we consider this factor in our analysis. We collect these monthly data from Kenneth French's website (http://mba.tuck.darmouth.edu).

We also use the Quality minus Junk (*QMJ*) factor of Asness, Frazzini, and Pedersen (2014), further explored by Asness, Frazzini, Israel, Moskowitz, and Pedersen (2018). These authors define a quality stock as an asset for which an investor would be willing to pay a higher price. These are stocks that are safe (low required rate of return), profitable (high return on equity), growing (high cash flow growth), and well-managed (high dividend payout ratio). Asness et al. (2014) show that the *QMJ* factor, which buys high-quality stocks and shorts low-quality (junk) stocks, earns significant risk-adjusted returns not only in the U.S. market, but also in 24 other countries. The *QMJ* factor is downloaded from the AQR Capital Management Database (www.aqr.com).

Finally, recent empirical evidence supports the presence of funding liquidity across a wide range of securities. Frazzini and Pedersen (2014) show that leverage constraints are strong and significantly reflected in the return differential between leveraged low-beta stocks and de-leveraged high-beta stocks. These authors argue that positive and highly significant risk-adjusted returns relative to traditional asset pricing models shown by portfolios sorted by the level of market beta are explained by shadow cost-of-borrowing constraints.[6] The authors illustrate their argument by proposing a market-neutral *BAB* factor consisting of the difference between long-leveraged low-beta stocks and short de-leveraged high-beta securities. This factor is downloaded from the AQR Capital Management Database.

3. A Simple Decomposition of Risk-Neutral Equity and Treasury Variances

As discussed by Bekaert and Hoerova (2014), the squared VIX reflects both stock market uncertainty and risk aversion. Uncertainty is captured by the physical expected variance, while risk aversion is proxied by the variance risk premium (*VRP*), which is the expected risk premium from selling equity variance in swap contracts. Equity variance risk premium is defined as

$$VRP_t^E = E_t^P\left(RVAR_{t+1}^E\right) - VIX_t^2, \quad (1)$$

[6] See also Asness, Frazzini, Gormsen, and Pedersen (2018) for additional evidence supporting this argument.

where VRP_t^E is equity variance risk premium, and $E_t^P\left(RVAR_{t+1}^E\right)$ is the expected conditional value of future realized variance of equity returns under physical probability P.

An extensive literature uses these components as potential predictors of stock market returns and industrial production growth. Bollerslev, Tauchen and Zhou (2009) show that the variance risk premium predicts future stock returns, and Bekaert and Hoerova (2014), using an improved model specification of volatility, show that the variance risk premium (risk aversion) has predictive power for future equity returns, but real activity is significantly predicted by conditional stock market variance (uncertainty). Indeed, in bivariate regressions using both *VRP* and conditional variance, these authors show that *VRP* is an overall better predictor of future stock returns than conditional variance, and that the squared of VIX fails to forecast future returns. On the other hand, opposite results are reported when predicting future real activity. Expected conditional variance is a stronger predictor of future production growth. More recently, Fan, Xiao, and Zhou (2018) propose a decomposition of the equity *VRP* into a pure second order *VRP* and a higher order risk premium. It turns out that *VRP* displays short-term predictive power for future returns, but the higher order risk premium contains a medium-term forecasting ability. More importantly, this decomposition improves market return forecasting both in-sample and out-of-sample. Finally, when predicting either real activity or financial returns, it is important to employ the risk-neutral variance of market equity as a predictor rather than volatility itself. Adrian, Crump, and Vogt (2017) argue that VIX strongly forecasts stock and bond returns up to a 24-month-horizon when nonlinearity is accounted for. This result may be associated with the recent findings of Danielsson, Valenzuela, and Zer (2018), who argue that volatility itself is not a significant predictor of financial crises, but unusually high and low volatilities are.

Under the same arguments, the Treasury *VRP* is defined as

$$VRP_t^T = E_t^P\left(RVAR_{t+1}^T\right) - MOVE_t^2, \qquad (2)$$

where VRP_t^T is Treasury variance risk premium, and $E_t^P\left(RVAR_{t+1}^T\right)$ is the expected conditional value of future realized variance of (composite) Treasury returns under the physical probability *P*.

In parallel research to the literature on the equity variance risk premium and using their own data on risk-neutral variance of Treasury returns, Choi et al. (2017) show that the term structure of implied Treasury variances is downward sloping, and that the slope has predictive power for future real activity at short horizons. Moreover, Mueller et al. (2016) report that short-term VRP_t^T predicts future bond returns at short-term horizons, and long-term VRP_t^T forecasts bond returns at longer horizons.

We next decompose risk-neutral variances into expected physical variances and the variance risk premium. There is a large body of literature on the econometrics of volatility forecasting. Rather than using high-frequency data and jumps in the spirit of Andersen, Bollerslev, and Diebold (2007), and the threshold bipower variation proposed by Corsi, Pirino, and Renò (2010), we follow a simple but powerful approach suggested by Zhou (2018) in which the square of VIX and past realized variances are employed as independent variables. Therefore, for the case of the expected realized variance of equity returns, we forecast future realized variance as:

$$\hat{E}_t\left(RVAR_{t+1}^E\right) = \hat{\beta}_0 + \hat{\beta}_1 VIX_t^2 + \hat{\beta}_2 RVAR_t^E \,. \tag{3}$$

In our sample period, simple regressions show that these two predictors explain approximately 85% of the variability of future realized equity variance.

We follow a similar approach for expected realized variance of Treasury returns. In this case, however, we also add expected (one-year-horizon) inflation, which we find to be a powerful predictor of future realized variance of Treasuries. The following model gives the expected (physical) future variance of Treasury bond returns:

$$\hat{E}_t\left(RVAR_{t+1}^T\right) = \hat{\beta}_0 + \hat{\beta}_1 MOVE_t^2 + \hat{\beta}_2 RVAR_t^T + \hat{\beta}_3 EINF_t \,. \tag{4}$$

In this case, ordinary least square (OLS) regressions show that the dependent variables explain around 66% of the variability of future realized variance of Treasury returns.

Figures 3 displays the conditional variances of equities and Treasury bonds using expressions (3) and (4), and Figure 4 shows the corresponding variance risk premia. Although the recession-associated peaks are clear in both figures, we also observe relevant differences among them, which motivates a competing analysis of both types of risk-neutral volatility in forecasting returns and real activity.

4. The In-Sample Predictability of Real Economic Activity and Financial Returns with VIX^2 and MOVE^2

Tables 2 through 6 contain the results from forecasting industrial production and several types of financial asset return with 1-, 3-, 6-, and 12-month horizons. In all cases we run a similar in-sample predictive regression,

$$Y_{t,t+\tau} = \alpha + \beta_1 X_t + \beta' Controls_t + \varepsilon_{t,t+\tau} \,,\ \tau = 1,3,6,12 \,, \tag{5}$$

where $Y_{t,t+\tau}$ is future real activity growth, $\Delta IPI_{t,t+\tau}$, future excess market return, $EXCMKET_{t,t+\tau}$, future excess Treasury bond return, $TRYRET_{t,t+\tau}$, future $HML_{t,t+\tau}$, or future $BAB_{t,t+\tau}$.[7] The predictor X_t is either VIX^2 or MOVE^2, or the variance risk premia and expected realized variances given by equations (1), (2), (3), and (4). All regressions control for the usual predictors employed in the literature. We include lagged value of the dependent variable, *TERM* and default (*DEF*) spreads, logarithm of the dividend yield (*DY*), *TED* spread, and size-based model-free Hansen and Jagannathan (1991) volatility bound (*HJ VOL*). In each panel and for each horizon, we employ that set of controls that maximize the *R*-squared statistic. For reasons of space, we report only the intercept and the slope estimated coefficient, β_1. It is well known that the overlap in the monthly data generates serial correlation in the disturbance term that must be corrected when calculating standard error. Following Bekaert and Hoerova (2014), we use the Newey–West (1987) HAC standard errors, which may improve power, over the Hodrick (1992) errors, so long as we select a large number of lags.

Table 2 shows forecasting results for industrial production growth for the four alternative horizons. In Panel A of Table 2, we report that the squared of VIX fails to predict real activity. However, as in Bekaert and Hoerova (2014), conditional expected realized variance is a significant predictor of production growth with the expected negative sign at the shortest horizon and at the 3-month horizon, with an adjusted *t*-statistic of 1.67. Therefore, increases in conditional equity variance tend to decrease real activity at relatively short horizons. Further, equity *VRP* is a significant predictor of real activity with the same negative sign at the shortest horizon. Indeed, for the one-month

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[7]As discussed later, *HML* and *BAB* are the only two risk factors for which VIX and/or MOVE show a significant forecasting capacity. To save space, we do not to report these results because they add no relevant information. In any case, all results are available from the authors upon request.

horizon, the slope coefficient is estimated with relatively more precision than the coefficient for the expected conditional variance. Higher equity-related uncertainty and/or risk aversion appear associated with a decrease in real activity in the short-run. Note that at longer horizons neither VIX^2 nor its components forecast significantly real activity. However, the *R*-squared statistic increases from 0.20 at the shortest horizon to 0.40 and 0.32 at the 3- and 6-month horizons, respectively indicating that other instruments contain relevant information about future real activity.

Panel B of Table 2 clearly shows that either $MOVE^2$ or its components fail to predict future real activity. At the shortest horizon, expected variance and *VRP* have the same signs as in the case of equity variance; however, neither is statistically different from zero. Note that the *R*-squared value reflects the relative importance of the controls employed in each regression; however, it does not reflect the relative predictive ability of VIX^2 or $MOVE^2$. It is also important to recall the evidence reported by González-Urteaga et al. (2018), who show that volatility spillovers from MOVE to VIX are strong and statistically significant, especially during bad economic times. Hence, our new evidence suggests that the information content captured from MOVE by VIX may be a key source of the embedded signal explaining the forecasting ability of the uncertainty and risk aversion components of VIX^2. It seems that the combined information contained in VIX, through its idiosyncratic information and the information sent by MOVE to VIX, makes the components of VIX strong forecasters of real activity at relatively short horizons.

Panels A and B of Table 3 shows results regarding future excess market return. Risk-neutral variance shows significant and positive predictive power of future returns at the 6- and 12-month horizons. Therefore, the two components of VIX^2 predict real activity at short horizons with a negative sign, while the expected variance component predicts stock returns at medium-long horizons with a positive sign, suggesting a positive relation between conditional variance and expected excess returns. This reflects the (theoretically expected) positive sign on the relation between risk and return for equity aggregate returns. As for real activity, $MOVE^2$ does not appear able to predict future equity returns, although the *VRP* associated with Treasuries presents a positive coefficient with a *t*-statistic of 1.57 at the shortest horizon. Again, given the connectedness dynamics evidence reported by González-Urteaga et al. (2018), this does not necessarily mean that MOVE does not have relevant information with respect to future market returns.

Panels A and B of Table 4 show forecasting results for (composite) Treasury excess returns. Neither VIX^2 nor $MOVE^2$ are significant predictors of Treasury excess returns. However, equity *VRP* is a powerful predictor of future Treasury returns with negative and statistically significant coefficients at the 3-, 6-, and 12-month horizons. It seems plausible that this result may be due partially to the spillover information from MOVE to VIX discussed above. Overall, at medium and long horizons, the in-sample results suggest that the expected variance of equity forecasts future equity returns, but equity *VRP* forecasts Treasury bond returns.

We check for the forecasting ability of risk-neutral variances regarding well known aggregate risk factors. We analyze the five Fama‒French (2015) factors, the momentum (*MOM*) factor of Carhart (1997), the Quality minus Junk (*QMJ*) factor of Asness et al. (2014), and Asness et al. (2018), and the Betting against Beta Factor (*BAB*) of Frazzini and Pedersen (2014). Overall, risk-neutral variance of either equity or Treasury bonds fails to predict risk factors. However, we find that risk-neutral variances do predict both *HML* and *BAB* at short horizons. To the best of our knowledge, this is the first time that such evidence has been reported. Recall that the differences between dynamic market betas of value and growth companies tend to be very large during bad economic times, and that the *BAB* factor reflects funding liquidity and tends to have highly negative return in bad times. It is interesting that it is precisely the *HML* and *BAB* factors for which risk-neutral variances have predictive power.

The results for the *HML* and *BAB* factors are shown in Panels A and B of Tables 5 and 6, respectively. VIX^2 significantly predicts both the *HML* and *BAB* factors with a negative sign at short horizons. Both results are estimated with high statistical precision. Increases in the square of VIX strongly signal future bad times, as proxied by negative realized returns (or high expected returns) in the *HML* and *BAB* factors. Interestingly, this holds even though the uncertainty and risk aversion components of VIX^2 affect *HML* and *BAB* very differently. In the case of *HML*, it is the expected variance component (and not the *VRP* component) that shows forecasting ability. However, in the case of *BAB*, it is the equity *VRP* component (not the expected variance) that has predictive ability. The future behavior of *HML* appears related more to uncertainty, while *BAB* responds more to risk aversion.

On the other hand, MOVE^2 fails to predict either *HML* or *BAB*. However, the Treasury *VRP* component significantly predicts *HML* at the shortest and medium horizons, and *BAB* at the 3-month horizon, both with positive sign.

5. Out-of-Sample Predictability of Real Economic Activity and Financial Returns with VIX^2 and MOVE^2: A Comparison Analysis

This section describes the tests and discusses the results of our out-of-sample forecasts of future real economic activity, and future financial returns for stocks, Treasury bonds and the *HML* and *BAB* factors using either VIX^2 or MOVE^2. We address the question: Which of the two risk-neutral volatilities are stronger predictors of future activity and asset returns? We employ two alternative statistics to test the out-of-sample accuracy of two (VIX^2 versus MOVE^2) competing models: the *t*-test proposed by Diebold and Mariano (1995) and the *F*-statistic of McCracken (2007). In our case, the two compared models are always nested. The restricted model contains only one predictive variable: either VIX^2 or MOVE^2, or the lagged dependent variable, *TERM*, *DEF*, *DY*, the *HJ* volatility bound, or *TED*. Given the in-sample forecasting evidence, the predictor is selected among the best predictors in that context across all dependent variables and horizons. The unrestricted model contains the selected individual predictor in the restricted model and either MOVE^2 or VIX^2.

Our methodology is as follows. The total sample period contains $T + P$ observations, where the initial in-sample estimation period employs information from 1 to T and the out-of-sample forecasting period is from $T + \tau$ to $T + P$, τ being the forecasting horizon. At each forecasting period $t = T + \tau, \ldots, T + P$, we estimate the two competing nested models using information up to the previous τ periods, generate the prediction, and compute the forecasting error. More formally, the restricted model is

$$Y_s = \alpha^R + \beta_1^R X_{s-\tau} + u_{Rs} \ , s = \tau + 1 \ldots, t - \tau, \tag{6}$$

where Y_s is one of the following: industrial production growth, excess market returns, excess Treasury bond returns, *HML* or *BAB*, and X_s is one of the competing predictors, including VIX^2 or MOVE^2.

The prediction under the restricted model is

$$\hat{Y}_{Rs} = \hat{\alpha}^R + \hat{\beta}_1^R X_{s-\tau}. \tag{7}$$

and the prediction error is

$$\hat{u}_{Rt} = Y_t - \hat{Y}_{Rt} . \tag{8}$$

Similarly, the unrestricted model includes the forecasting individual variable in the restricted model and either $MOVE^2$ or VIX^2, denoted as Z_s in the following equation:

$$Y_s = \alpha^U + \beta_1^U X_{s-\tau} + \beta_2^U Z_{s-\tau} + u_{Us} \;, s = \tau + 1 \ldots, t - \tau. \tag{9}$$

The unrestricted prediction and forecasting error are

$$\hat{Y}_{Us} = \hat{\alpha}^U + \hat{\beta}_1^U X_{s-\tau} + \hat{\beta}_2^U Z_{s-\tau}, \tag{10}$$

$$\hat{u}_{Ut} = Y_t - \hat{Y}_{Ut}, \tag{11}$$

where Z_s is any of the competing predictors, including VIX^2 and $MOVE^2$. We next compute the vector of loss differentials, denoted *d*, which compares the two squared errors at each month *t* and the mean-squared forecasting error (*MSE*) for each model:

$$d_t = \hat{u}_{Rt}^2 - \hat{u}_{Ut}^2 \;, t = T + \tau \ldots T + P \;, \tag{12}$$

$$MSE_R = \left(P - \tau + 1\right)^{-1} \sum_{t=T+\tau}^{T+P} \hat{u}_{Rt}^2 \;, \tag{13}$$

$$MSE_U = \left(P - \tau + 1\right)^{-1} \sum_{t=T+\tau}^{T+P} \hat{u}_{Ut}^2 \;. \tag{14}$$

The two statistics for testing equal forecasting accuracy have the null that the loss differentials are zero, on average. The Diebold–Mariano (1995) statistic is a *t*-test expressed as

$$MSE(t) = \left(P - \tau + 1\right)^{-1/2} \frac{\bar{d}}{\sqrt{\hat{S}_d}}, \tag{15}$$

where $\bar{d} = \left(P - \tau + 1\right)^{-1} \sum_{t=T+\tau}^{T+P} d_t$ and $\hat{S}_d$ is a consistent estimator of the variance of the loss differential that admits heteroskedasticity and autocorrelation. We employ the

Newey–West (1987) specification and, following Clark and McCracken (2012), a lag length $k = 1.5\ \tau$. Hence,

$$\hat{S}_d = \sum_{j=-k}^{k} \left(\frac{k - |\, j\, |}{k} \right) \left(P - \tau - j + 1 \right)^{-1} \sum_{t=T+\tau}^{T+P} \left(d_t - \bar{d} \right) \left(d_{t-j} - \bar{d} \right). \qquad (16)$$

The McCracken (2007) statistic is an *F*-test given by

$$MSE(F) = \left(P - \tau + 1 \right) \frac{MSE_R - MSE_U}{MSE_U}. \qquad (17)$$

Note that the loss differentials are measured with an error, since the beta coefficients are unknown. This implies that the exact distribution of both statistics is also unknown and that the asymptotic distribution can be obtained only under restrictive assumptions that include non-nested models.[8] For the case of nested models, Clark and McCracken (2012) suggest deriving the asymptotic distribution by a fixed regressor bootstrap and show that the test statistics based on the proposed bootstrap have good size properties and better finite-sample power than alternative bootstraps. This method is based on the wild fixed regressor bootstrap developed by Gonçalves and Killian (2004) but adapted to the multi-step framework of out-of-sample forecasts. We implement this method via the followings steps:

1. We estimate both the restricted and unrestricted models using the full sample period. We save the coefficients of the restricted model and compute the residuals from the unrestricted model as follows:

   $\hat{u}_{Ut} = Y_t - \hat{\alpha}^U - \hat{\beta}_1^U X_{s-\tau} - \hat{\beta}_2^U Z_{s-\tau}\ ,\ t = 1 + \tau \ldots T + P$.

2. We assume and estimate an MA (τ – 1) process to capture the implicit serial correlation in the residuals from a τ-step-ahead forecast,

[8] See West (1996) and Clark and McCracken (2001) for a discussion.

$$\hat{u}_{Ut} = \varepsilon_t + \theta_1 \varepsilon_{t-1} + \ldots + \theta_{\tau-1} \varepsilon_{t-(\tau-1)},\ t = 1 + \tau \ldots T + P\ .$$

3. We simulate a sequence of independent and identically distributed $N(0,1)$ random variables denoted by η_t and generate artificial residuals by using the estimates of the MA process as follows:

$$\hat{u}^*_{Ut} = \eta_t \hat{\varepsilon}_t + \hat{\theta}_1 \eta_{t-1} \hat{\varepsilon}_{t-1} + \ldots + \hat{\theta}_{\tau-1} \eta_{t-(\tau-1)} \hat{\varepsilon}_{t-(\tau-1)},\ t = 1 + \tau \ldots T + P\ .$$

4. We simulate an artificial series of the dependent variable using the artificial residual and imposing the null hypothesis that the additional variable, Z_s, does not predict:

$$\hat{Y}^*_t = \hat{\alpha}^R + \hat{\beta}^R_1 X_{s-\tau} + u^*_{Ut}\ ,\ t = 2\tau + 1 \ldots T + P\ .$$

5. We compute both *MSE*(*t*)-statistics and *MSE(F)*-statistics using these artificial data as if they were the original data.
6. We repeat steps 3 through 5 5,000 times and the *p*-value is the percentage of times the simulated statistic is greater than the real statistic.

Our purpose is not to do a general horse race to decide which is the best predictive model, but we are interested in the forecasting performance of VIX^2 versus MOVE^2. Therefore, we concentrate on the predictive competency of the equity and Treasury risk-neutral variances. Table 7 presents a summary of the out-of-sample comparative results between VIX^2 and MOVE^2. We employ the relative mean-squared error suggested by Clark and McCracken (2012), which is given by $RMSE = \sqrt{MSE^U} \big/ \sqrt{MSE^R}$, where restricted and unrestricted *MSE* are given by equations (13) and (14), respectively. We also report the *p*-values associated with the null that the *t*-based *MSE* or the *F*-based *MSE* of expressions (15) and (17) are equal to zero, respectively. When the *RMSE* statistic is significantly less than 1, this implies that the inclusion of either VIX^2 or $MOVE^2$ improves the out-of-sample forecasting capacity of the competing predictor.

Panel A of Table 7 shows the out-of-sample forecasting exercise of future real activity. At the shortest horizon, neither VIX^2 nor $MOVE^2$ significantly outperforms the other. However, both volatilities are equally necessary to forecast at the 3- and 6-month horizons, and both fail to improve prediction of industrial production growth over each other at the longest horizon. Note that at the 12-month horizon, the *p*-value of the *t*-statistic indicates that we can reject that both forecasting errors are equal, but the inclusion of $MOVE^2$ in addition to VIX^2 causes the forecasting errors to be higher, since *RMSE* is greater than 1. Panel B of Table 7 shows that at the shortest horizon and at the 10% level, $MOVE^2$ better predicts future stock market excess returns than VIX^2. This is an important result. Recall that in bad economic times, the directional connectedness from MOVE to VIX dominates the effects of VIX over MOVE. However, for the remainder of the horizons, both risk-neutral volatilities are equally relevant. On the contrary, in Panel C of Table 7 and regarding Treasury excess returns, VIX^2 significantly improves the prediction over $MOVE^2$ at the shortest horizon but, at the longest horizon, the opposite result is obtained. $MOVE^2$ is a superior predictor of Treasury returns at the 12-month horizon. In Panel D, we show that VIX^2 significantly outperforms $MOVE^2$ when predicting *HML* at the 3-month horizon, but there is nothing statistically significant over and above this result. Finally, in Panel D of Table 7, we show that VIX^2 significantly improves the forecasting of *BAB* over $MOVE^2$ for both, the shortest and longest horizons. This result suggests that funding liquidity, as proxied by *BAB*, is closely related to the previous behavior of stock market risk-neutral volatility, at least for extreme horizons. Overall, VIX^2 significantly outperforms $MOVE^2$ in 4 out of 20 cases, while $MOVE^2$ improves VIX^2 only in 2 cases. VIX^2

(relative to $MOVE^2$) is a necessary predictor in 45% of cases, and $MOVE^2$ (relative to VIX^2) in 25% of all possibilities. The only clear advantage of VIX^2 over $MOVE^2$ seems to concentrate around forecasting the *HML* and *BAB* risk factors.[9]

6. Conclusions

Empirical evidence regarding relative forecasting ability between equity risk-neutral variance and Treasury risk-neutral variance is surprisingly scarce. This paper contributes to the literature by conducting a competing forecasting analysis between both implied variances. The in-sample analysis shows that VIX^2 dominates $MOVE^2$ either directly or indirectly through its uncertainty and risk aversion components. At the shortest horizon, increases in expected conditional variance of equity returns and/or variance risk premium are associated with a future decrease in real activity, while we find a significant opposite sign with respect to future market returns at long horizons. Similar to real activity, increases in the variance risk premium of equity returns decreases Treasury returns at the three longest horizons. Interestingly, given the counter-cyclical variation of the *HML* and *BAB* factors, we find that VIX^2 and its uncertainty component are significant forecasters of both factors, but with the opposite sign to the one reported for market excess returns, and at short rather than at long horizons. Both VIX^2 and its expected conditional variance component have a negative relation with the future behavior of *HML*. VIX^2 also has a significant and negative relation with future returns of the *BAB* portfolio. Once again, this is the case at the shortest horizons. Moreover, the equity variance risk premium has a positive correlation with future behavior of the *BAB* factor, while the Treasury variance risk premium has a positive relation with the future behavior of both the *HML* and *BAB* factors.

[9] Detailed out-of-sample forecasting results using the procedure described above are reported in Tables A.1 through A.5 of the online Appendix.

On the other hand, our out-of-sample predictive exercise shows that, overall, for future real activity and future excess market returns, and for most horizons, VIX^2 and $MOVE^2$ complement each other. Both risk-neutral volatilities appear important when using an out-of-sample framework, at least regarding real activity and market returns. Neither one seems to dominate the other in terms of out-of-sample predictability of future real activity. VIX^2 improves the forecasting of Treasury bond returns at the shortest horizon, while $MOVE^2$ improves the forecasting capacity of the stock market and Treasury bond returns at the shortest and longest horizons, respectively. Note that González-Urteaga et al. (2018) report that total unconditional connectedness from 1988 to 2017 between VIX and MOVE is 28%, which suggests that, on average, there are idiosyncratic components that may explain our out-of-sample forecasting results in terms of the complementary results between both implied volatilities. It is true that with respect to aggregate risk factors, VIX^2 is the only risk-neutral volatility with some out-of-sample forecasting capacity.

Future research might analyze how the spillover connectedness dynamics reported by González-Urteaga et al. (2018) specifically affect our forecasting results. In other words, given that MOVE is a net sender of volatility to VIX, it would be important to study the consequences of this result on the forecasting ability of these risk-neutral variances. More precisely, it would be interesting to determine the percentage of total predictive capacity of the square of VIX that is due to the risk-neutral volatility transmission received from MOVE.

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Table 1. Summary Statistics VIX and MOVE. April 1988-September 2017

	VIX	MOVE
Mean	0.1949	0.0965
Volatility	0.0731	0.0259
Minimum	0.0951	0.0481
Maximum	0.5989	0.2140
Skewness	1.7367	0.9999
Kurtosis	4.8872	2.6046
AR(1)	0.8405	0.8539

The VIX Index is risk-neutral one-month expected stock market volatility for the S&P 500 Index. It is computed by averaging the weighted prices of puts and calls on the S&P 500 Index over a wide range of strike prices. The MOVE index is the Merrill Lynch Option Volatility Estimate Index. It is a term structure weighted index of the normalized implied volatility on one-month Treasury options, which are weighted on 2-, 5-, 10-, and 30-year contracts. The statistics employ monthly data and observations on the last day of each month.

Table 2. In-Sample Forecasting of Industrial Production Growth for Alternative Horizons with Statistically Significant Controls. Risk-Neutral Variance and its Components, May 1988-June 2017.

Panel A: Forecasting of Industrial Production Growth with VIX^2

	h = 1 *VIX² + lagged IPI + Controls*	*h = 3* *VIX² + lagged IPI + Controls*	*h = 6* *VIX² + lagged IPI + Controls*	*h = 12* *VIX² + lagged IPI + Controls*
$\hat{\alpha}$	0.013 (4.60)	0.007 (2.73)	0.004 (2.63)	0.004 (2.91)
$\hat{\beta}_1$ (VIX^2)	0.007 (0.05)	-0.016 (-1.54)	0.000 (0.01)	0.016 (1.45)
Adj R^2	0.188	0.403	0.323	0.246

	h = 1 $E^P(RVAR^E)$ *+ lagged IPI + Controls*	*h = 3* $E^P(RVAR^E)$ *+ lagged IPI + Controls*	*h = 6* $E^P(RVAR^E)$ *+ lagged IPI + Controls*	*h = 12* $E^P(RVAR^E)$ *+ lagged IPI + Controls*
$\hat{\alpha}$	0.011 (4.71)	0.006 (2.38)	0.003 (2.39)	0.004 (2.80)
$\hat{\beta}_1$ $E^P(RVAR^E)$	-0.029 (-2.07)	-0.015 (-1.67)	-0.003 (-0.30)	0.013 (1.25)
Adj R^2	0.206	0.402	0.324	0.242

	h = 1 VRP^E *+ lagged IPI + Controls*	*h = 3* VRP^E *+ lagged IPI + Controls*	*h = 6* VRP^E *+ lagged IPI + Controls*	*h = 12* VRP^E *+ lagged IPI + Controls*
$\hat{\alpha}$	0.012 (5.44)	0.008 (3.33)	0.003 (2.97)	0.004 (3.06)
$\hat{\beta}_1$ (VRP^E)	-0.035 (-2.31)	-0.000 (-0.03)	-0.004 (-0.57)	-0.001 (-0.32)
Adj R^2	0.211	0.392	0.324	0.229

Panel B: In-Sample Forecasting of Industrial Production Growth with MOVE^2

	h = 1 *MOVE² + lagged IPI + Controls*	*h = 3* *MOVE² + lagged IPI + Controls*	*h = 6* *MOVE² + lagged IPI + Controls*	*h = 12* *MOVE² + lagged IPI + Controls*
$\hat{\alpha}$	0.013 (5.13)	0.008 (3.23)	0.004 (3.20)	0.004 (3.03)
$\hat{\beta}_1$ $(MOVE^2)$	0.007 (0.08)	-0.031 (-0.56)	-0.061 (-1.05)	-0.009 (-0.16)
Adj R^2	0.187	0.393	0.328	0.229

	h = 1 $E^P(RVAR^T)$ *+ lagged IPI + Controls*	*h = 3* $E^P(RVAR^T)$ *+ lagged IPI + Controls*	*h = 6* $E^P(RVAR^T)$ *+ lagged IPI + Controls*	*h = 12* $E^P(RVAR^T)$ *+ lagged IPI + Controls*
$\hat{\alpha}$	0.013 (4.75)	0.008 (3.16)	0.004 (3.05)	0.003 (2.84)
$\hat{\beta}_1$ $E^P(RVAR^T)$	-0.062 (-0.51)	-0.036 (-0.48)	-0.038 (-0.54)	0.018 (0.22)
Adj R^2	0.189	0.393	0.324	0.230

	h = 1 VRP^T *+ lagged IPI + Controls*	*h = 3* VRP^T *+ lagged IPI + Controls*	*h = 6* VRP^T *+ lagged IPI + Controls*	*h = 12* VRP^T *+ lagged IPI + Controls*
$\hat{\alpha}$	0.013 (5.06)	0.008 (3.33)	0.004 (3.03)	0.004 (3.07)
$\hat{\beta}_1$ (VRP^T)	-0.108 (-0.54)	0.016 (0.28)	0.077 (1.60)	0.045 (1.1)
Adj R^2	0.191	0.392	0.327	0.231

This table shows the results of predicting OLS regressions of future industrial production growth for 1-, 3-, 6-, and 12-month horizons. The predictors are one of VIX^2, MOVE^2, conditional expected realized variance of the S&P 500 Index or composite Treasury bond returns, and variance risk premium (*VRP*) of VIX^2 or MOVE^2. We control for the lagged of the dependent variable, *TERM*, *DEF*, *DY*, the *HJ* volatility bound of Nieto and Rubio (2014), and *TED*. We report the *t*-statistic from Newey-West/ HAC standard errors.

Table 3. In-Sample Forecasting of Excess Market Return for Alternative Horizons with Statistically Significant Controls. Risk-Neutral Variance and its Components, May 1988-June 2017.

Panel A: Forecasting of Market Excess Return with VIX^2

	h = 1 *VIX^2 + lagged EXCMKT + Controls*	*h = 3* *VIX^2 + lagged EXCMKT + Controls*	*h = 6* *VIX^2 + lagged EXCMKT + Controls*	*h = 12* *VIX^2 + lagged EXCMKT + Controls*
$\hat{\alpha}$	0.004	-0.011	-0.016	-0.016
	(0.87)	(-1.25)	(-2.14)	(-1.72)
$\hat{\beta}_1$ (VIX^2)	0.051	0.089	0.131	0.088
	(0.45)	(0.99)	(2.15)	(2.92)
Adj R^2	0.001	0.028	0.085	0.144

	h = 1 *$E^P(RVAR^E)$ + lagged EXCMKT + Controls*	*h = 3* *$E^P(RVAR^E)$ + lagged EXCMKT + Controls*	*h = 6* *$E^P(RVAR^E)$ + lagged EXCMKT + Controls*	*h = 12* *$E^P(RVAR^E)$ + lagged EXCMKT + Controls*
$\hat{\alpha}$	0.006	-0.007	-0.011	-0.013
	(2.12)	(-0.82)	(-1.64)	(-2.09)
$\hat{\beta}_1$ $E^P(RVAR^E)$	0.015	0.002	0.074	0.060
	(0.19)	(0.03)	(2.08)	(2.81)
Adj R^2	0.000	0.015	0.058	0.127

	h = 1 *VRP^E + lagged EXCMKT + Controls*	*h = 3* *VRP^E + lagged EXCMKT + Controls*	*h = 6* *VRP^E + lagged EXCMKT + Controls*	*h = 12* *VRP^E + lagged EXCMKT + Controls*
$\hat{\alpha}$	0.005	-0.009	-0.009	-0.011
	(2.10)	(-1.13)	(-1.30)	(.1.72)
$\hat{\beta}_1$ (VRP^E)	-0.065	-0.123	-0.045	-0.016
	(-0.52)	(-1.12)	(-0.80)	(-0.49)
Adj R^2	0.001	0.032	0.042	0.103

Panel B: In-Sample Forecasting of Market Excess Return with $MOVE^2$

	h = 1 *$MOVE^2$ + lagged EXCMKT + Controls*	*h = 3* *$MOVE^2$ + lagged EXCMKT + Controls*	*h = 6* *$MOVE^2$ + lagged EXCMKT + Controls*	*h = 12* *$MOVE^2$ + lagged EXCMKT + Controls*
$\hat{\alpha}$	0.013	-0.003	-0.005	-0.008
	(2.09)	(-0.32)	(-0.74)	(-1.24)
$\hat{\beta}_1$ ($MOVE^2$)	-0.704	-0.553	-0.385	-0.329
	(-0.99)	(-1.04)	(-1.09)	(-0.95)
Adj R^2	0.072	0.028	0.049	0.115

	h = 1 *$E^P(RVAR^T)$ + lagged EXCMKT + Controls*	*h = 3* *$E^P(RVAR^T)$ + lagged EXCMKT + Controls*	*h = 6* *$E^P(RVAR^T)$ + lagged EXCMKT + Controls*	*h = 12* *$E^P(RVAR^T)$ + lagged EXCMKT + Controls*
$\hat{\alpha}$	0.008	-0.004	-0.006	-0.008
	(1.43)	(-0.43)	(-0.84)	(-1.23)
$\hat{\beta}_1$ $E^P(RVAR^T)$	-0.222	-0.376	-0.258	-0.276
	(-0.35)	(-0.74)	(-0.63)	(-0.62)
Adj R^2	0.000	0.019	0.042	0.108

	h = 1 *VRP^T + lagged EXCMKT + Controls*	*h = 3* *VRP^T + lagged EXCMKT + Controls*	*h = 6* *VRP^T + lagged EXCMKT + Controls*	*h = 12* *VRP^T + lagged EXCMKT + Controls*
$\hat{\alpha}$	0.006	-0.007	-0.009	-0.011
	(2.38)	(-0.91)	(-1.19)	(-1.66)
$\hat{\beta}_1$ (VRP^T)	1.818	0.808	0.533	0.331
	(1.57)	(1.31)	(1.17)	(1.37)
Adj R^2	0.017	0.025	0.047	0.108

This table shows the results of predicting OLS regressions of future stock market excess return for 1-, 3-, 6-, and 12-month horizons. The predictors are one of VIX^2, $MOVE^2$, conditional expected realized variance of the S&P 500 Index or composite Treasury bond returns, and the variance risk premium (*VRP*) of VIX^2 or $MOVE^2$. We control for the lagged of the dependent variable, *TERM*, *DEF*, *DY*, the *HJ* volatility bound of Nieto and Rubio (2014) and *TED*. We report the *t*-statistic from Newey-West/ HAC standard errors.

Table 4. In-Sample Forecasting of Excess Treasury Bond Return for Alternative Horizons with Statistically Significant Controls. Risk-Neutral Variance and its Components, May 1988-June 2017.

Panel A: In-Sample Forecasting of Excess Treasury Bond Return with VIX^2

	h = 1 VIX^2 + lagged TRYRET + Controls	*h = 3* VIX^2 + lagged TRYRET + Controls	*h = 6* VIX^2 + lagged TRYRET + Controls	*h = 12* VIX^2 + lagged TRYRET + Controls
$\hat{\alpha}$	-0.001	0.001	0.002	0.002
	(-0.58)	(0.25)	(1.30)	(1.91)
$\hat{\beta}_1$ (VIX^2)	0.056	0.029	0.000	0.008
	(1.39)	(0.78)	(0.01)	(0.52)
Adj R^2	0.075	0.001	0.019	0.162

	h = 1 $E^P(RVAR^E)$ + lagged TRYRET + Controls	*h = 3* $E^P(RVAR^E)$ + lagged TRYRET + Controls	*h = 6* $E^P(RVAR^E)$ + lagged TRYRET + Controls	*h = 12* $E^P(RVAR^E)$ + lagged TRYRET + Controls
$\hat{\alpha}$	0.000	0.002	0.002	0.002
	(0.03)	(1.18)	(1.89)	(2.83)
$\hat{\beta}_1$ $E^P(RVAR^E)$	0.046	0.001	-0.015	-0.003
	(0.98)	(0.02)	(-0.99)	(-0.29)
Adj R^2	0.069	-0.001	0.023	0.160

	h = 1 VRP^E + lagged TRYRET + Controls	*h = 3* VRP^E + lagged TRYRET + Controls	*h = 6* VRP^E + lagged TRYRET + Controls	*h = 12* VRP^E + lagged TRYRET + Controls
$\hat{\alpha}$	0.001	0.001	0.002	0.002
	(1.02)	(0.91)	(1.37)	(2.98)
$\hat{\beta}_1$ (VRP^E)	-0.008	-0.057	-0.035	-0.023
	(-0.13)	(-2.31)	(-2.54)	(-2.49)
Adj R^2	0.061	0.007	0.028	0.169

Panel B: In-Sample Forecasting of Excess Treasury Bond Return with $MOVE^2$

	h = 1 $MOVE^2$ + lagged TRYRET + Controls	*h = 3* $MOVE^2$ + lagged TRYRET + Controls	*h = 6* $MOVE^2$ + lagged TRYRET + Controls	*h = 12* $MOVE^2$ + lagged TRYRET + Controls
$\hat{\alpha}$	0.001	0.000	0.002	0.001
	(0.27)	(0.02)	(0.97)	(0.99)
$\hat{\beta}_1$ ($MOVE^2$)	0.060	0.169	0.025	0.104
	(0.22)	(0.76)	(0.18)	(1.08)
Adj R^2	0.064	-0.001	0.019	0.168

	h = 1 $E^P(RVAR^T)$ + lagged TRYRET + Controls	*h = 3* $E^P(RVAR^T)$ + lagged TRYRET + Controls	*h = 6* $E^P(RVAR^T)$ + lagged TRYRET + Controls	*h = 12* $E^P(RVAR^T)$ + lagged TRYRET + Controls
$\hat{\alpha}$	-0.002	0.001	0.002	0.001
	(-0.80)	(0.42)	(1.06)	(0.82)
$\hat{\beta}_1$ $E^P(RVAR^T)$	0.368	0.060	-0.034	0.096
	(1.31)	(0.26)	(-0.19)	(0.74)
Adj R^2	0.068	-0.005	0.019	0.165

	h = 1 VRP^T + lagged TRYRET + Controls	*h = 3* VRP^T + lagged TRYRET + Controls	*h = 6* VRP^T + lagged TRYRET + Controls	*h = 12* VRP^T + lagged TRYRET + Controls
$\hat{\alpha}$	0.001	0.002	0.002	0.002
	(1.14)	(1.48)	(1.76)	(3.42)
$\hat{\beta}_1$ (VRP^T)	0.582	-0.419	-0.154	-0.123
	(1.20)	(-1.16)	(-1.06)	(-1.54)
Adj R^2	0.069	0.004	0.021	0.164

This table shows the results of predicting OLS regressions of future Treasury bond excess return for 1-, 3-, 6-, and 12-month horizons. The predictors are one of VIX^2, $MOVE^2$, conditional expected realized variance of the S&P 500 Index or composite Treasury bond returns, and the variance risk premium (*VRP*) of VIX^2 or $MOVE^2$. We control for the lagged of the dependent variable, *TERM*, *DEF*, *DY*, the *HJ* volatility bound of Nieto and Rubio (2014) and *TED*. We report the *t*-statistic from Newey-West/ HAC standard errors.

Table 5. In-Sample Forecasting of *HML* for Alternative Horizons with Statistically Significant Controls. Risk-Neutral Variance and its Components, May 1988-June 2017.

Panel A: In-Sample Forecasting of *HML* with VIX^2

	h = 1 VIX^2 *+ lagged HML + Controls*	*h = 3* VIX^2 *+ lagged HML + Controls*	*h = 6* VIX^2 *+ lagged HML + Controls*	*h = 12* VIX^2 *+ lagged HML + Controls*
$\hat{\alpha}$	0.018 (2.62)	0.006 (2.73)	0.018 (2.64)	0.013 (2.49)
$\hat{\beta}_1$ (VIX^2)	-0.107 (-2.70)	-0.110 (-2.34)	-0.046 (-1.32)	-0.023 (-0.99)
Adj R^2	0.051	0.060	0.054	0.039
	h = 1 $E^P(RVAR^E)$ *+ lagged HML + Controls*	*h = 3* $E^P(RVAR^E)$ *+ lagged HML + Controls*	*h = 6* $E^P(RVAR^E)$ *+ lagged HML + Controls*	*h = 12* $E^P(RVAR^E)$ *+ lagged HML + Controls*
$\hat{\alpha}$	0.016 (2.29)	0.005 (2.35)	0.016 (2.41)	0.013 (2.33)
$\hat{\beta}_1$ $E^P(RVAR^E)$	-0.076 (-2.08)	-0.092 (-2.31)	-0.018 (-0.79)	0.001 (0.04)
Adj R^2	0.042	0.052	0.041	0.031
	h = 1 VRP^E *+ lagged HML + Controls*	*h = 3* VRP^E *+ lagged HML + Controls*	*h = 6* VRP^E *+ lagged HML + Controls*	*h = 12* VRP^E *+ lagged HML + Controls*
$\hat{\alpha}$	0.015 (2.16)	0.002 (0.78)	0.017 (2.47)	0.013 (2.49)
$\hat{\beta}_1$ (VRP^E)	0.039 (0.32)	0.001 (0.01)	0.048 (0.94)	0.048 (1.61)
Adj R^2	0.031	0.009	0.047	0.047

Panel B: In-Sample Forecasting of *HML* with $MOVE^2$

	h = 1 $MOVE^2$ *+ lagged HML + Controls*	*h = 3* $MOVE^2$ *+ lagged HML + Controls*	*h = 6* $MOVE^2$ *+ lagged HML + Controls*	*h = 12* $MOVE^2$ *+ lagged HML + Controls*
$\hat{\alpha}$	0.020 (2.53)	0.006 (1.38)	0.018 (2.46)	0.013 (2.37)
$\hat{\beta}_1$ ($MOVE^2$)	-0.517 (-1.63)	-0.432 (-1.06)	-0.179 (-0.77)	-0.038 (-0.30)
Adj R^2	0.041	0.027	0.043	0.032
	h = 1 $E^P(RVAR^T)$ *+ lagged HML + Controls*	*h = 3* $E^P(RVAR^T)$ *+ lagged HML + Controls*	*h = 6* $E^P(RVAR^T)$ *+ lagged HML + Controls*	*h = 12* $E^P(RVAR^T)$ *+ lagged HML + Controls*
$\hat{\alpha}$	0.018 (1.73)	0.005 (1.04)	0.016 (2.05)	0.013 (2.19)
$\hat{\beta}_1$ $E^P(RVAR^T)$	-0.270 (-0.51)	-0.369 (-0.76)	-0.018 (-0.07)	-0.001 (-0.04)
Adj R^2	0.032	0.018	0.038	0.031
	h = 1 VRP^T *+ lagged HML + Controls*	*h = 3* VRP^T *+ lagged HML + Controls*	*h = 6* VRP^T *+ lagged HML + Controls*	*h = 12* VRP^T *+ lagged HML + Controls*
$\hat{\alpha}$	0.013 (1.82)	0.001 (0.79)	0.015 (2.34)	0.012 (2.19)
$\hat{\beta}_1$ (VRP^T)	1.128 (2.84)	0.611 (1.52)	0.537 (2.32)	0.108 (0.91)
Adj R^2	0.045	0.020	0.053	0.032

This table shows the results of predicting OLS regressions of future *HML* return for 1, -3-, 6-, and 12-month horizons. The predictors are one of VIX^2, $MOVE^2$, conditional expected realized variance of the S&P 500 Index or composite Treasury bond returns, and the variance risk premium (*VRP*) of VIX^2 or $MOVE^2$. We control for the lagged of the dependent variable, *TERM*, *DEF*, *DY*, the *HJ* volatility bound of Nieto and Rubio (2014) and *TED*. We report the *t*-statistic from Newey-West/ HAC standard errors.

Table 6. In-Sample Forecasting of *BAB* for Alternative Horizons with Statistically Significant Controls. Risk-Neutral Variance and its Components, May 1988-June 2017.

Panel A: In-Sample Forecasting of *BAB* with VIX^2

	h = 1 VIX^2 *+ lagged BAB + Controls*	*h = 3* VIX^2 *+ lagged BAB + Controls*	*h = 6* VIX^2 *+ lagged BAB + Controls*	*h = 12* VIX^2 *+ lagged BAB + Controls*
$\hat{\alpha}$	0.046	0.041	0.048	0.030
	(4.68)	(4.07)	(4.39)	(2.70)
$\hat{\beta}_1$ (VIX^2)	-0.221	-0.134	-0.077	-0.058
	(-3.25)	(-1.74)	(-1.37)	(-1.28)
Adj R^2	0.109	0.173	0.219	0.295

	h = 1 $E^P(RVAR^E)$ *+ lagged BAB + Controls*	*h = 3* $E^P(RVAR^E)$ *+ lagged BAB + Controls*	*h = 6* $E^P(RVAR^E)$ *+ lagged BAB + Controls*	*h = 12* $E^P(RVAR^E)$ *+ lagged BAB + Controls*
$\hat{\alpha}$	0.039	0.036	0.037	0.027
	(4.13)	(3.79)	(3.99)	(2.48)
$\hat{\beta}_1$ $E^P(RVAR^E)$	-0.044	-0.012	0.005	-0.013
	(-0.55)	(-0.18)	(0.11)	(-0.38)
Adj R^2	0.061	0.129	0.196	0.278

	h = 1 VRP^E *+ lagged BAB + Controls*	*h = 3* VRP^E *+ lagged BAB + Controls*	*h = 6* VRP^E *+ lagged BAB + Controls*	*h = 12* VRP^E *+ lagged BAB + Controls*
$\hat{\alpha}$	0.042	0.038	0.039	0.028
	(4.65)	(4.07)	(4.31)	(2.62)
$\hat{\beta}_1$ (VRP^E)	0.310	0.217	0.149	0.072
	(3.14)	(3.76)	(3.72)	(1.90)
Adj R^2	0.113	0.192	0.243	0.293

Panel B: In-Sample Forecasting of *BAB* with $MOVE^2$

	h = 1 $MOVE^2$ *+ lagged BAB + Controls*	*h = 3* $MOVE^2$ *+ lagged BAB + Controls*	*h = 6* $MOVE^2$ *+ lagged BAB + Controls*	*h = 12* $MOVE^2$ *+ lagged BAB + Controls*
$\hat{\alpha}$	0.044	0.040	0.038	0.028
	(4.59)	(4.24)	(4.29)	(2.47)
$\hat{\beta}_1$ ($MOVE^2$)	-0.508	-0.339	-0.044	-0.088
	(-1.27)	(-1.03)	(-0.15)	(-0.33)
Adj R^2	0.064	0.135	0.196	0.278

	h = 1 $E^P(RVAR^T)$ *+ lagged BAB + Controls*	*h = 3* $E^P(RVAR^T)$ *+ lagged BAB + Controls*	*h = 6* $E^P(RVAR^T)$ *+ lagged BAB + Controls*	*h = 12* $E^P(RVAR^T)$ *+ lagged BAB + Controls*
$\hat{\alpha}$	0.041	0.036	0.036	0.027
	(4.23)	(3.94)	(3.92)	(2.43)
$\hat{\beta}_1$ $E^P(RVAR^T)$	-0.287	-0.022	0.098	-0.076
	(-0.56)	(-0.06)	(0.25)	(-0.24)
Adj R^2	0.060	0.129	0.199	0.277

	h = 1 VRP^T *+ lagged BAB + Controls*	*h = 3* VRP^T *+ lagged BAB + Controls*	*h = 6* VRP^T *+ lagged BAB + Controls*	*h = 12* VRP^T *+ lagged BAB + Controls*
$\hat{\alpha}$	0.038	0.035	0.037	0.027
	(3.97)	(3.74)	(3.99)	(2.45)
$\hat{\beta}_1$ (VRP^T)	0.838	0.878	0.299	0.094
	(1.16)	(2.54)	(1.09)	(0.38)
Adj R^2	0.064	0.143	0.199	0.277

This table shows the results of predicting OLS regressions of future *BAB* return for 1-, -3-, 6-, and 12-month horizons. The predictors one of VIX^2, $MOVE^2$, conditional expected realized variance of the S&P 500 Index or composite Treasury bond returns, and the variance risk premium (*VRP*) of VIX^2 or $MOVE^2$. We control for the lagged of the dependent variable, *TERM*, *DEF*, *DY*, the *HJ* volatility bound of Nieto and Rubio (2014) and *TED*. We report the *t*-statistic from Newey-West/ HAC standard errors.

Table 7. Out-of-Sample Forecasting Performance of VIX^2 and $MOVE^2$, May 1988-June 2017.

Panel A: Out-of-Sample Forecasting of Industrial Production Growth

	h = 1		*h = 3*		*h = 6*		*h = 12*	
	VIX^2 improves $MOVE^2$	$MOVE^2$ improves VIX^2	VIX^2 improves $MOVE^2$	$MOVE^2$ improves VIX^2	VIX^2 improves $MOVE^2$	$MOVE^2$ improves VIX^2	VIX^2 improves $MOVE^2$	$MOVE^2$ improves VIX^2
RMSE	0.987	1.005	0.966	0.997	0.996	0.990	1.013	1.001
p-value (*t*)	0.322	0.749	0.004	0.030	0.023	0.016	0.095	0.040
p-value (*F*)	0.291	0.701	0.000	0.015	0.005	0.003	0.856	0.057
Result	NO	NO	YES	YES	YES	YES	NO	NO

Panel B: Out-of-Sample Forecasting of Stock Market Excess Return

	h = 1		*h = 3*		*h = 6*		*h = 12*	
	VIX^2 improves $MOVE^2$	$MOVE^2$ improves VIX^2	VIX^2 improves $MOVE^2$	$MOVE^2$ improves VIX^2	VIX^2 improves $MOVE^2$	$MOVE^2$ improves VIX^2	VIX^2 improves $MOVE^2$	$MOVE^2$ improves VIX^2
RMSE	1.002	0.997	0.997	0.989	0.977	0.983	0.986	0.994
p-value (*t*)	0.277	0.064	0.064	0.006	0.005	0.001	0.003	0.023
p-value (*F*)	0.250	0.073	0.051	0.002	0.003	0.000	0.000	0.005
Result	NO	YES	YES	YES	YES	YES	YES	YES

Panel C: Out-of-Sample Forecasting of Treasury Bond Excess Return

	h = 1		*h = 3*		*h = 6*		*h = 12*	
	VIX^2 improves $MOVE^2$	$MOVE^2$ improves VIX^2	VIX^2 improves $MOVE^2$	$MOVE^2$ improves VIX^2	VIX^2 improves $MOVE^2$	$MOVE^2$ improves VIX^2	VIX^2 improves $MOVE^2$	$MOVE^2$ improves VIX^2
RMSE	0.993	1.004	1.004	1.005	1.005	1.007	1.034	0.995
p-value (*t*)	0.047	0.444	0.100	0.331	0.147	0.271	0.248	0.018
p-value (*F*)	0.030	0.513	0.291	0.463	0.384	0.612	0.999	0.006
Result	YES	NO	NO	NO	NO	NO	NO	YES

Table 7 (continued). Out-of-Sample Forecasting Performance of VIX^2 and $MOVE^2$, May 1988-June 2017.

Panel D: Out-of-Sample Forecasting of HML								
	h = 1		*h = 3*		*h = 6*		*h = 12*	
	VIX^2 improves $MOVE^2$	$MOVE^2$ improves VIX^2	VIX^2 improves $MOVE^2$	$MOVE^2$ improves VIX^2	VIX^2 improves $MOVE^2$	$MOVE^2$ improves VIX^2	VIX^2 improves $MOVE^2$	$MOVE^2$ improves VIX^2
RMSE	1.005	1.005	0.990	1.004	1.012	1.008	1.013	1.003
p-value (*t*)	0.846	0.851	0.024	0.197	0.117	0.624	0.095	0.123
p-value (*F*)	0.722	0.728	0.001	0.445	0.758	0.704	0.963	0.142
Result	NO	NO	YES	NO	NO	NO	NO	NO

Panel E: Out-of-Sample Forecasting of BAB								
	h = 1		*h = 3*		*h = 6*		*h = 12*	
	VIX^2 improves $MOVE^2$	$MOVE^2$ improves VIX^2	VIX^2 improves $MOVE^2$	$MOVE^2$ improves VIX^2	VIX^2 improves $MOVE^2$	$MOVE^2$ improves VIX^2	VIX^2 improves $MOVE^2$	$MOVE^2$ improves VIX^2
RMSE	0.989	1.003	1.021	1.005	1.010	1.004	0.922	1.002
p-value (*t*)	0.160	0.911	0.144	0.113	0.032	0.107	0.013	0.041
p-value (*F*)	0.053	0.856	0.991	0.261	0.758	0.266	0.000	0.101
Result	YES	NO	NO	NO	NO	NO	YES	NO

This table shows the out-of-sample forecast accuracy of either VIX^2 or $MOVE^2$, comparing the unrestricted model that contains either VIX^2 or $MOVE^2$ and the additional standard predictor with the restricted model that includes only the standard predictor where this predictor can also be VIX^2 or $MOVE^2$. *RMSE* is the relative mean-squared forecasting error that compares the mean-squared forecasting error of the restricted model and the mean-squared forecasting error of the unrestricted model. The *p*-value (*t*) and *p*-value (*F*) are the probability values associated with the two statistics given by expressions (15) and (17) testing the equal forecasting ability of the unrestricted and restricted models. They are obtained by an efficient bootstrap method for simulating asymptotic critical values.

Figure 1. VIX and MOVE: Daily Data between April 4, 1988 and October 5, 2017

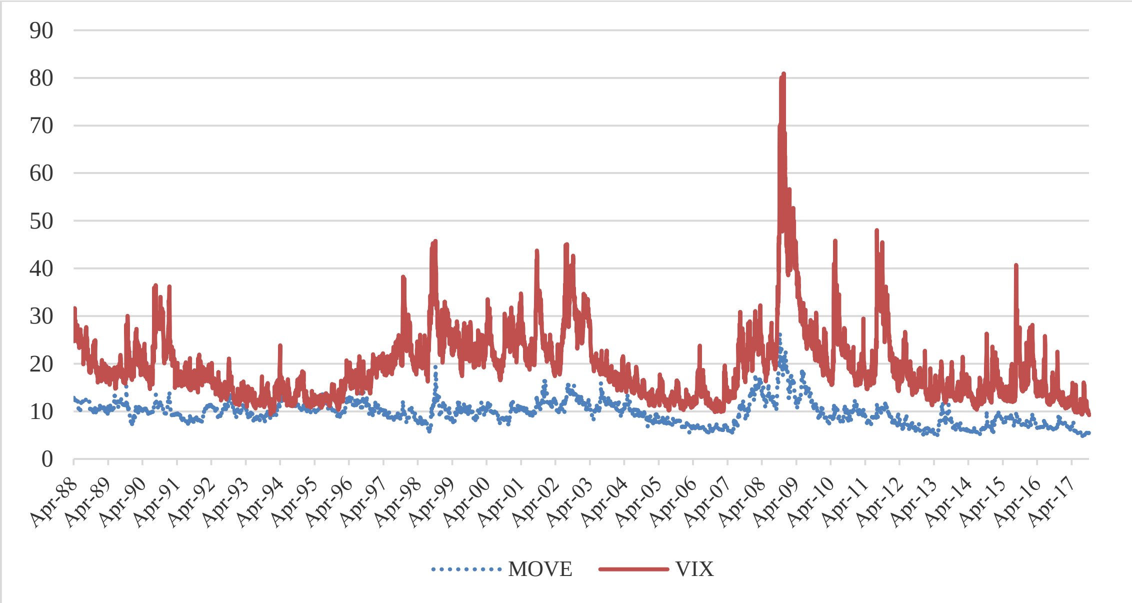

Figure 2. Monthly Volatilities of VIX and MOVE Estimated with Daily Data within Each Month between April 1988 and September 2017

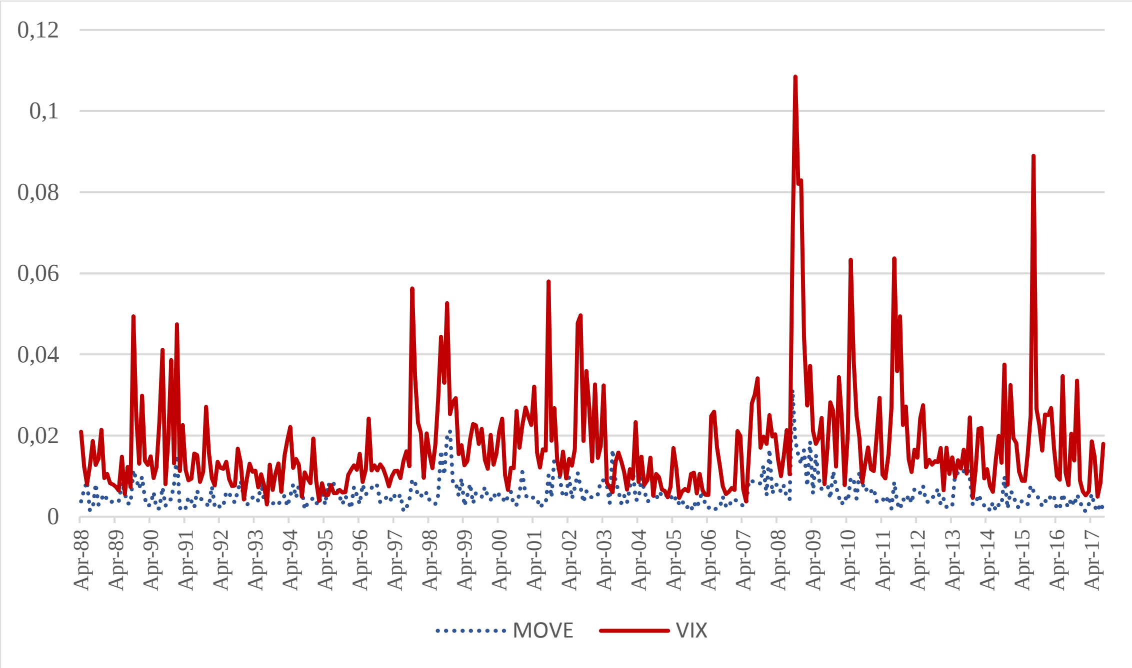

Figure 3. Expected Conditional Variances for Equity and Treasury Bond Returns: Monthly Data between May 1988 and August 2017

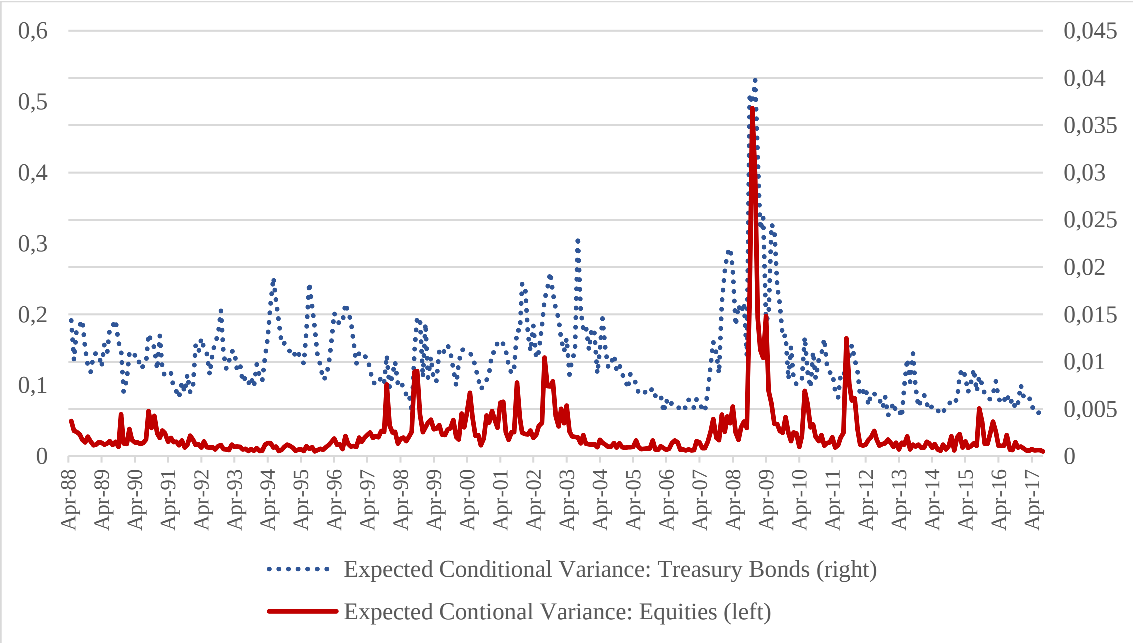

Figure 4. Variance Risk Premium for Equity and Treasury Bond Returns: Monthly Data between May 1988 and August 2017