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Reexamining financial and economic predictability with new estimators of realized variance and variance risk premium*

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Abstract

This study explores the predictive power of new estimators of the equity variance risk premium and conditional variance for future excess stock market returns, economic activity, and financial instability, both during and after the last global financial crisis. These estimators are obtained from new parametric and semiparametric asymmetric extensions of the heterogeneous autoregressive model. Using these new specifications, we determine that the equity variance risk premium is a predictor of future excess stock returns, whereas conditional variance predicts them only for long horizons. Moreover, a comparison of the overall results reveals that the conditional variance gains predictive power during the global financial crisis period. Furthermore, both the variance risk premium and conditional variance are determined to be predictors of future financial instability, whereas conditional variance is determined to be the only predictor of economic activity for all horizons. Before the global financial crisis period, the new parametric asymmetric specification of the heterogeneous autoregressive model gains predictive power in comparison to previous work in the literature. However, the new time-varying coefficient models are the ones showing considerably higher predictive power for stock market returns and financial instability during the financial crisis, suggesting that an extreme volatility period requires models that can adapt quickly to turmoil.

JEL-Classifications: C22; C51; C52; C53; C58; G17

Keywords: Net measures; Nonparametric methods; Predictability; Realized variance; Variance risk premium; VIX

1 Introduction

A recurrent question in the financial literature is whether stock returns are predictable. No clear evidence exists of this predictability, and it often depends on the predictors used. Wilcox (2007) and Lettau and Van Nieuwerburgh (2008) state that a large consensus exists regarding dividend- and earnings-price ratios being predictors of stock market behavior (see also Campbell and Shiller, 1988). Other researchers such as Bollerslev et al. (2009, 2011, 2012, 2014), Drechsler and Yaron (2011), Galaix (2012), Bekaer and Hoerova (2014) and Kelly and Jiang (2014) indicate that the predictability of stock returns is stronger when the variance risk premium (VRP) is included in models as a predictor. Another stream of literature states that stock returns are not predictable; for example, Bossaerts and Hillion (1999) observe that out-of-sample prediction is not possible for stock returns, and Welch and Goyal (2008) state that standard predictive variables are not statistically significant both in-sample and out-of-sample. Furthermore, Bossaerts and Hillion (1999) run regressions of 1-month excess returns on the dividend yield, short-term yield, and bond yield for 14 countries and implement several selection criteria from relevant statistics literature. Similarly, Welch and Goyal (2008) run regressions for early 2006 using the dividend price ratio, dividend yield, earnings-price ratio, dividend-earnings (payout) ratio, various interest rates and spreads, inflation rates, book-to-market ratio, and volatility as predictors. However, none of these studies consider the VRP as a potential predictor of future stock returns. Furthermore, Ang and Bekaert (2007) conclude that long-run predictability is nonsignificant by studying whether various dividend yields can predict excess stock returns, and Campbell and Thompson (2008) determine that the out-of-sample predictability of future excess stock returns is small but meaningful by analyzing several subsample periods and a set of predictors that does not include the VRP.

In this paper, by decomposing the squared CBOE volatility index (VIX) into the equity VRP and conditional variance (CV) of the stock market proposed by Bekaer and Hoerova (2014), we explore the predictive power of new models of the VRP and CV for future excess stock returns, economic activity, and financial instability; see also Bloom (2009). Realized variance (RV) has often been used as a proxy of CV in relevant studies, such as that by Bollerslev et al. (2009). Furthermore, Barndorff-Nielsen et al. (2010) propose realized semivariance as the first asymmetric measure of RV. This measure decomposes RV into a positive component and a negative component corresponding to positive and negative high-frequency returns, respectively. However, this measure does not capture how unsettling positive or negative returns are likely to be for current volatility and investment opportunities. To overcome this caveat, we propose a new asymmetric measure of RV inspired by the studies on asymmetric oil price changes by Hamilton (1996) and Ramos and Veiga (2011), called the net realized variance (NRV). The concept is not only to decompose RV into positive and negative components but also to consider more extreme returns and use them to replace the lagged daily positive and negative realized semivariance terms in the semivariance heterogeneous autoregressive (SHAR) model of Patton and Sheppard (2015) and the semivariance heterogeneous autoregressive-Q (SHARQ) model of Bollerslev et al. (2016). Furthermore, the proposed models are extended to allow for flexible time-varying coefficients that are estimated nonparametrically. In contrast to Chen et al. (2017), who introduce time-varying coefficients in their heterogeneous autoregressive (HAR) model as functions of time, coefficients change with the realized quarticity, as proposed by Bollerslev et al. (2016). Notably, Bianchi et al. (2017) report that U.S. stock returns are priced in the cross section by considering a multifactor model in which macroeconomic risk factors and risk premiums have time-varying coefficients in order to capture the instability in such factors and premiums.

Guided by relevant studies, such as those by Bollerslev et al. (2014) and Bekaer and Hoerova (2014), we employ ordinary least squares regressions with standard errors obtained using the procedure of Newey and West (1987) to compare the predictive power of various models. The predictive power of the VRP and CV is measured in terms of the statistical significance of the potential predictors and adjusted R^2 values. For robustness, we run regressions where we include other potential predictors, such as the real 3-month rate, logarithm of the dividend yield, credit spread (CS), and term spread (TS) (see Bekaer and Hoerova, 2014, for the use of similiar regressors in a robust analysis).

On the basis of our results, we answer two main questions: (1) whether asymmetric measures of RV increase the predictive power of the VRP and CV; and (2) whether CV-and consequently the VRP-obtained from time-varying coefficient models are superior predictors of stock market returns, economic activity, and financial instability than those obtained from parametric specifications. The answer to both of these questions is affirmative. Asymmetric extensions of the HAR model are crucial because they are superior in predictive power to models that do not include asymmetric measures of RV. Moreover, the predictive power of the VRP often increases when models with time-varying coefficients are used.

This paper makes several contributions to the literature. First, we propose novel asymmetric extensions of the HAR model that use an estimator of RV asymmetry, which resolves the caveats of realized semivariance. Second, we use nonparametric methods to estimate analogous asymmetric models with time-varying coefficients as functions of the realized quarticity. Third, we calculate various monthly VRP forecasts with the new specifications of RV and compare their predictive power of financial instability and economic activity with that of competitive benchmark models. The results of this comparison indicate that some of the new specifications substantially increase the predictive power of the VRP and CV. Finally, our results reinforce those obtained by researchers such as Bollerslev et al. (2009, 2011, 2012, 2014) and Bekaer and Hoerova (2014).

The remainder of this paper is organized as follows: Section 2 presents an alternative asymmetric measure of RV as well as new extensions of the HAR model. Section 3 reports the estimation results, and Section 4 tests the ability of the new predictors to predict stock market returns, economic activity, and financial instability, as well as providing some discussion. Finally, Section 5 concludes the paper.

2 Novel RV models

Since high-frequency data are available, RV has been a major focus of research into accounting for uncertainty in financial investments. Among numerous other applications, RV is considered a proxy of economic uncertainty (see Bekaer and Hoerova, 2014) and has a critical role in estimating and forecasting the VRP, which itself is a measure of risk aversion to uncertainty. It is obtained as $RV_t = \sum_{i=1}^{M} r_{t,i}^2$, where $r_{t,i}$ is the price return at time i of day t, and M is the total number of intraday values.

The VRP is a risk compensation measure used by investors to determine investors' degree of risk aversion to uncertainty, often defined as the difference between implied market variance and actual RV (see Feunou et al., 2015). Technically, the VRP is defined as the difference between the conditional return variance, determined using a "risk-neutral" probability measure, and the RV over the following month; that is,

$$VRP_t = VIX_t^2 - E_t[RV_{t+1}^{(22)}], \tag{1}$$

where $E_t[RV_{t+1}^{(22)}]$ is proxied by the forecast of the monthly S&P 500 RV estimates. Commonly, the HAR model of Corsi (2009) is used to forecast $RV_{t+1}^{(22)}$ using past RVs at various time frequencies. This measure does not account for the asymmetric response of volatility. Yet, negative shocks have a stronger effect on volatility, and consequently, on the forecasts of RV and the VRP, than positive shocks of the same magnitude. Investors dislike the uncertainty embedded in negative shocks because the likelihood of high losses increases. Thus, we believe that incorporating the volatility asymmetry effect into RV models will increase the power of the VRP in predicting future stock returns, economic activity, and financial instability.

One method to proceed is decomposing the RV into positive and negative semivariances, calculated by summing high-frequency positive and negative squared returns (see Barndorff-Nielsen et al., 2010; Patton and Sheppard, 2015). In the next subsection, we propose an asymmetric measure of RV that focuses on the effect of extreme returns on volatility.

2.1 Alternative asymmetric measure of realized variance

As mentioned, volatility responds asymmetrically to positive and negative shocks of the same magnitude, with negative shocks having a larger effect on volatility. This is the so-called leverage effect (see Christie, 1982; Campbell and Hentschel, 1992; Bollerslev et al., 2006). Although asymmetry and leverage are not exactly the same, we use them interchangeably hereafter.[1]

The first researchers to consider leverage effects in the context of a heterogeneous market hypothesis are Corsi et al. (2012), who model the leverage effect by incorporating past negative returns at several frequencies. More recently, Patton and Sheppard (2015) incorporate the realized semivariance estimator of Barndorff-Nielsen et al. (2010) into the HAR model. Their results indicate that although intraday returns are often small, critical information must be disentangled from both positive and negative intraday returns. Nevertheless, Hamilton (1996) suggest that investors do not react quickly to what could be a jump; however, they should change their behavior when they appreciate a large shock compared not only with the immediate past but also with a longer past horizon. Thus, if one wants to measure how unsettling extreme positive returns are likely to be for volatility, calculating the amount by which current prices have risen over a given period is appropriate. This leads to the concept of positive NRV (see Hamilton, 1996, 2003; Ramos and Veiga, 2011) in the context of net oil price changes, which is a measure of the variance of positive extreme returns that drive investors to change strategy. In this paper, we calculate the NRV of the current day using net returns, which is the difference between the current log-price and logarithm of the largest price over the previous day, $r_{t,i}^* = \log(p_{t,i}) - \log(\max(p_{t-1,M}, \ldots, p_{t-1,1}))$. The proposed positive NRV estimator for day t is calculated as

$$NRV_t^+ = \sum_{i=1}^{M} r_{t,i}^{*2} I(r_{t,i}^* \geq 0). \tag{2}$$

[1] Leverage is a special case of asymmetry (see, for example, McAleer, 2014).

Similarly, a measure of net negative realized variance is calculated as

$$NRV_t^- = \sum_{i=1}^{M} r_{t,i}^{*2} I(r_{t,i}^* < 0). \tag{3}$$

2.2 Parametric NRV models

The first RV model suggested in this paper extends the HAR model of Corsi (2009) to include the NRV to measure uncertainty in extreme returns as

$$RV_t = \beta_0 + \beta_1^+ NRV_{t-1}^+ + \beta_1^- NRV_{t-1}^- + \beta_2 RV_{t-1|t-5} + \beta_3 RV_{t-1|t-22} + u_t,$$

where NRV^+ and NRV^- are defined as in equations (2) and (3), respectively, $RV_{t-j|t-h} = \frac{1}{h+1-j}\sum_{i=j}^{h} RV_{t-i}$ with $j \leq h$. Therefore,RV_{t-1}, $RV_{t-1|t-5}$ and $RV_{t-1|t-22}$ correspond to the daily, weekly, and monthly lag RVs. This extension of the HAR model is named net asymmetric HAR (NHAR). The purpose of this model is to improve the estimation and forecast power of the RV's tail values, which are likely to be the predictors of extreme investment behavior.

Although RV is a consistent estimator of integrated volatility under certain conditions, it is often affected by measurement errors in finite samples. To account for these, Bollerslev et al. (2016) propose a new family of models named HARQ for the RV, which are basically HAR models whose coefficients are linear functions of the realized quarticity. Thus, the bias related to the estimated error of RV is corrected at each time step. The formula of the HARQ model is

$$RV_t = \beta_0 + (\beta_1 + \beta_{1Q} RQ_{t-1}^{1/2}) RV_{t-1} + \beta_2 RV_{t-1|t-5} + \beta_3 RV_{t-1|t-22} + u_t. \tag{4}$$

Similarly, their SHARQ model substitutes the RV in (4) with the realized semivariance of Barndorff-Nielsen et al. (2010). They prove empirically that their models outperform the HAR model and its extensions, and in some cases, the SHAR model of Patton and Sheppard (2015) in forecasting RV.

Furthermore, a natural extension is to consider the NRV and net realized quarticity, $RQ_t^* \equiv \frac{M}{3}\sum_{i=1}^{M} r_{t,i}^{*4}$, to correct for the estimation error in the NRV at each time step. The proposed model, named the net HARQ (NHARQ) model, is formulated as

$$RV_t = \beta_0 + (\beta_1^+ + \beta_{1Q}^+ RQ_{t-1}^{*1/2}) NRV_{t-1}^+ + (\beta_1^- + \beta_{1Q}^- RQ_{t-1}^{*1/2}) NRV_{t-1}^- + \beta_2 RV_{t-1|t-5} + \beta_3 RV_{t-1|t-22} + u_t. \tag{5}$$

The coefficients of NRV^+ and NRV^- also change with the net realized quarticity to account for possible measurement errors in the NRV estimators.

In this paper, we do not consider the presence of jumps. Patton and Sheppard (2015) demonstrate that specifications that include jumps (for example, the HAR-J) have poor performance in comparison with the SHAR model.

2.3 Time-varying coefficients models

The innovative idea of Bollerslev et al. (2006) to include time-varying coefficients for correcting measurement errors in the HAR model may be extended with nonparametric techniques. Bollerslev et al. (2016) indicate that the measurement error is stronger for the daily lagged RV, although it still exists for the weekly and monthly lagged RVs, and they model it as a linear function of the square root of the lagged realized quarticity. Instead, we propose allowing for linear and nonlinear relationships as required. The model is expressed as follows:

$$RV_t = X_t'\beta_t + u_t, \quad t = 1, 2, \ldots, T, \tag{6}$$

Depending on the regressors, we denote the time-varying coefficient models as either tv-SHARQ or tv-NHARQ.

Nonparametric methods are not convenient for models with numerous regressors because their rate of convergence decreases as the number of regressors increases. Semiparametric methods such as model (6) are typical alternatives, which maintain a great level of flexibility and a satisfactory rate of convergence. The coefficients in (6) are unknown functions of the square root of the realized quarticity. We call this a time-varying coefficient linear model. In the nonparametric literature, time-varying coefficients may be an unknown function of time as $\beta_t = f(t/T)$, or an unknown function of a random variable z_t as $\beta_t = f(z_t)$. Robinson (1989) introduces the unknown function of time as $\beta_t = f(t/T)$, which is generalized in various contexts in studies by researchers such as (Cai, 2007; Kristensen, 2012; Orbe et al., 2005; Phillips et al., 2017; Casas et al., 2017, amongst many others). In addition, Chen et al. (2017) apply it to the HAR model of Corsi (2009) for the RV of S&P 500 index returns. It is a flexible approach but its forecast is inconsistent because no information exists from the dependent variable at time $T+1$. Our coefficients instead change depending on the dynamics of the square root of the realized quarticity. Theoretical results obtained using this approach have been studied by Cai et al. (2009), whereas Das (2005) and Henderson et al. (2015) have used the approach for instrumental variables and SUR frameworks, respectively.

The estimations and forecasts of model (6) are performed using the local linear (LL) nonparametric estimator. First proposed by Fan and Gijbels (1996) and widely used since, this estimator requires that the function $f(\cdot)$ has a second derivative in the region where z_t, in our problem $RQ_{t-1}^{1/2}$, is defined. The LL estimator is chosen over the Nadaraya-Watson estimator because of the superior properties at the LL estimator's boundary; specifically, the LL estimator is asymptotically unbiased at the boundary, which is an advantage in the out-of-sample prediction. In fact, initial forecasts obtained using the LL estimator in our models are superior those obtained using the Nadaraya-Watson estimator. It is widely known that the LL estimator is sometimes negative for finite samples, even when the dependent variable is always positive, such as in our application. Asymptotically, this is not the case, and the number of negative values decreases as T increases. One method of avoiding this problem is to use the $\log RV_t$ series, as in Chen et al. (2017). Instead, we use the RV_t series following the example of Bekaer and Hoerova (2014) and interpolate the possible few negative LL estimates.

The tv-NHARQ model is given by

$$RV_t = \beta_0(z_{t-1}) + \beta_1^+(z_{t-1})NRV_{t-1}^+ + \beta_1^-(z_{t-1})NRV_{t-1}^- + \beta_2(z_{t-1})RV_{t-1|t-5} + \beta_3(z_{t-1})RV_{t-1|t-22} + u_t.$$

Coefficients $\beta_t = \big(\beta_0(z_{t-1}), \beta_1^+(z_{t-1}), \beta_1^-(z_{t-1}), \beta_2(z_{t-1}), \beta_3(z_{t-1})\big)'$ and their first derivatives $\beta_t^{(1)}$ are estimated, following the notation in Cai (2007) using

$$\begin{pmatrix} \hat{\beta}_t \\ \hat{\beta}_t^{(1)} \end{pmatrix} = \begin{pmatrix} S_{T,0}(z_{t-1}) & S_{T,1}(z_{t-1}) \\ S_{T,1}(z_{t-1}) & S_{T,2}(z_{t-1}) \end{pmatrix}^{-1} \begin{pmatrix} T_{T,0}(z_{t-1}) \\ T_{T,1}(z_{t-1}) \end{pmatrix}$$

where

$$S_{T,k}(z_{t-1}) = T^{-1}\sum_{t=1}^{T} X_t X_t'(Z - z_{t-1})^k K_b(Z - z_{t-1}) \text{ and } T_{T,k} = \sum_{t=1}^{T} X_t (Z - z_{t-1})^k K_b(Z - z_{t-1}) RV_t$$

for $k = 0, 1, 2, 3$. Variable Z is the vector of all $RQ^{*1/2}$ in the training sample, and $z_{t-1} = RQ_{t-1}^{*1/2}$ is the conditional value. The kernel function $K_b(u) = K(u/b)/b$, is a symmetric continuous function with support in [-1, 1] and bandwidth b. The bandwidth should reach zero slower than T approaches infinity, and in practice, it is calculated through cross-validation. In addition, if the process (X_t, Z_t, u_t) is stationary, then the estimator is consistent and asymptotically normal. The condition of stationarity can be relaxed to α-mixing processes and Z can be an I(1) process; details can be found in Cai et al. (2009). Estimators of the tv-SHARQ model are defined similarly for the realized semivariance and $RQ_{t-1}^{1/2}$.

3 In-sample performance

Our empirical results are based on the S&P 500 index, and its RV is used as the benchmark to compare models' estimation power. High-frequency prices for the index are obtained from 1-minute close prices.[2] The sample comprises observations of the RV and its asymmetric measures with a total of 3,020 daily observations ranging from July 1, 2004, to June 28, 2016. Figure 1 shows the autocorrelation function (ACF) of the RV. The ACF decays slowly toward zero, suggesting the existence of long memory. Furthermore, Figure 2 presents the daily realized semivariance and NRV estimates. We observe that the RV^- shows larger values of volatility than the RV^+. This difference is larger for the NRV measures whose scale is larger than that of the RV because they measure more extreme variability.

Table 1 lists the coefficient estimates, p-values, R^2, mean square errors (MSEs), and mean values of the QLIKE loss function for the parametric specifications, whereas Table 2 lists the MSE and QLIKE for the semiparametric specifications of RV.[3] The main indication of the results in Table 1 is that the coefficient estimates of the new measure of uncertainty decrease in magnitude;specifically, β_1^+ and β_1^- in the NHAR and NHARQ models are smaller in absolute value than their counterparts in the SHAR and SHARQ models. Similarly, these coefficients are smaller for the NHARQ than for the SHARQ model. This is expected as the scale of NRV is larger. Moreover, the β_1^- estimates are larger in absolute value than

[2] Detailed information can be found on `http://download-stock-data.webs.com/`.

[3] The QLIKE loss function of Patton (2011) is given by $QLIKE_t \equiv \frac{RV_t}{ERV_t} - \log \frac{RV_t}{ERV_t} - 1$, where ERV_t corresponds to the estimated realized variance at day t obtained with the selected models.

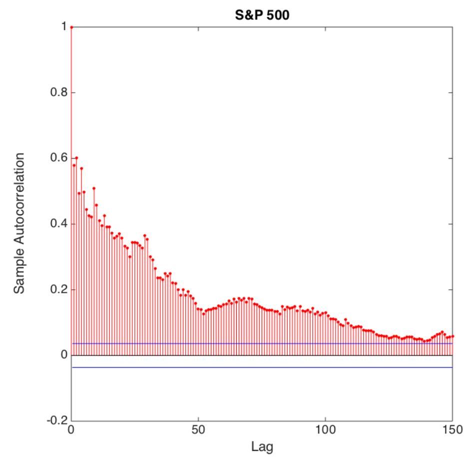

Figure 1: Autocorrelation function of daily S&P 500 realized variance ranging from July 1, 2004 till Jun 28, 2016.

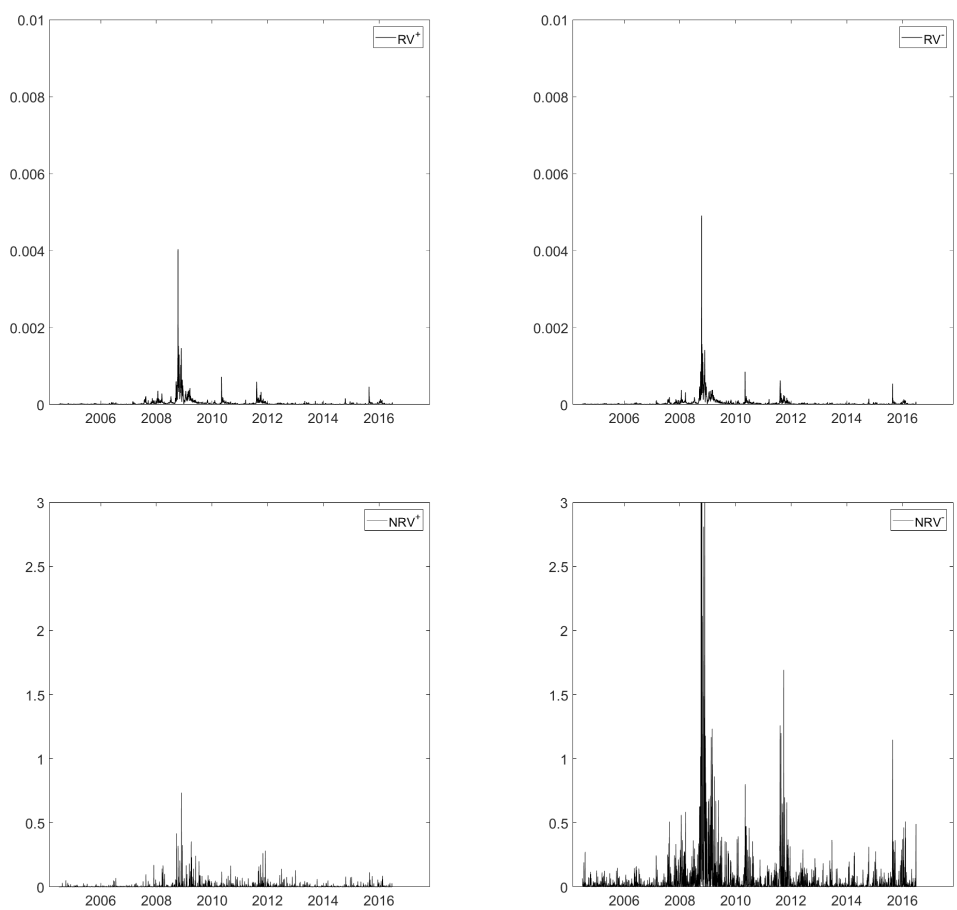

Figure 2: Daily S&P 500 realized semivariance (first row) and net RV (second row). Positive (first column) and negative (second column) measures ranging from July 1, 2004 till Jun 28, 2016.

β_1^+ for most models. This result agrees with Patton and Sheppard (2015), who obtain similar evidence for the SHAR model. Furthermore, the β_1^- estimates are statistically significant for all models, whereas the estimates of β_1^+ are nonsignificant for the NHAR, SHARQ, and NHARQ models, which is a clear sign of leverage in the data. In addition, we observe that the magnitude of the sum of β_2 and β_3 coefficients slightly decreases when using models that account for the effect of the realized quarticity, such as the HARQ and SHARQ models. The model with the highest R^2 is the SHARQ, followed by the HARQ and NHARQ models. Moreover, these models have the smallest MSE and QLIKE loss function values. The results in Table 2 indicate that the time-varying coefficient models have lower values of MSE, but the QLIKE loss function values are higher than those obtained with the parametric specifications.

In the next section, we analyze the out-of-sample forecast performance of all models for financial instability and economic output.

4 Financial and economic predictability

The VRP is used as a proxy of risk aversion, whereas RV is considered a proxy of economic uncertainty (see Bekaer and Hoerova, 2014). The monthly VRP is obtained as in (1), using the monthly RV forecasts as well as the VIX_t^2, which as in Bekaer and Hoerova (2014), is expressed in monthly percentages squared, i.e. $\mathrm{VIX}^2/12$ where VIX is the quoted VIX index level in annualized percent. The analysis period ranges from August, 2008, to July, 2016. Moreover, the last financial and sovereign debt crises are included in the sample.

Figure 3 illustrates the VRP estimates obtained using some of the discussed parametric and time-varying coefficient models. We observe that parametric measures of the VRP have peaks during 2008-2009, which correspond to the global financial crisis and European sovereign debt crisis; furthermore, the second peak is lower in magnitude than the first. Forecasts of the VRP with rolling and increasing window schemes are similar when parametric specifications of the RV are used, whereas semiparametric models seem to be more effective with the increasing window scheme, which uses a larger number of data points in the training set.[4] Moreover, the tv-SHARQ models provides the largest values of the VRP among all models.

4.1 Predictability of excess stock market returns

Bollerslev et al. (2009), Bekaer and Hoerova (2014), Bollerslev et al. (2014) and Bollerslev et al. (2015) observe that the VRP is a significant predictor of future stock returns by running regressions of future excess returns on the VRP. However, the equity risk premium is explained by multiple factors (see, for instance, Ang and Bekaert, 2007; Menzly et al., 2004). To avoid the misspecification of univariate regressions, Bekaer and Hoerova (2014) consider models in which the VRP and CV are simultaneously used as predictors of future excess stock returns, indicating that CV is often rejected as a predictor.

[4]A large enough number of observations in the training sample is important for the nonparametric methodologies since these estimators can suffer from large biases mainly at spatial points with sparse neighborhoods (see Xu and Phillips, 2011, for evidence on this issue).

Table 1: Parametric models' estimation results.

The table reports estimated parameters of benchmarks and alternative models, their p-values in parenthesis and R^2s of the estimated models together with MSE and QLIKE as measures of goodness of fit. The value of the MSE is multiplied by $1e+06$. ◊ means that the variable is not significant at any relevant level (1%, 5% and 10%) of significance.

	S&P 500					
	HAR	SHAR	NHAR	HARQ	SHARQ	NHARQ
β_0	0.000	0.000	0.000	0.000◊	0.000◊	0.000◊
	(0.014)	(0.011)	(0.006)	(0.977)	(0.403)	(0.873)
β_1	0.106			0.711		
	(0.000)			(0.000)		
β_1^+		-0.331	-0.0004		-0.154◊	-0.0002◊
		(0.015)	(0.001)		(0.484)	(0.422)
β_1^-		0.475	0.0001		1.698	0.0005
		(0.000)	(0.000)		(0.000)	(0.000)
β_2	0.581	0.600	0.580	0.368	0.388	0.666
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
β_3	0.206	0.217	0.225	-0.032◊	-0.054◊	0.039◊
	(0.000)	(0.000)	(0.000)	(0.349)	(0.114)	(0.261)
β_{1Q}				-31.584		
				(0.000)		
β_{1Q}^+					-359.270	-0.0001◊
					(0.002)	(0.872)
β_{1Q}^-					226.100	-0.0002
					(0.015)	(0.000)
R^2	0.468	0.410	0.482	0.545	0.565	0.538
MSE	0.034	0.033	0.033	0.029	0.028	0.029
QLIKE	0.239	0.237	0.232	0.147	0.149	0.187

Table 2: semiparametric model's goodness of fit

The table provides in-sample measures of goodness-of-fit for semiparametric models. The value of the MSE is multiplied by $1e+06$.

	tv-SHARQ	tv-NHARQ
MSE	0.026	0.022
QLIKE	1.876	0.224

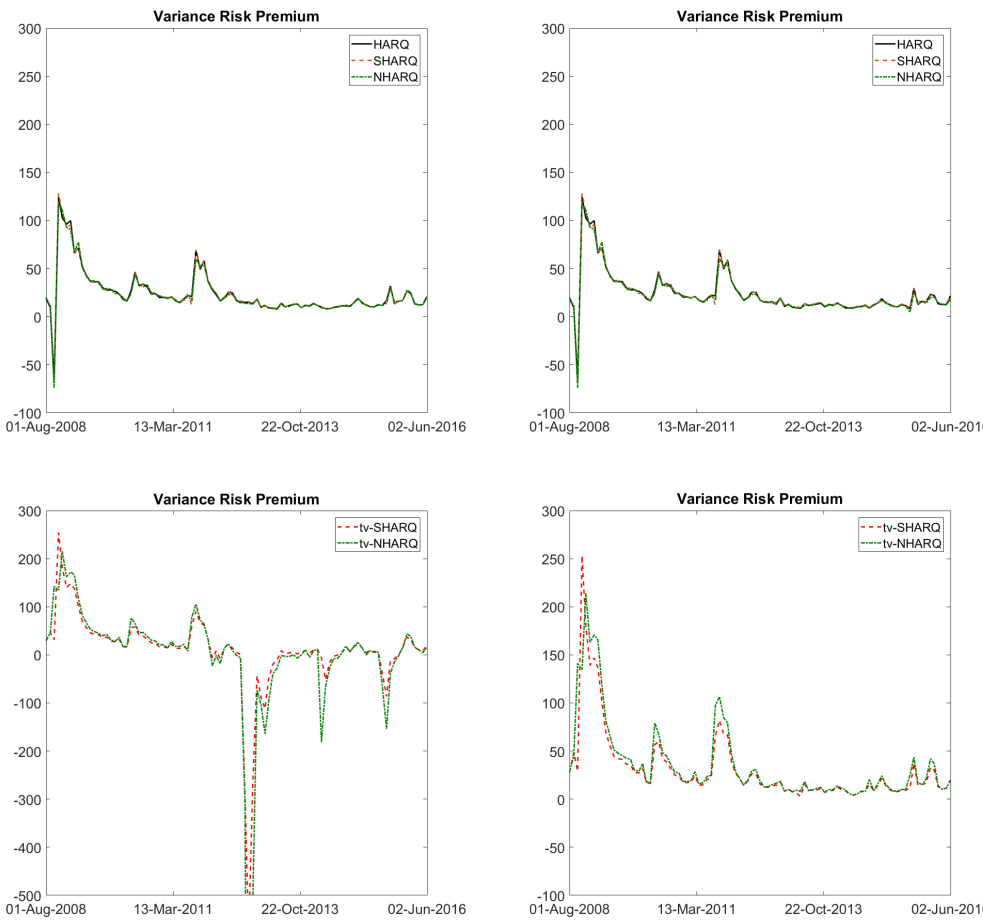

Figure 3: Monthly series of variance risk premia obtained with parametric (first row) and semiparametric models (second row), using RW (left column) and IW (right column) schemes.

Following Bollerslev et al. (2009) and Bekaer and Hoerova (2014), we run regressions of S&P 500 future excess returns, first on VIX^2 and a set of regressors X_t, and second on the VRP, the CV measures obtained using the specifications presented in Section 2, and X_t. Specifically, the following equations are used:

$$h^{-1}r_{t,t+h} = a(h) + b(h)VIX_t^2 + e(h)X_t + u_{t,t+h}, \quad (7)$$

$$h^{-1}r_{t,t+h} = a(h) + c(h)VRP_t + d(h)CV_t + e(h)X_t + u_{t,t+h}, \quad (8)$$

where $r_{t,t+h}$ denotes the $h = 1, 2, ..., 12$ month excess returns of the S&P 500.[5] The set of control variables X_t includes other potential predictors such as (1) the real 3-month rate (3MTB), which is the 3-month T-bill minus CPI inflation; (2) the logarithm of the dividend yield (log(DY)); (3) the CS obtained using the difference between Moody's BAA and AAA bond yield indices; and (4) the TS calculated using the difference between the 10-year and 3-month treasury yields. All variables are expressed in annualized percentages (see Bekaer and Hoerova, 2014, for the use of the same predictors). The R^2 values from these regressions, where the dependent variables are composed by overlapping return observations, can be spuriously large when the horizon h increases (see Campbell et al., 1997). Moreover, the t-statistics for testing the hypothesis about $a(h)$, $b(h)$, $c(h)$, $d(h)$ and $e(h)$ may not follow a standard normal distribution because the standard errors of the ordinary least squares estimates can also be subject to bias. However, as observed by Bollerslev et al. (2014), the VRP is less persistent at a frequency of 1 month, and therefore, the finite sample bias is small. Furthermore, the overlap in monthly data can make the regression disturbance autocorrelated and affect the standard errors of the estimates. Hence, as in Bekaer and Hoerova (2014), we use robust Newey-West standard errors.

4.1.1 Period 2008–2016 including the global financial crisis

Tables 3–5 present the results of the regressions. Regarding the 1-month horizon, we observe that the VRP is a predictor of stock market returns in all regressions, and that CV is a statistically significant predictor only for the tv-NHARQ model. The regression with the highest adjusted R^2 is that where the VRP and CV are obtained directly from RV (Table 3). The sign of the VRP is positive, which means that an increase in the VRP today will positively affect the stock excess returns next month. This is in concordance with Bollerslev et al. (2009), Han and Zhou (2011), Bekaer and Hoerova (2014) and Bollerslev et al. (2014). They confirm that stocks with a high VRP have more volatility, and consequently, are riskier and tend to command more expected returns. Among the set of control variables, only the TS is not a predictor of returns. Surprisingly, the CS has a negative sign; however, Bollerslev et al. (2009) and Bekaer and Hoerova (2014) report negative coefficients for the CS in univariate and multivariate excess return regressions, respectively. Regarding the real 3-month rate, we observe that it also has a negative relationship with future stock market returns. During the period of analysis characterized by high volatility, financial instability, and a low and even negative real 3-month rate, an increase of the interest of safe securities might be an incentive for investors to move capital from stock markets to

[5] Results on univariate and bivariate regressions can be founded in the Supplementary Appendix.

banks or even to invest in goods, leading to a decrease of stock prices and consequently of stock returns. Furthermore, VIX^2 is a predictor of stock market returns with positive coefficients.

Conclusions on the predictability of equity returns drawn using models (7) and (8) for the 3-month horizon are similar: VIX^2 and the VRP are predictors of future stock returns, whereas CV is not. Furthermore, the magnitude of the coefficients of the VRP often decreases compared with those of the previous horizon. The regression with the strongest predictive power includes the VRP and CV obtained with the time-varying NHARQ model and IW scheme (Table 4). The adjusted R^2 values increase substantially and are higher than those reported in the literature. All potential predictors in the set X_t are statistically significant. The logarithm of the dividend yield has consistent positive coefficients, whereas the CS and TS consistently have negative coefficients.[6]

Finally, when we consider the horizon of 12 months, we observe that VIX^2, the VRP, and CV are predictors of future stock returns for the majority of regressions. Moreover, the adjusted R^2 values increase despite being smaller than those reported for the 3-month horizon (Table 5). Among the set of regressors, only the real 3-month rate is statistically significant, but the sign of its coefficients remains negative. The regressions with high predictive power are still those whose VRP and CV are obtained using the time-varying coefficient models.

Overall, we conclude that the VIX^2 and VRP are predictors of future stock returns for all horizons, whereas the CV is only a predictor for the 12-month horizon. Depending on the horizon, real 3-month rate, and logarithm of the dividend yield, the CS and TS are also predictors of future excess stock market returns. Furthermore, we obtain a stronger predictive power using the time-varying coefficient models with net measures of RV for the 3- and 12-month horizons.

4.1.2 Period 1990–2007, excluding the global financial crisis

Now, we analyze the performance of the proposed estimators of the VRP and CV, and the set X_t of potential predictors used in the previous subsection during the period before the last crisis.[7] This period ranges from January 1990 to December 2007, and coincides with the period analyzed by Bollerslev et al. (2009).

Tables 6–8 show the results. Regarding the 1-month horizon, we still observe that the VRP is a predictor of future excess returns, whereas CV is not. The sign of this relationship is also positive, but the magnitude of the VRP's coefficients is smaller. Furthermore, the predictive power decreases: the best predictive regression reaches an adjusted R^2 of 0.159 (compared with the 0.197 obtained previously) with predictors obtained from the time-varying coefficient SHARQ model and IW scheme. From the set X_t, we also observe a difference; specifically, only the real 3-month rate is statistically significant among all extra variables, and its negative sign is maintained.

[6] Bollerslev et al. (2009) also report negative coefficients for the TS in univariate excess return regressions.

[7] We only consider the models that take the measurement error correction in consideration for two reasons: first, the predictors of the alternative models have never been selected as the best predictors in the previous sample period and second legibility of tables.

Table 3: Stock excess return regressions: Horizon 1 month (period 2008-2016).

Regressions (monthly observations) with variance risk premium, conditional variance, real 3-month rate, the logarithm of dividend yield, credit spread and term spread. The standard errors presented below the estimated parameters are the Newey-West standard errors using $max[3, 2 \cdot horizon]$ lags. ◇ means that the variable is not significant at any relevant level (1%, 5% and 10%) of significance.

	Panel A: Parametric and semiparametric measures of VRP and CV																	
Constant	-6.548	-4.222◇	-4.918◇	-4.959◇	-4.935◇	-4.969◇	-4.780◇	-4.800◇	-4.582◇	-4.566◇	-4.608◇	-4.576◇	-4.547◇	-4.576◇	-5.663	-4.968◇	-6.307	-6.825
	(3.361)	(3.741)	(3.687)	(3.687)	(3.672)	(3.674)	(3.699)	(3.702)	(3.730)	(3.731)	(3.688)	(3.684)	(3.733)	(3.728)	(3.449)	(3.666)	(3.412)	(3.603)
$R3MT$	-4.156	-3.382	-3.623	-3.584	-3.647	-3.608	-3.645	-3.600	-3.477	-3.467	-3.551	-3.562	-3.599	-3.608	-4.225	-3.933	-4.177	-4.340
	(2.075)	(1.986)	(2.129)	(2.148)	(2.127)	(2.146)	(2.076)	(2.095)	(2.077)	(2.085)	(2.067)	(2.069)	(2.033)	(2.040)	(2.094)	(2.088)	(2.093)	(2.076)
$log(DY)$	21.550	18.588	19.234	19.519	19.239	19.525	19.148	19.386	19.116	19.053	19.256	19.044	19.329	19.272	21.359	19.946	21.563	21.771
	(6.808)	(6.817)	(6.903)	(6.845)	(6.895)	(6.836)	(6.896)	(6.844)	(6.882)	(6.895)	(6.830)	(6.880)	(6.933)	(6.966)	(6.775)	(6.819)	(6.832)	(7.121)
CS	-6.815	-7.612	-7.257	-7.341	-7.243	-7.333	-7.299	-7.381	-7.631	-7.572	-7.720	-7.581	-7.727	-7.584	-6.917	-7.270	-6.854	-6.638
	(2.714)	(2.655)	(2.701)	(2.684)	(2.701)	(2.684)	(2.700)	(2.683)	(2.646)	(2.646)	(2.609)	(2.623)	(2.625)	(2.632)	(2.745)	(2.705)	(2.729)	(2.448)
TS	-0.903◇	-1.034◇	-0.959◇	-0.990◇	-0.953◇	-0.986◇	-0.968◇	-1.000◇	-1.020◇	-1.027◇	-1.028◇	-1.023◇	-1.047◇	-1.051◇	-1.130◇	-0.989◇	-0.976◇	-0.904◇
	(0.655)	(0.666)	(0.667)	(0.667)	(0.667)	(0.666)	(0.668)	(0.668)	(0.666)	(0.666)	(0.662)	(0.663)	(0.670)	(0.671)	(0.703)	(0.667)	(0.682)	(0.657)
VIX^2	0.031																	
	(0.017)																	
VRP_{RV}		0.082																
		(0.026)																
RV		0.027◇																
		(0.023)																
$VRP_{HAR_{RW}}$			0.067															
			(0.023)															
$CV_{HAR_{RW}}$			0.028◇															
			(0.022)															
$VRP_{HAR_{IW}}$				0.067														
				(0.023)														
$CV_{HAR_{IW}}$				0.028◇														
				(0.022)														
$VRP_{SHAR_{RW}}$					0.066													
					(0.023)													
$CV_{SHAR_{RW}}$					0.029◇													
					(0.022)													
$VRP_{SHAR_{IW}}$						0.066												
						(0.023)												
$CV_{SHAR_{IW}}$						0.029◇												
						(0.022)												
$VRP_{NHAR_{RW}}$							0.066											
							(0.023)											
$CV_{NHAR_{RW}}$							0.029◇											
							(0.022)											
$VRP_{NHAR_{IW}}$								0.067										
								(0.023)										
$CV_{NHAR_{IW}}$								0.029◇										
								(0.022)										
$VRP_{HARQ_{RW}}$									0.082									
									(0.024)									
$CV_{HARQ_{RW}}$									0.027◇									
									(0.023)									
$VRP_{HARQ_{IW}}$										0.081								
										(0.024)								
$CV_{HARQ_{IW}}$										0.027◇								
										(0.023)								
$VRP_{SHARQ_{RW}}$											0.083							
											(0.023)							
$CV_{SHARQ_{RW}}$											0.028◇							
											(0.023)							
$VRP_{SHARQ_{IW}}$												0.081						
												(0.023)						
$CV_{SHARQ_{IW}}$												0.028◇						
												(0.022)						
$VRP_{NHARQ_{RW}}$													0.080					
													(0.025)					
$CV_{NHARQ_{RW}}$													0.030◇					
													(0.022)					
$VRP_{NHARQ_{IW}}$														0.076				
														(0.025)				
$CV_{NHARQ_{IW}}$														0.030◇				
														(0.021)				
$VRP_{tv-SHARQ_{RW}}$															0.034			
															(0.019)			
$CV_{tv-SHARQ_{RW}}$															0.029◇			
															(0.018)			
$VRP_{tv-SHARQ_{IW}}$																0.050		
																(0.021)		
$CV_{tv-SHARQ_{IW}}$																0.017◇		
																(0.022)		
$VRP_{tv-NHARQ_{RW}}$																	0.032	
																	(0.018)	
$CV_{tv-NHARQ_{RW}}$																	0.031	
																	(0.018)	
$VRP_{tv-NHARQ_{IW}}$																		0.027◇
																		(0.024)
$CV_{tv-NHARQ_{IW}}$																		0.036◇
																		(0.029)
Adj. R^2	0.157	0.197	0.172	0.173	0.171	0.172	0.173	0.174	0.187	0.185	0.189	0.186	0.179	0.175	0.175	0.164	0.149	0.149

Table 4: Stock excess return regressions: Horizon 3 months (period 2008–2016).

Regressions (monthly observations) with variance risk premium, conditional variance, real 3-month rate, the logarithm of dividend yield, credit spread and term spread. The standard errors presented below the estimated parameters are the Newey-West standard errors using $max[3, 2 \cdot horizon]$ lags. ◊ means that the variable is not significant at any relevant level (1%, 5% and 10%) of significance.

	Panel A: Parametric and semiparametric measures of VRP and CV																	
Constant	-3.598	-2.899◊	-2.841◊	-2.860◊	-2.870◊	-2.882◊	-2.895◊	-2.905◊	-2.866◊	-2.885◊	-2.973◊	-2.988◊	-2.901◊	-2.965◊	-3.376	-3.209◊	-3.556	-2.751◊
	(1.827)	(2.133)	(2.044)	(2.046)	(2.040)	(2.042)	(2.072)	(2.073)	(2.117)	(2.122)	(2.109)	(2.118)	(2.169)	(2.178)	(1.951)	(2.077)	(1.883)	(2.101)
$R3MT$	-4.763	-4.525	-4.509	-4.491	-4.527	-4.508	-4.555	-4.537	-4.503	-4.509	-4.562	-4.575	-4.564	-4.583	-4.780	-4.707	-4.766	-4.182
	(1.440)	(1.608)	(1.649)	(1.670)	(1.639)	(1.660)	(1.613)	(1.632)	(1.635)	(1.638)	(1.598)	(1.595)	(1.599)	(1.598)	(1.441)	(1.518)	(1.448)	(1.857)
$log(DY)$	12.630	11.706	11.512	11.646	11.547	11.673	11.640	11.738	11.683	11.694	11.856	11.823	11.824	11.872	12.598	12.224	12.636	11.893
	(3.983)	(4.259)	(4.170)	(4.123)	(4.180)	(4.130)	(4.226)	(4.181)	(4.210)	(4.234)	(4.214)	(4.271)	(4.269)	(4.325)	(4.007)	(4.223)	(4.000)	(4.039)
CS	-2.976	-3.214	-3.178	-3.217	-3.166	-3.208	-3.166	-3.198	-3.278	-3.246	-3.266	-3.211	-3.292	-3.221	-3.004	-3.087	-2.983	-3.521
	(1.180)	(1.063)	(1.092)	(1.078)	(1.094)	(1.080)	(1.089)	(1.076)	(1.053)	(1.056)	(1.047)	(1.058)	(1.035)	(1.044)	(1.180)	(1.100)	(1.182)	(1.158)
TS	-0.965	-0.998	-0.983	-0.998	-0.980	-0.995	-0.984	-0.997	-1.001	-1.002	-0.998	-0.996	-1.009	-1.007	-1.025	-0.984	-0.978	-0.950
	(0.325)	(0.308)	(0.314)	(0.308)	(0.315)	(0.309)	(0.313)	(0.308)	(0.308)	(0.307)	(0.309)	(0.310)	(0.305)	(0.303)	(0.327)	(0.312)	(0.329)	(0.319)
VIX^2	0.019																	
	(0.009)																	
VRP_{RV}		0.034																
		(0.014)																
RV		0.017◊																
		(0.011)																
$VRP_{HAR_{RW}}$			0.036															
			(0.013)															
$CV_{HAR_{RW}}$			0.017◊															
			(0.012)															
$VRP_{HAR_{IW}}$				0.036														
				(0.013)														
$CV_{HAR_{IW}}$				0.017◊														
				(0.012)														
$VRP_{SHAR_{RW}}$					0.035													
					(0.013)													
$CV_{SHAR_{RW}}$					0.017◊													
					(0.012)													
$VRP_{SHAR_{IW}}$						0.035												
						(0.013)												
$CV_{SHAR_{IW}}$						0.017◊												
						(0.012)												
$VRP_{NHAR_{RW}}$							0.033											
							(0.013)											
$CV_{NHAR_{RW}}$							0.018											
							(0.011)											
$VRP_{NHAR_{IW}}$								0.033										
								(0.013)										
$CV_{NHAR_{IW}}$								0.018										
								(0.011)										
$VRP_{HARQ_{RW}}$									0.038									
									(0.016)									
$CV_{HARQ_{RW}}$									0.017◊									
									(0.012)									
$VRP_{HARQ_{IW}}$										0.037								
										(0.016)								
$CV_{HARQ_{IW}}$										0.017◊								
										(0.012)								
$VRP_{SHARQ_{RW}}$											0.036							
											(0.016)							
$CV_{SHARQ_{RW}}$											0.018							
											(0.011)							
$VRP_{SHARQ_{IW}}$												0.034						
												(0.015)						
$CV_{SHARQ_{IW}}$												0.018						
												(0.011)						
$VRP_{NHARQ_{RW}}$													0.036					
													(0.017)					
$CV_{NHARQ_{RW}}$													0.018					
													(0.011)					
$VRP_{NHARQ_{IW}}$														0.033				
														(0.016)				
$CV_{NHARQ_{IW}}$														0.018				
														(0.011)				
$VRP_{tv-SHARQ_{RW}}$															0.019			
															(0.009)			
$CV_{tv-SHARQ_{RW}}$															0.018			
															(0.009)			
$VRP_{tv-SHARQ_{IW}}$																0.023		
																(0.009)		
$CV_{tv-SHARQ_{IW}}$																0.015		
																(0.013)		
$VRP_{tv-NHARQ_{RW}}$																	0.019	
																	(0.009)	
$CV_{tv-NHARQ_{RW}}$																	0.019	
																	(0.009)	
$VRP_{tv-NHARQ_{IW}}$																		0.032
																		(0.012)
$CV_{tv-NHARQ_{IW}}$																		0.003◊
																		(0.023)
Adj. R^2	0.441	0.447	0.450	0.450	0.449	0.449	0.446	0.447	0.450	0.449	0.447	0.445	0.446	0.443	0.443	0.437	0.435	0.455

Table 5: Stock excess return regressions: Horizon 12 months (period 2008-2016)

Regressions (monthly observations) with variance risk premium, conditional variance, real 3-month rate, the logarithm of dividend yield, credit spread and term spread. The standard errors presented below the estimated parameters are the Newey-West standard errors using $max[3, 2 \cdot horizon]$ lags. ◇ means that the variable is not significant at any relevant level (1%, 5% and 10%) of significance.

	Panel A: Parametric and semiparametric measures of VRP and CV																	
Constant	-0.151◇	0.078◇	0.097◇	0.084◇	0.097◇	0.084◇	0.098◇	0.090◇	0.057◇	0.062◇	0.030◇	0.041◇	0.042◇	0.055◇	-0.418◇	0.115◇	-0.323◇	0.003◇
	(0.809)	(0.826)	(0.843)	(0.832)	(0.841)	(0.832)	(0.848)	(0.834)	(0.826)	(0.819)	(0.819)	(0.814)	(0.835)	(0.825)	(0.883)	(0.841)	(0.834)	(0.840)
$R3MT$	-0.948	-0.867	-0.864	-0.859	-0.867	-0.863	-0.874	-0.868	-0.873	-0.869	-0.888	-0.886	-0.892	-0.887	-0.936	-0.911	-0.941	-0.837
	(0.425)	(0.434)	(0.448)	(0.451)	(0.448)	(0.450)	(0.442)	(0.445)	(0.436)	(0.438)	(0.431)	(0.432)	(0.425)	(0.428)	(0.430)	(0.445)	(0.430)	(0.503)
$log(DY)$	2.341◇	2.044◇	1.977◇	2.029◇	1.973◇	2.029◇	1.993◇	2.035◇	2.079◇	2.068◇	2.124◇	2.091◇	2.126◇	2.103◇	2.372◇	2.072◇	2.323◇	2.221◇
	(1.763)	(1.825)	(1.878)	(1.856)	(1.875)	(1.855)	(1.875)	(1.849)	(1.834)	(1.825)	(1.818)	(1.814)	(1.839)	(1.828)	(1.785)	(1.819)	(1.792)	(1.797)
CS	-0.264◇	-0.367◇	-0.340◇	-0.360◇	-0.340◇	-0.359◇	-0.343◇	-0.362◇	-0.368◇	-0.371◇	-0.369◇	-0.366◇	-0.370◇	-0.374◇	-0.237◇	-0.360◇	-0.245◇	-0.383◇
	(0.478)	(0.428)	(0.433)	(0.430)	(0.433)	(0.430)	(0.430)	(0.428)	(0.426)	(0.426)	(0.429)	(0.430)	(0.419)	(0.419)	(0.495)	(0.427)	(0.495)	(0.347)
TS	-0.306◇	-0.315◇	-0.311◇	-0.314◇	-0.310◇	-0.314◇	-0.312◇	-0.315◇	-0.315◇	-0.315◇	-0.314◇	-0.313◇	-0.317◇	-0.318◇	-0.231◇	-0.317◇	-0.251◇	-0.302◇
	(0.261)	(0.260)	(0.263)	(0.260)	(0.264)	(0.261)	(0.263)	(0.261)	(0.260)	(0.260)	(0.260)	(0.261)	(0.259)	(0.259)	(0.261)	(0.262)	(0.262)	(0.270)
VIX^2	0.008																	
	(0.003)																	
VRP_{RV}		0.013																
		(0.004)																
RV		0.007																
		(0.003)																
$VRP_{HAR_{RW}}$			0.013															
			(0.005)															
$CV_{HAR_{RW}}$			0.007															
			(0.004)															
$VRP_{HAR_{IW}}$				0.013														
				(0.005)														
$CV_{HAR_{IW}}$				0.007														
				(0.004)														
$VRP_{SHAR_{RW}}$					0.013													
					(0.004)													
$CV_{SHAR_{RW}}$					0.007													
					(0.004)													
$VRP_{SHAR_{IW}}$						0.013												
						(0.004)												
$CV_{SHAR_{IW}}$						0.007												
						(0.004)												
$VRP_{NHAR_{RW}}$							0.013											
							(0.004)											
$CV_{NHAR_{RW}}$							0.007											
							(0.004)											
$VRP_{NHAR_{IW}}$								0.013										
								(0.004)										
$CV_{NHAR_{IW}}$								0.007										
								(0.004)										
$VRP_{HARQ_{RW}}$									0.013									
									(0.005)									
$CV_{HARQ_{RW}}$									0.007									
									(0.003)									
$VRP_{HARQ_{IW}}$										0.014								
										(0.005)								
$CV_{HARQ_{IW}}$										0.007								
										(0.003)								
$VRP_{SHARQ_{RW}}$											0.013							
											(0.005)							
$CV_{SHARQ_{RW}}$											0.007							
											(0.003)							
$VRP_{SHARQ_{IW}}$												0.013						
												(0.005)						
$CV_{SHARQ_{IW}}$												0.007						
												(0.003)						
$VRP_{NHARQ_{RW}}$													0.013					
													(0.005)					
$CV_{NHARQ_{RW}}$													0.008					
													(0.003)					
$VRP_{NHARQ_{IW}}$														0.013				
														(0.005)				
$CV_{NHARQ_{IW}}$														0.008				
														(0.003)				
$VRP_{tv-SHARQ_{RW}}$															0.007			
															(0.002)			
$CV_{tv-SHARQ_{RW}}$															0.008			
															(0.002)			
$VRP_{tv-SHARQ_{IW}}$																0.011		
																(0.004)		
$CV_{tv-SHARQ_{IW}}$																0.005◇		
																(0.004)		
$VRP_{tv-NHARQ_{RW}}$																	0.007	
																	(0.002)	
$CV_{tv-NHARQ_{RW}}$																	0.008	
																	(0.002)	
$VRP_{tv-NHARQ_{IW}}$																		0.010
																		(0.004)
$CV_{tv-NHARQ_{IW}}$																		0.005◇
																		(0.006)
Adj. R^2	0.330	0.341	0.342	0.343	0.342	0.343	0.340	0.342	0.338	0.340	0.336	0.337	0.333	0.335	0.344	0.339	0.344	0.330

At the 3-month horizon, the VRP is again a predictor of stock market returns, whereas the CV is not. However, the magnitude of the VRP's coefficients is higher in comparison with those of a more recent sample period and the predictability decreases. The best predictive regression, which is that with the NHARQ model predictors, has an R^2 of 0.324. In addition, regarding the set of extra predictors, we observe that the real 3-month rate and logarithm of the dividend yield are statistically significant, and that the log(DY) has expected positive coefficients.

Finally, at the 12-month horizon, in contrast to the previous sample period, the CV has no predictability, and the magnitude of the VRP's coefficients is larger. The best predictive regression is that where the regressors are obtained using the NHARQ model and IW scheme.

Moreover, the R^2 values before the crisis are higher than those obtained for the previous sample period and 12-month horizon. Among the potential predictors, only the real 3-month rate is statistically significant. The same evidence is obtained for the previous sample period.

The main conclusions drawn from the precrisis period compared with the postcrisis period are as follows: First, during the last financial crisis, CV gains predictive power at least at the 12-month horizon. Second, the predictability is higher at the 1- and 3-month horizons when the crisis and postcrisis periods are considered, whereas at the 12-month horizon it decreases. This does not occur in the precrisis period because the R^2 values increase with the horizon. Third, the NHARQ model predictors are effective at the 3- and 12-month horizons, whereas the time-varying coefficient NHARQ and SHARQ models are superior for the stock market return predictability in the sample, including the crisis and postcrisis periods, which suggests that a period of greater volatility requires models that can adapt quickly to turbulence. Finally, we believe that our results reinforce those reported by Bollerslev et al. (2009), and that we substantially increase the predictive power of the VRP by considering either net estimator of RV and time-varying coefficient models.

4.2 Predictability of economic activity

Some previous research stands that increases in volatility (uncertainty shocks) can be transmitted to the economic activity by leading to a quick deceleration of the aggregate output and an increase of unemployment (see, for example, Bloom, 2009; Bachmann et al., 2013). Therefore, as in Bekaer and Hoerova (2014), we use the VIX^2, VRP and CV measures proposed in this paper to study their performance when predicting the economic activity, which is proxied by industrial production growth.[8]

Some research states that increases in volatility (uncertainty shocks) can be transmitted to the economic activity by leading to a quick deceleration of the aggregate output and an increase in unemployment(see, for example, Bloom, 2009; Bachmann et al., 2013). Therefore, as in Bekaer and Hoerova (2014), we use the VIX^2, VRP, and CV measures to study their performance in predicting economic activity, which is proxied by industrial

[8]The industrial production growth is the log-difference of the total industrial production index (see Bekaer and Hoerova, 2014, for the use of the same proxy).

Table 6: Stock excess return regressions: Horizon 1 month (period 1990-2007).

Regressions (monthly observations) with variance risk premium, conditional variance, real 3-month rate, the logarithm of dividend yield, credit spread and term spread. The standard errors presented below the estimated parameters are the Newey-West standard errors using $max[3, 2 \cdot horizon]$ lags. ◊ means that the variable is not significant at any relevant level (1%, 5% and 10%) of significance.

	Panel A: Parametric and semiparametric measures of VRP and CV										
Constant	0.426◊	0.208◊	0.153◊	0.098◊	0.096◊	0.277◊	0.376◊	-0.241◊	-0.368◊	0.280◊	-0.277◊
	(2.046)	(2.075)	(2.077)	(2.063)	(2.075)	(2.087)	(2.085)	(2.376)	(2.043)	(2.090)	(2.248)
$R3MT$	-1.342	-1.299	-1.289	-1.275	-1.271	-1.331	-1.333	-1.200	-1.132	-1.316	-1.202
	(0.379)	(0.382)	(0.381)	(0.377)	(0.379)	(0.386)	(0.385)	(0.404)	(0.347)	(0.370)	(0.386)
$log(DY)$	2.324◊	2.431◊	2.422◊	2.511◊	2.441◊	2.461◊	2.341◊	2.527◊	2.931◊	2.580◊	2.584◊
	(1.727)	(1.704)	(1.694)	(1.707)	(1.676)	(1.732)	(1.722)	(1.723)	(1.710)	(1.722)	(1.679)
CS	-0.644◊	-0.731◊	-0.741◊	-0.826◊	-0.798◊	-0.618◊	-0.635◊	-1.035◊	-0.491◊	-0.453◊	-1.005◊
	(1.653)	(1.669)	(1.674)	(1.671)	(1.682)	(1.639)	(1.653)	(1.623)	(1.664)	(1.692)	(1.660)
TS	-0.478◊	-0.429◊	-0.414◊	-0.403◊	-0.395◊	-0.450◊	-0.454◊	-0.321◊	-0.359◊	-0.470◊	-0.331◊
	(0.429)	(0.434)	(0.431)	(0.433)	(0.431)	(0.430)	(0.429)	(0.473)	(0.420)	(0.438)	(0.457)
VRP_{RV}	0.062										
	(0.024)										
RV	-0.027◊										
	(0.046)										
$VRP_{HARQ_{RW}}$		0.054									
		(0.025)									
$CV_{HARQ_{RW}}$		-0.003◊									
		(0.052)									
$VRP_{HARQ_{IW}}$			0.052								
			(0.025)								
$CV_{HARQ_{IW}}$			0.002◊								
			(0.052)								
$VRP_{SHARQ_{RW}}$				0.049							
				(0.024)							
$CV_{SHARQ_{RW}}$				0.011◊							
				(0.050)							
$VRP_{SHARQ_{IW}}$					0.049						
					(0.025)						
$CV_{SHARQ_{IW}}$					0.011◊						
					(0.053)						
$VRP_{NHARQ_{RW}}$						0.057					
						(0.023)					
$CV_{NHARQ_{RW}}$						-0.025◊					
						(0.054)					
$VRP_{NHARQ_{IW}}$							0.059				
							(0.023)				
$CV_{NHARQ_{IW}}$							-0.023◊				
							(0.051)				
$VRP_{tv-SHARQ_{RW}}$								0.041			
								(0.017)			
$CV_{tv-SHARQ_{RW}}$								0.047◊			
								(0.036)			
$VRP_{tv-SHARQ_{IW}}$									0.058		
									(0.019)		
$CV_{tv-SHARQ_{IW}}$									-0.353◊		
									(0.308)		
$VRP_{tv-NHARQ_{RW}}$										0.043	
										(0.017)	
$CV_{tv-NHARQ_{RW}}$										-0.011◊	
										(0.050)	
$VRP_{tv-NHARQ_{IW}}$											0.039◊
											(0.026)
$CV_{tv-NHARQ_{IW}}$											0.074◊
											(0.308)
Adj. R^2	0.158	0.152	0.152	0.151	0.151	0.155	0.155	0.149	0.159	0.154	0.149

Table 7: Stock excess return regressions: Horizon 3 months (period 1990-2007).

Regressions (monthly observations) with variance risk premium, conditional variance, real 3-month rate, the logarithm of dividend yield, credit spread and term spread. The standard errors presented below the estimated parameters are the Newey-West standard errors using $max[3, 2 \cdot horizon]$ lags. ◊ means that the variable is not significant at any relevant level (1%, 5% and 10%) of significance.

	Panel A: Parametric and semiparametric measures of VRP and CV										
Constant	0.018◊	0.076◊	0.079◊	0.122◊	0.090◊	0.197◊	0.224◊	-0.768◊	-0.219◊	-0.100◊	-0.697◊
	(1.866)	(1.877)	(1.882)	(1.875)	(1.890)	(1.864)	(1.894)	(1.974)	(1.850)	(1.853)	(2.107)
$R3MT$	-1.294	-1.309	-1.311	-1.319	-1.309	-1.351	-1.338	-1.128	-1.234	-1.269	-1.180
	(0.354)	(0.361)	(0.362)	(0.361)	(0.360)	(0.367)	(0.366)	(0.356)	(0.327)	(0.341)	(0.363)
$log(DY)$	2.744	2.725	2.694	2.754	2.683	2.723	2.634	2.594	2.936	2.852	2.906
	(1.614)	(1.614)	(1.607)	(1.631)	(1.603)	(1.646)	(1.621)	(1.614)	(1.678)	(1.630)	(1.597)
CS	-1.296◊	-1.230◊	-1.199◊	-1.221◊	-1.207◊	-1.077◊	-1.134◊	-1.755◊	-1.301◊	-1.342◊	-1.534
	(1.670)	(1.672)	(1.667)	(1.667)	(1.663)	(1.671)	(1.652)	(1.690)	(1.654)	(1.736)	(1.652)
TS	-0.402◊	-0.416◊	-0.415◊	-0.426◊	-0.410◊	-0.448◊	-0.437◊	-0.202◊	-0.365◊	-0.381◊	-0.298◊
	(0.387)	(0.392)	(0.392)	(0.392)	(0.390)	(0.393)	(0.394)	(0.406)	(0.374)	(0.376)	(0.387)
VRP_{RV}	0.061										
	0.015										
RV	0.029◊										
	(0.030)										
$VRP_{HARQ_{RW}}$		0.063									
		(0.016)									
$CV_{HARQ_{RW}}$		0.020◊									
		(0.038)									
$VRP_{HARQ_{IW}}$			0.064								
			(0.017)								
$CV_{HARQ_{IW}}$			0.017◊								
			(0.039)								
$VRP_{SHARQ_{RW}}$				0.063							
				(0.016)							
$CV_{SHARQ_{RW}}$				0.015◊							
				(0.039)							
$VRP_{SHARQ_{IW}}$					0.063						
					(0.017)						
$CV_{SHARQ_{IW}}$					0.018◊						
					(0.039)						
$VRP_{NHARQ_{RW}}$						0.068					
						(0.016)					
$CV_{NHARQ_{RW}}$						-0.009◊					
						(0.049)					
$VRP_{NHARQ_{IW}}$							0.068				
							(0.017)				
$CV_{NHARQ_{IW}}$							0.001◊				
							(0.042)				
$VRP_{tv-SHARQ_{RW}}$								0.055			
								(0.011)			
$CV_{tv-SHARQ_{RW}}$								0.088			
								(0.030)			
$VRP_{tv-SHARQ_{IW}}$									0.058		
									(0.014)		
$CV_{tv-SHARQ_{IW}}$									-0.042◊		
									(0.135)		
$VRP_{tv-NHARQ_{RW}}$										0.054	
										(0.011)	
$CV_{tv-NHARQ_{RW}}$										0.046◊	
										(0.037)	
$VRP_{tv-NHARQ_{IW}}$											0.048
											(0.015)
$CV_{tv-NHARQ_{IW}}$											0.180◊
											(0.177)
Adj. R^2	0.318	0.319	0.319	0.320	0.319	0.324	0.323	0.321	0.317	0.316	0.318

Table 8: Stock excess return regressions: Horizon 12 months (period 1990-2007).

Regressions (monthly observations) with variance risk premium, conditional variance, real 3-month rate, the logarithm of dividend yield, credit spread and term spread. The standard errors presented below the estimated parameters are the Newey-West standard errors using $max[3, 2 \cdot horizon]$ lags. ◊ means that the variable is not significant at any relevant level (1%, 5% and 10%) of significance.

	Panel A: Parametric and semiparametric measures of VRP and CV										
Constant	-2.170◊	-2.106◊	-2.091◊	-2.093◊	-2.048◊	-2.181◊	-2.028◊	-2.631◊	-2.509	-2.582	-2.742
	(1.342)	(1.358)	(1.356)	(1.382)	(1.363)	(1.337)	(1.374)	(1.680)	(1.294)	(1.414)	(1.422)
$R3MT$	-0.904	-0.922	-0.930	-0.926	-0.928	-0.922	-0.935	-0.805	-0.830	-0.814	-0.799
	(0.279)	(0.282)	(0.279)	(0.288)	(0.279)	(0.288)	(0.281)	(0.322)	(0.266)	(0.292)	(0.332)
$log(DY)$	1.290◊	1.268◊	1.211◊	1.354◊	1.166◊	1.375◊	1.207◊	1.513◊	1.574◊	1.569◊	1.595◊
	(1.265)	(1.258)	(1.240)	(1.261)	(1.251)	(1.269)	(1.238)	(1.444)	(1.408)	(1.364)	(1.339)
CS	1.018◊	1.127◊	1.191◊	1.093◊	1.202◊	1.137◊	1.162◊	0.691◊	0.771◊	0.660◊	0.712◊
	(1.032)	(1.000)	(0.992)	(1.006)	(0.984)	(1.003)	(1.000)	(0.984)	(1.070)	(1.031)	(1.128)
TS	-0.141◊	-0.157◊	-0.157◊	-0.161◊	-0.153◊	-0.148◊	-0.158◊	-0.049◊	-0.083◊	-0.062◊	-0.056◊
	(0.203)	(0.207)	(0.205)	(0.212)	(0.205)	(0.209)	(0.205)	(0.257)	(0.193)	(0.216)	(0.229)
VRP_{RV}	0.050										
	(0.014)										
RV	-0.021◊										
	(0.041)										
$VRP_{HARQ_{RW}}$		0.052									
		(0.015)									
$CV_{HARQ_{RW}}$		-0.033◊									
		(0.052)									
$VRP_{HARQ_{IW}}$			0.054								
			(0.016)								
$CV_{HARQ_{IW}}$			-0.038◊								
			(0.054)								
$VRP_{SHARQ_{RW}}$				0.050							
				(0.015)							
$CV_{SHARQ_{RW}}$				-0.032◊							
				(0.055)							
$VRP_{SHARQ_{IW}}$					0.053						
					(0.015)						
$CV_{SHARQ_{IW}}$					-0.040◊						
					(0.054)						
$VRP_{NHARQ_{RW}}$						0.049					
						(0.014)					
$CV_{NHARQ_{RW}}$						-0.035◊					
						(0.056)					
$VRP_{NHARQ_{IW}}$							0.054				
							(0.015)				
$CV_{NHARQ_{IW}}$							-0.042◊				
							(0.053)				
$VRP_{tv-SHARQ_{RW}}$								0.034			
								(0.004)			
$CV_{tv-SHARQ_{RW}}$								0.041			
								(0.024)			
$VRP_{tv-SHARQ_{IW}}$									0.034		
									(0.006)		
$CV_{tv-SHARQ_{IW}}$									0.025◊		
									(0.072)		
$VRP_{tv-NHARQ_{RW}}$										0.033	
										(0.004)	
$CV_{tv-NHARQ_{RW}}$										0.044	
										(0.015)	
$VRP_{tv-NHARQ_{IW}}$											0.031
											(0.008)
$CV_{tv-NHARQ_{IW}}$											0.091◊
											(0.117)
Adj. R^2	0.552	0.555	0.559	0.553	0.558	0.553	0.560	0.532	0.532	0.533	0.533

production growth.[9]

Tables 9–11 indicate the results of industrial production regressions. The first notable result is that the VIX^2 is a predictor of economic activity at all considered horizons, with a negative sign. At the 1-month horizon, both the VRP and CV are predictors of future economic activity with negative coefficients. Moreover, the regression that achieves the highest predictive power includes the VRP and CV obtained with the tv-SHARQ model. The coefficient of CV is the lowest in absolute value of all regressions, and the adjusted R^2 is 0.250. Conclusions for the 3-month horizon differ slightly. Although CV remains a predictor of economic predictability, the VRP does not in the most predictive regression, whose regressors are obtained with the HARQ model and rolling window scheme. The signs of the relationships are maintained. Finally, regarding the 12-month horizon, we observe again that only CV is a predictor of economic activity, the sign of its coefficients is still negative, and the best predictor is from the tv-NHARQ model; furthermore, the predictability for this horizon seems to decrease because the adjusted R^2 values are smaller than those for previous horizons (Table 11). Similar results are obtained by Bekaer and Hoerova (2014).

Overall, we conclude that CV predicts future economic activity at all horizons, whereas the VRP predicts it only at the 1-month horizon.

4.3 Predictability of financial instability

A stable financial system can allocate resources efficiently to access and manage financial risks, maintain a high level of employment in the economy, and eliminate relative price movements of real or financial assets that will affect monetary stability. Therefore, monitoring financial instability is of great interest. We use as a proxy of financial instability the CISS indicator, which is an indicator of financial stress provided by the European Monetary Union (see Bekaer and Hoerova, 2014, for the use of the same indicator).

Tables 12–14 show results of the predictability of financial instability using the proposed measures of the VRP and CV, as well as the values of the CISS indicator for 1-, 3-, and 12-month horizons; the VRP and CV accurately predict financial instability at all three horizons. The highest adjusted R^2 values of 0.554, 0.481, and 0.244 are obtained using the tv-NHARQ estimators of the VRP and CV for the 1-, 3-, and 12-month horizons, respectively. As expected, the relationship between predictors and financial instability is always positive.

[9]The industrial production growth is the log-difference of the total industrial production index (see Bekaer and Hoerova, 2014, for the use of the same proxy).

Table 9: Industrial production regressions: Horizon 1 month.

Regressions (monthly observations) with variance risk premium and conditional variance. The standard errors presented below the estimated parameters are the Newey-West standard errors using $max[3, 2 \cdot horizon]$ lags. ◇ means that the variable is not significant at any relevant level (1%, 5% and 10%) of significance.

	Parametric and semiparametric measures of VRP and CV																	
Constant	0.377	0.421	0.407	0.400	0.409	0.402	0.413	0.406	0.414	0.411	0.418	0.417	0.423	0.419	0.362	0.391	0.369	0.369
	(0.096)	(0.104)	(0.104)	(0.105)	(0.103)	(0.104)	(0.102)	(0.103)	(0.108)	(0.110)	(0.109)	(0.110)	(0.106)	(0.107)	(0.103)	(0.094)	(0.101)	(0.095)
VIX^2	-0.007																	
	(0.001)																	
VRP_{RV}		-0.010																
		(0.003)																
RV		-0.007																
		(0.001)																
$VRP_{HAR_{RW}}$			-0.009															
			(0.003)															
$CV_{HAR_{RW}}$			-0.007															
			(0.001)															
$VRP_{HAR_{IW}}$				-0.009														
				(0.003)														
$CV_{HAR_{IW}}$				-0.007														
				(0.001)														
$VRP_{SHAR_{RW}}$					-0.009													
					(0.003)													
$CV_{SHAR_{RW}}$					-0.007													
					(0.001)													
$VRP_{SHAR_{IW}}$						-0.009												
						(0.003)												
$CV_{SHAR_{IW}}$						-0.007												
						(0.001)												
$VRP_{NHAR_{RW}}$							-0.010											
							(0.003)											
$CV_{NHAR_{RW}}$							-0.007											
							(0.001)											
$VRP_{NHAR_{IW}}$								-0.009										
								(0.003)										
$CV_{NHAR_{IW}}$								-0.007										
								(0.001)										
$VRP_{HARQ_{RW}}$									-0.010									
									(0.004)									
$CV_{HARQ_{RW}}$									-0.007									
									(0.001)									
$VRP_{HARQ_{IW}}$										-0.009								
										(0.004)								
$CV_{HARQ_{IW}}$										-0.007								
										(0.001)								
$VRP_{SHARQ_{RW}}$											-0.010							
											(0.003)							
$CV_{SHARQ_{RW}}$											-0.007							
											(0.001)							
$VRP_{SHARQ_{IW}}$												-0.010						
												(0.004)						
$CV_{SHARQ_{IW}}$												-0.007						
												(0.001)						
$VRP_{NHARQ_{RW}}$													-0.010					
													(0.003)					
$CV_{NHARQ_{RW}}$													-0.007					
													(0.001)					
$VRP_{NHARQ_{IW}}$														-0.010				
														(0.003)				
$CV_{NHARQ_{IW}}$														-0.007				
														(0.001)				
$VRP_{tv-SHARQ_{RW}}$															-0.008			
															(0.001)			
$CV_{tv-SHARQ_{RW}}$															-0.007			
															(0.001)			
$VRP_{tv-SHARQ_{IW}}$																-0.009		
																(0.002)		
$CV_{tv-SHARQ_{IW}}$																-0.005		
																(0.001)		
$VRP_{tv-NHARQ_{RW}}$																	-0.007	
																	(0.001)	
$CV_{tv-NHARQ_{RW}}$																	-0.007	
																	(0.001)	
$VRP_{tv-NHARQ_{IW}}$																		-0.007
																		(0.002)
$CV_{tv-NHARQ_{IW}}$																		-0.008
																		(0.002)
Adj. R^2	0.246	0.245	0.241	0.240	0.242	0.240	0.244	0.242	0.242	0.241	0.243	0.243	0.245	0.244	0.240	0.250	0.239	0.238

Table 10: Industrial production regressions: Horizon 3 months.

Regressions (monthly observations) with variance risk premium and conditional variance. The standard errors presented below the estimated parameters are the Newey-West standard errors using $max[3, 2 \cdot horizon]$ lags. ◇ means that the variable is not significant at any relevant level (1%, 5% and 10%) of significance.

	Parametric and semiparametric measures of VRP and CV																	
Constant	0.373	0.308	0.320	0.315	0.322	0.318	0.324	0.319	0.310	0.306	0.314	0.312	0.312	0.308	0.384	0.363	0.377	0.347
	(0.078)	(0.087)	(0.085)	(0.085)	(0.085)	(0.085)	(0.084)	(0.084)	(0.087)	(0.088)	(0.087)	(0.088)	(0.086)	(0.088)	(0.084)	(0.079)	(0.082)	(0.080)
VIX^2	-0.007																	
	(0.001)																	
VRP_{RV}		-0.003◇																
		(0.003)																
RV		-0.008																
		(0.001)																
$VRP_{HAR_{RW}}$			-0.004◇															
			(0.003)															
$CV_{HAR_{RW}}$			-0.008															
			(0.001)															
$VRP_{HAR_{IW}}$				-0.003◇														
				(0.003)														
$CV_{HAR_{IW}}$				-0.008														
				(0.001)														
$VRP_{SHAR_{RW}}$					-0.004◇													
					(0.003)													
$CV_{SHAR_{RW}}$					-0.008													
					(0.001)													
$VRP_{SHAR_{IW}}$						-0.003◇												
						(0.003)												
$CV_{SHAR_{IW}}$						-0.008												
						(0.001)												
$VRP_{NHAR_{RW}}$							-0.004◇											
							(0.003)											
$CV_{NHAR_{RW}}$							-0.008											
							(0.001)											
$VRP_{NHAR_{IW}}$								-0.004◇										
								(0.003)										
$CV_{NHAR_{IW}}$								-0.008										
								(0.001)										
$VRP_{HARQ_{RW}}$									-0.003◇									
									(0.003)									
$CV_{HARQ_{RW}}$									-0.008									
									(0.001)									
$VRP_{HARQ_{IW}}$										-0.003◇								
										(0.003)								
$CV_{HARQ_{IW}}$										-0.008								
										(0.001)								
$VRP_{SHARQ_{RW}}$											-0.003◇							
											(0.003)							
$CV_{SHARQ_{RW}}$											-0.008							
											(0.001)							
$VRP_{SHARQ_{IW}}$												-0.003◇						
												(0.003)						
$CV_{SHARQ_{IW}}$												-0.008						
												(0.001)						
$VRP_{NHARQ_{RW}}$													-0.003◇					
													(0.003)					
$CV_{NHARQ_{RW}}$													-0.008					
													(0.001)					
$VRP_{NHARQ_{IW}}$														-0.003◇				
														(0.003)				
$CV_{NHARQ_{IW}}$														-0.008				
														(0.001)				
$VRP_{tv-SHARQ_{RW}}$															-0.007			
															(0.001)			
$CV_{tv-SHARQ_{RW}}$															-0.007			
															(0.001)			
$VRP_{tv-SHARQ_{IW}}$																-0.005		
																(0.002)		
$CV_{tv-SHARQ_{IW}}$																-0.009		
																(0.000)		
$VRP_{tv-NHARQ_{RW}}$																	-0.007	
																	(0.001)	
$CV_{tv-NHARQ_{RW}}$																	-0.007	
																	(0.001)	
$VRP_{tv-NHARQ_{IW}}$																		-0.005
																		(0.002)
$CV_{tv-NHARQ_{IW}}$																		-0.010
																		(0.002)
Adj. R^2	0.460	0.492	0.481	0.488	0.480	0.486	0.481	0.487	0.486	0.489	0.481	0.483	0.483	0.488	0.458	0.468	0.455	0.483

Table 11: Industrial production regressions: Horizon 12 months.

Regressions (monthly observations) with variance risk premium and conditional variance. The standard errors presented below the estimated parameters are the Newey-West standard errors using $max[3, 2 \cdot horizon]$ lags. ◇ means that the variable is not significant at any relevant level (1%, 5% and 10%) of significance.

	Parametric and semiparametric measures of VRP and CV																	
Constant	0.217 (0.076	0.160 (0.070)	0.168 (0.071)	0.165 (0.070)	0.170 (0.071)	0.167 (0.070)	0.172 (0.071)	0.169 (0.070)	0.159 (0.070)	0.157 (0.071)	0.162 (0.071)	0.161 (0.072)	0.160 (0.070)	0.157 (0.070)	0.225 (0.083)	0.206 (0.072)	0.220 (0.080)	0.190 (0.067)
VIX^2	-0.0014 (0.0006)																	
VRP_{RV}		0.0017◇ (0.0011)																
RV		-0.0024 (0.0003)																
$VRP_{HAR_{RW}}$			0.0015◇ (0.0010)															
$CV_{HAR_{RW}}$			-0.0023 (0.0003)															
$VRP_{HAR_{IW}}$				0.0016◇ (0.0011)														
$CV_{HAR_{IW}}$				-0.0023 (0.0003)														
$VRP_{SHAR_{RW}}$					0.0014◇ (0.0010)													
$CV_{SHAR_{RW}}$					-0.0022 (0.0003)													
$VRP_{SHAR_{IW}}$						0.0015◇ (0.0011)												
$CV_{SHAR_{IW}}$						-0.0022 (0.0003)												
$VRP_{NHAR_{RW}}$							0.0013◇ (0.0010)											
$CV_{NHAR_{RW}}$							-0.0022 (0.0003)											
$VRP_{NHAR_{IW}}$								0.0014◇ (0.0011)										
$CV_{NHAR_{IW}}$								-0.0022 (0.0003)										
$VRP_{HARQ_{RW}}$									0.0019 (0.0011)									
$CV_{HARQ_{RW}}$									-0.0024 (0.0003)									
$VRP_{HARQ_{IW}}$										0.0019 (0.0012)								
$CV_{HARQ_{IW}}$										-0.0024 (0.0003)								
$VRP_{SHARQ_{RW}}$											0.0017◇ (0.0011)							
$CV_{SHARQ_{RW}}$											-0.0023 (0.0003)							
$VRP_{SHARQ_{IW}}$												0.0017◇ (0.0011)						
$CV_{SHARQ_{IW}}$												-0.0023 (0.0003)						
$VRP_{NHARQ_{RW}}$													0.0019◇ (0.0012)					
$CV_{NHARQ_{RW}}$													-0.0023 (0.0003)					
$VRP_{NHARQ_{IW}}$														0.0019◇ (0.0012)				
$CV_{NHARQ_{IW}}$														-0.0023 (0.0003)				
$VRP_{tv-SHARQ_{RW}}$															-0.0014 (0.0006)			
$CV_{tv-SHARQ_{RW}}$															-0.0016 (0.0008)			
$VRP_{tv-SHARQ_{IW}}$																-0.0002◇ (0.0008)		
$CV_{tv-SHARQ_{IW}}$																-0.0033 (0.0003)		
$VRP_{tv-NHARQ_{RW}}$																	-0.0014 (0.0006)	
$CV_{tv-NHARQ_{RW}}$																	-0.0015 (0.0007)	
$VRP_{tv-NHARQ_{IW}}$																		0.0003◇ (0.0007)
$CV_{tv-NHARQ_{IW}}$																		-0.0049 (0.0004)
Adj. R^2	0.083	0.195	0.176	0.187	0.172	0.183	0.175	0.185	0.186	0.188	0.173	0.172	0.184	0.187	0.078	0.134	0.073	0.209

Table 12: Financial instability regressions: Horizon 1 month.

Regressions (monthly observations) with variance risk premium and conditional variance. The standard errors presented below the estimated parameters are the Newey-West standard errors using $max[3, 2 \cdot horizon]$ lags. ◇ means that the variable is not significant at any relevant level (1%, 5% and 10%) of significance.

	Parametric and semiparametric measures of VRP and CV																	
Constant	4.154	3.972	3.897	3.877	3.905	3.885	3.943	3.925	3.890	3.895	3.897	3.914	3.898	3.914	4.298	4.099	4.258	3.967
	(0.453)	(0.500)	(0.480)	(0.480)	(0.479)	(0.479)	(0.479)	(0.480)	(0.498)	(0.497)	(0.500)	(0.498)	(0.494)	(0.492)	(0.464)	(0.437)	(0.460)	(0.391)
VIX^2	0.038																	
	(0.007)																	
VRP_{RV}		0.048																
		(0.011)																
RV		0.035																
		(0.005)																
$VRP_{HAR_{RW}}$			0.053															
			(0.011)															
$CV_{HAR_{RW}}$			0.033															
			(0.004)															
$VRP_{HAR_{IW}}$				0.055														
				(0.012)														
$CV_{HAR_{IW}}$				0.033														
				(0.004)														
$VRP_{SHAR_{RW}}$					0.053													
					(0.011)													
$CV_{SHAR_{RW}}$					0.034													
					(0.004)													
$VRP_{SHAR_{IW}}$						0.054												
						(0.012)												
$CV_{SHAR_{IW}}$						0.033												
						(0.004)												
$VRP_{NHAR_{RW}}$							0.051											
							(0.011)											
$CV_{NHAR_{RW}}$							0.034											
							(0.004)											
$VRP_{NHAR_{IW}}$								0.052										
								(0.011)										
$CV_{NHAR_{IW}}$								0.034										
								(0.004)										
$VRP_{HARQ_{RW}}$									0.053									
									(0.012)									
$CV_{HARQ_{RW}}$									0.033									
									(0.004)									
$VRP_{HARQ_{IW}}$										0.053								
										(0.012)								
$CV_{HARQ_{IW}}$										0.033								
										(0.004)								
$VRP_{SHARQ_{RW}}$											0.053							
											(0.012)							
$CV_{SHARQ_{RW}}$											0.033							
											(0.004)							
$VRP_{SHARQ_{IW}}$												0.052						
												(0.012)						
$CV_{SHARQ_{IW}}$												0.034						
												(0.005)						
$VRP_{NHARQ_{RW}}$													0.053					
													(0.012)					
$CV_{NHARQ_{RW}}$													0.034					
													(0.004)					
$VRP_{NHARQ_{IW}}$														0.052				
														(0.011)				
$CV_{NHARQ_{IW}}$														0.034				
														(0.005)				
$VRP_{tv-SHARQ_{RW}}$															0.039			
															(0.006)			
$CV_{tv-SHARQ_{RW}}$															0.034			
															(0.007)			
$VRP_{tv-SHARQ_{IW}}$																0.045		
																(0.009)		
$CV_{tv-SHARQ_{IW}}$																0.027		
																(0.002)		
$VRP_{tv-NHARQ_{RW}}$																	0.038	
																	(0.006)	
$CV_{tv-NHARQ_{RW}}$																	0.036	
																	(0.007)	
$VRP_{tv-NHARQ_{IW}}$																		0.050
																		(0.007)
$CV_{tv-NHARQ_{IW}}$																		0.012
																		(0.004)
Adj. R^2	0.505	0.510	0.522	0.526	0.521	0.526	0.517	0.521	0.518	0.517	0.517	0.515	0.517	0.515	0.519	0.514	0.516	0.554

Table 13: Financial instability regressions: Horizon 3 months.

Regressions (monthly observations) with variance risk premium and conditional variance. The standard errors presented below the estimated parameters are the Newey-West standard errors using $max[3, 2 \cdot horizon]$ lags. ◊ means that the variable is not significant at any relevant level (1%, 5% and 10%) of significance.

	Parametric and semiparametric measures of VRP and CV																	
Constant	4.246 (0.576)	4.123 (0.630)	4.071 (0.611)	4.048 (0.612)	4.077 (0.609)	4.053 (0.610)	4.103 (0.610)	4.082 (0.611)	4.057 (0.631)	4.061 (0.630)	4.058 (0.632)	4.075 (0.629)	4.054 (0.630)	4.067 (0.627)	4.377 (0.599)	4.204 (0.569)	4.336 (0.591)	4.098 (0.538)
VIX^2	0.034 (0.006)																	
VRP_{RV}		0.041 (0.010)																
RV		0.032 (0.004)																
$VRP_{HAR_{RW}}$			0.044 (0.010)															
$CV_{HAR_{RW}}$			0.031 (0.004)															
$VRP_{HAR_{IW}}$				0.046 (0.011)														
$CV_{HAR_{IW}}$				0.030 (0.003)														
$VRP_{SHAR_{RW}}$					0.044 (0.010)													
$CV_{SHAR_{RW}}$					0.031 (0.004)													
$VRP_{SHAR_{IW}}$						0.045 (0.011)												
$CV_{SHAR_{IW}}$						0.031 (0.003)												
$VRP_{NHAR_{RW}}$							0.042 (0.010)											
$CV_{NHAR_{RW}}$							0.031 (0.004)											
$VRP_{NHAR_{IW}}$								0.044 (0.010)										
$CV_{NHAR_{IW}}$								0.031 (0.004)										
$VRP_{HARQ_{RW}}$									0.045 (0.011)									
$CV_{HARQ_{RW}}$									0.030 (0.003)									
$VRP_{HARQ_{IW}}$										0.045 (0.011)								
$CV_{HARQ_{IW}}$										0.031 (0.004)								
$VRP_{SHARQ_{RW}}$											0.045 (0.011)							
$CV_{SHARQ_{RW}}$											0.031 (0.004)							
$VRP_{SHARQ_{IW}}$												0.044 (0.011)						
$CV_{SHARQ_{IW}}$												0.031 (0.004)						
$VRP_{NHARQ_{RW}}$													0.045 (0.011)					
$CV_{NHARQ_{RW}}$													0.031 (0.004)					
$VRP_{NHARQ_{IW}}$														0.044 (0.011)				
$CV_{NHARQ_{IW}}$														0.031 (0.004)				
$VRP_{tv-SHARQ_{RW}}$															0.035 (0.005)			
$CV_{tv-SHARQ_{RW}}$															0.030 (0.006)			
$VRP_{tv-SHARQ_{IW}}$																0.039 (0.008)		
$CV_{tv-SHARQ_{IW}}$																0.026 (0.002)		
$VRP_{tv-NHARQ_{RW}}$																	0.034 (0.005)	
$CV_{tv-NHARQ_{RW}}$																	0.032 (0.006)	
$VRP_{tv-NHARQ_{IW}}$																		0.043 (0.007)
$CV_{tv-NHARQ_{IW}}$																		0.014 (0.004)
Adj. R^2	0.451	0.45	0.457	0.46	0.456	0.46	0.454	0.457	0.456	0.455	0.456	0.454	0.456	0.455	0.463	0.454	0.459	0.481

Table 14: Financial instability regressions: Horizon 12 months.

Regressions (monthly observations) with variance risk premium and conditional variance. The standard errors presented below the estimated parameters are the Newey-West standard errors using $max[3, 2 \cdot horizon]$ lags. ◇ means that the variable is not significant at any relevant level (1%, 5% and 10%) of significance.

	Parametric and semiparametric measures of VRP and CV																	
Constant	4.618	4.601	4.586	4.556	4.590	4.560	4.598	4.573	4.566	4.567	4.559	4.576	4.560	4.566	4.747	4.607	4.705	4.568
	(0.904)	(0.991)	(0.984)	(0.985)	(0.982)	(0.982)	(0.978)	(0.979)	(0.999)	(1.000)	(0.996)	(0.995)	(1.000)	(1.000)	(0.903)	(0.923)	(0.913)	(0.932)
VIX^2	0.018																	
	(0.006)																	
VRP_{RV}		0.019																
		(0.012)																
RV		0.018																
		(0.004)																
$VRP_{HAR_{RW}}$			0.020															
			(0.012)															
$CV_{HAR_{RW}}$			0.017															
			(0.004)															
$VRP_{HAR_{IW}}$				0.021														
				(0.013)														
$CV_{HAR_{IW}}$				0.017														
				(0.004)														
$VRP_{SHAR_{RW}}$					0.020													
					(0.012)													
$CV_{SHAR_{RW}}$					0.017													
					(0.004)													
$VRP_{SHAR_{IW}}$						0.021												
						(0.013)												
$CV_{SHAR_{IW}}$						0.017												
						(0.004)												
$VRP_{NHAR_{RW}}$							0.019											
							(0.011)											
$CV_{NHAR_{RW}}$							0.018											
							(0.004)											
$VRP_{NHAR_{IW}}$								0.020										
								(0.012)										
$CV_{NHAR_{IW}}$								0.017										
								(0.004)										
$VRP_{HARQ_{RW}}$									0.021									
									(0.014)									
$CV_{HARQ_{RW}}$									0.017									
									(0.004)									
$VRP_{HARQ_{IW}}$										0.021								
										(0.014)								
$CV_{HARQ_{IW}}$										0.017								
										(0.004)								
$VRP_{SHARQ_{RW}}$											0.021							
											(0.013)							
$CV_{SHARQ_{RW}}$											0.017							
											(0.004)							
$VRP_{SHARQ_{IW}}$												0.020						
												(0.013)						
$CV_{SHARQ_{IW}}$												0.017						
												(0.004)						
$VRP_{NHARQ_{RW}}$													0.021					
													(0.014)					
$CV_{NHARQ_{RW}}$													0.017					
													(0.004)					
$VRP_{NHARQ_{IW}}$														0.021				
														(0.013)				
$CV_{NHARQ_{IW}}$														0.017				
														(0.004)				
$VRP_{tv-SHARQ_{RW}}$															0.019			
															(0.005)			
$CV_{tv-SHARQ_{RW}}$															0.014			
															(0.007)			
$VRP_{tv-SHARQ_{IW}}$																0.019		
																(0.009)		
$CV_{tv-SHARQ_{IW}}$																0.016		
																(0.002)		
$VRP_{tv-NHARQ_{RW}}$																	0.018	
																	(0.006)	
$CV_{tv-NHARQ_{RW}}$																	0.016	
																	(0.006)	
$VRP_{tv-NHARQ_{IW}}$																		0.021
																		(0.010)
$CV_{tv-NHARQ_{IW}}$																		0.012
																		(0.004)
Adj. R^2	0.231	0.222	0.222	0.224	0.222	0.224	0.222	0.223	0.223	0.223	0.224	0.223	0.224	0.223	0.224	0.223	0.244	0.229

5 Conclusions

We propose new parametric and semiparametric asymmetric extensions of the HAR model that consider how unsettling positive and negative returns are likely to be for the volatility and current investment decisions and allow the coefficients to be time varying.

Using the decomposition of VIX^2 into the equity VRP and CV of stock market returns, we test our specifications by analyzing the predictive power of the VRP and CV for future excess stock returns, economic activity, and financial instability. We observe that the VRP is a predictor of future excess stock returns for short, medium, and long horizons, for the periods before, during, and after the global financial crisis. Furthermore, both variables are predictors of financial instability at all horizons with positive coefficients. However, regarding the economic activity during and after the crisis, the VRP loses predictive power in favor of CV. CV is a predictor of the future economic activity at all horizons with a negative coefficient, whereas the VRP is a predictor only at the 1-month horizon.

In conclusion, the best model in terms of stock market return predictability varies depending on the sample period. During and after the global financial crisis, asymmetric time-varying coefficient models are often the most effective at predicting stock market returns. These models are more flexible and adapt quicker to changes in periods of high volatility. However, regarding the precrisis period, models using the NRV as a measure of asymmetry have the highest predictive ability for the stock market returns. Regarding financial instability predictions during and after the crisis, the same conclusion is drawn: the best forecasts of the VRP and CV are obtained using time-varying coefficient models.

Overall, asymmetric extensions of the HAR model, often with time-varying coefficients, are crucial for increasing the predictive power of the VRP, especially in the context of stock market returns and financial instability.

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