University of Pretoria
Department of Economics Working Paper Series

A Note on Investor Happiness and the Predictability of Realized Volatility of Gold

Matteo Bonato
University of Johannesburg and IPAG Business School
Konstantinos Gkillas
University of Patras – University Campus
Rangan Gupta
University of Pretoria
Christian Pierdzioch
Helmut Schmidt University
Working Paper: 2020-04
January 2020

Department of Economics
University of Pretoria
0002, Pretoria
South Africa
Tel: +27 12 420 2413

A Note on Investor Happiness and the Predictability of Realized Volatility of Gold

Matteo Bonato[a], Konstantinos Gkillas[b], Rangan Gupta[c], Christian Pierdzioch[d]

January 2020

Abstract

We apply the heterogeneous autoregressive realized volatility (HAR-RV) model to examine the importance of investor happiness in predicting the daily realized volatility of gold returns. We estimate daily realized volatility by employing intraday data providing both in-sample and out-of-sample predictions. Our in-sample results reveal that realized volatility is negatively linked to investor happiness. Moreover, our out-of-sample results show that extending the HAR-RV model to include investor happiness significantly improves the accuracy of forecasts of realized volatility at short- and medium-run forecast horizons.

JEL classification: G15; G17; Q02

Keywords: Investor Happiness; Gold; Realized Volatility; Forecasting

[a] Department of Economics and Econometrics, University of Johannesburg, Auckland Park, South Africa; IPAG Business School, 184 Boulevard Saint-Germain, 75006 Paris, France. Email address: matteobonato@gmail.com.

[b] Department of Business Administration, University of Patras – University Campus, Rio, P.O. Box 1391, 26500 Patras, Greece; Email address: gillask@upatras.gr.

[c] Department of Economics, University of Pretoria, Pretoria, 0002, South Africa; E-mail address: rangan.gupta@up.ac.za.

[d] Corresponding author. Department of Economics, Helmut Schmidt University, Holstenhofweg 85, P.O.B. 700822, 22008 Hamburg, Germany; Email address: c.pierdzioch@hsu-hh.de.

Acknowledgements:

The research of C. Pierdzioch was supported by the German Science Foundation (Project: Exploring the experience-expectation nexus in macroeconomic forecasting using computational text analysis and machine learning; Project number: 275693836).

1 Introduction

One of the main assumptions in financial models is investors' rationality and homogeneity which in turn do not allow any space for irrational behaviors in equity (asset) pricing. However, the growth of behavioral economics has resulted in researchers investigating the importance of investor sentiment in the prediction of first- and second-moment movements in equity markets (see e.g. Balcilar et al. 2018). Yet, investor sentiment is not directly measurable or observable. Traditionally, two routes have been taken for the measurement of investor sentiment (Bathia and Bredin 2013, Bathia et al. 2016). According to the first viewpoint, different market-based indicators can be used to measure investor sentiment (see Baker and Wurgler, 2006, 2007). Examples include trading volume, closed-end fund discount, initial public offering (IPO) first-day returns, IPO volume, option implied volatilities (VIX), or mutual fund flows, which can be used as proxies for investor sentiment. The second viewpoint encompasses survey-based indices (e.g. University of Michigan Consumer Sentiment Index, the UBS/GALLUP Index for Investor Optimism or investment newsletters). Da et al. (2015) proposed an investor-sentiment index by using Internet search data from millions of households in the US on a daily basis. In doing so, they used specific 'economic' keywords reflecting investor sentiment towards economic developments. A third approach has been put forward which extracts metrics of investor sentiment from news and contents of social media (see also Garcia 2013).

As noted by Da et al. (2015), an important limitation of market-based measures is that they turn out to be the equilibrium product of many economic forces and not of investor sentiment, despite their somewhat ready availability and relatively high frequency. Furthermore, in comparison with survey-based measures of investor sentiment, the search-based sentiment measure appears to confer an advantage with respect to frequency, in that it is of daily frequency contrary to survey-based measures which are mainly of monthly or quarterly frequency. It should also be mentioned that search-based measures display attitudes instead of investigating them; therefore, they are not that susceptible to measurement errors. Lastly, a search-based measure is not overshadowed by the preoccupation that it may be triggered by answers in survey data without undergoing any cross-verification with data on actual behavior by some kind of impartial external evaluation. Emphasizing these possible concerns, Da et al. (2015) argued that their method, and in general the third approach associated with the internet-based measure of investor sentiment, is less opaque than the other two alternative market- and survey-based approaches.

Building on this logic, a large number of recent studies have examined the impact of daily happiness index extracted from Twitter as a proxy for investor sentiment by analysing the predictability of returns and volatility of international equity markets (see, for example, Zhang et al. 2016, 2018, You et al. 2017, and Reboredo and Ugolini 2018). The appeal of this index emanates from the fact that it is global in nature, given the dominance of Twitter users in countries serving as major players in the global financial system. In light of this, one can argue that if the happiness index causes movements in equity markets, it should also be able to possess similar predictive ability for a global market, just like gold —a traditional safe haven (Baur and Lucey 2010, Baur and McDermott 2010), in which investors seek refuge due to its portfolio diversification benefits during periods of heightened general economic uncertainty and geopolitical risks (Bouoiyour et al. 2018, and Beckmann et al. 2019), which in turn is likely to result in weak investor sentiment, i.e., unhappiness (Zhang 2018).

Understandably, investors are interested in forecasting the volatility of gold returns in the pricing of related derivatives which is also important for hedging strategies. Naturally, a great number of studies have been conducted on gold volatility forecasting (see, Pierdzioch et al. 2016, and Fang et al. 2018 for detailed reviews). Generally, previous analyses mainly employed a great selection of models from the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) family; however, more recently, in many studies mixed-frequency and boosting approaches have been used so as to illuminate the role that a large number of macroeconomic and financial variables play as well as controlling for model uncertainty. Bearing in mind that rich information involved in intraday data leads to more precise estimates and forecasts of daily volatility for commodity markets, including gold (as highlighted by Asai et al. 2019, forthcoming, and Gkillas et al. 2019), we build on previous studies by forecasting the realized volatility (RV) of gold returns (derived based on 5- minute-interval intraday data) by employing a modified version of the Heterogeneous Autoregressive (HAR) model introduced by Corsi (2009). More specifically, we extend the basic HAR-RV model with information on investor sentiment as captured by the happiness index for the daily period spanning from 9th September, 2008 to 30th May, 2017. To our knowledge, this is the first paper to analyze the role of the happiness index in out-of-sample forecasting realized volatility of the gold market. The only related paper to our work is the study by Balcilar et al. (2017) who use a higher-order causality-in-quantiles test in order to analyze the in-sample predictability of Da et al.'s (2015) Financial and Economic Attitudes Revealed by Search (FEARS) index on gold returns and intraday volatility. While no significant sentiment effect is observed on daily gold returns, Balcilar et al. (2017) found that sentiment drives intraday volatility in the gold market. Campbell (2008) underscored that the ultimate test of any predictive model (with regard to the econometric methodologies and predictors employed) is in its out-of-sample performance, and hence, our analysis can be considered to be a robust extension of Balcilar et al. (2017), since in-sample predictability does not necessarily translate into out-of-sample forecasting gains.

We present the the we use in our empirical analysis in Section 2 and our data in Section 3. We summarize our empirical results in Section 4. We find that realized volatility is negatively linked to investor happiness in our in-sample analysis, while investor happiness significantly improves the accuracy of forecasts at short- and medium-run forecast horizons. In Sectio 5, we conclude the paper.

2 Methods

Following Andersen et al. (2012), we measure the daily realized volatility of gold returns with the use of the median realized variance (MRV) employing intraday data. MRV is a jump-robust estimator of integrated variance. [1] We compute MRV as follows:

$$MRV_t = \frac{\pi}{6-4\sqrt{3}+\pi} \frac{T}{T-2} \sum_{i=2}^{T-1} med\left(|r_{t,i-1}|, |r_{t,i}|, |r_{t,i+1}|\right)^2, \tag{1}$$

[1] In order to avoid any confusion, it is important to emphasize that we use in this research the terms realized volatility and realized variance interchangeably.

where $r_{t,i}$ denotes intraday gold return i within day t, and $i = 1,..,T$ is the number of intraday gold returns within a day. According to Andersen et al. (2012), MRV is less biased in the presence of market-microstructure noise.

We use variants of the HAR-RV model (Corsi 2009) to model and forecast the daily realized volatility of gold returns. Despite its apparently simple structure, the HAR-RV model allow the properties of realized volatility such as long memory and multi-scaling behavior to be captured. The benchmark HAR-RV model is given by

$$RV_{t+h}=\beta_0 + \beta_d\ RV_t + \beta_w\ RV_{w,t} + \beta_m\ RV_{m,t} + \varepsilon_{t+h}, \tag{2}$$

where the index h denotes $h-$days-ahead realized volatility. We set $h = 1,5,22$, and follow earlier setting in using the average daily realized volatility when $h > 1$. In addition, $RV_{w,t}$ is the average RV from day $t-5$ to day $t-1$, while $RV_{m,t}$ denotes the average RV^j from day $t-22$ to day $t-1$. When we add investor happiness (HA) to the benchmark HAR-RV model, we get the following extended HAR-RV-HA model:

$$RV^j_{t+h}=\beta_0 + \beta_d\ RV_t + \beta_w\ RV_{w,t} + \beta_m\ RV_{m,t} + \theta\ HA_t + \varepsilon_{t+h}. \tag{3}$$

In order to study how HA fares as compared to other predictors widely studied in earlier literature, we further extend, as a robustness check, the model given in Equation (3) to include measures of realized kurtosis (RKU) and realized skewness (RSK). Like Amaya et al. (2015), we employ RSK as a measure of the asymmetry of the daily return distribution of gold returns and RKU as a measure which allow us to account for extreme occurrences in the daily gold return distribution. Following earlier studies, we compute RSK and RKU as follows:

$$RSK_t=\frac{\sqrt{T}\sum_{i=1}^{T} r_{t,i}^3}{(\sum_{i=1}^{T} r_{t,i}^2)^{3/2}}, \qquad RKU_t=\frac{T\sum_{i=1}^{T} r_{t,i}^4}{(\sum_{i=1}^{T} r_{t,i}^2)^2}, \tag{4}$$

where scaling by $\sqrt{T}$ and T, respectively, implies that the magnitudes correspond to daily skewness and kurtosis.

In order to examine out-of-sample predictability of RV, we make use of a fixed-length daily rolling-estimation window comprising 1400 daily data, which is roughly half the sample size, as our benchmark, but we also study a somewhat shorter (1300 data) and a somewhat longer (1500 data) rolling-estimation window. In addition, we study a recursive estimation window (with 1400 data to compute the initial estimates). We use the variant of the Diebold and Mariano (1995) test proposed by Harvey, Leybourne and Newbold (1997) to test whether the forecasts implied by the HAR-RV-HA model are more accurate than the forecasts we obtain from its competitor models.[2] In order to study forecast accuracy, we use the relative forecast errors of the models to take into consideration the impact of heteroskedasticity on our results (e.g., Bollerslev and Ghysels 1996).

3 Data

Intraday data on gold futures traded in NYMEX over a 24-hour trading day are used (pit and electronic) in order to compute measures of realized volatility on a daily basis. We obtain futures price data in continuous format from `www.disktrading.com` and `www.kibot.com`. Providing that there is increase in activity, the position is rolled over to the next available contract close to expiration of a contract. Daily returns are constructed as the end of day (New York time) log price difference (close-to-close). In particular, in the case of intraday returns, we obtain 5-minute prices via last-tick interpolation, and afterwards we compute 5-minute returns by obtaining the log-differences of these prices which are then utilized to compute the realized moments.

As far as our daily proxy for investor sentiment is concerned, the daily happiness index data are retrieved from the website: `https://hedonometer.org/api.html`. A natural language processing technique based on a random sampling of about 10% (50 million) of all messages posted in Twitter's Gardenhose feed derives the raw daily happiness scores. The 5,000 most frequent words are merged by Hedonometer.org from four different corpora: (i) Google Books, (ii) New York Times articles, (iii) Music Lyrics, and (iv) Twitter messages, leading to a rich set of almost 10,000 unique words, in order to measure the happiness of the atoms of language. Then,

[2] All computations are carried out using the R programming environment (R Core Team 2019). Results for the Diebold-Mariano test are computed using the R package "forecast" (Hyndman 2017, Hyndman and Khandakar 2008).

with the aid of Amazon's Mechanical Turk service, each of these words was scored on a nine-point scale of happiness by Hedonometer.org, with 1 corresponding to "sad" and 9 to "happy". Words in English-written messages are collected into a "large bag" (including about 100 million words per day), and a happiness score is assigned the "bag" on the basis of the average happiness score of the words which are found in this bag.

– Please include Table 1 about here. –

Our study spans from 9th September, 2008 to 30th May, 2017. The start and end dates of the dataset are only dependent on the availability of the happiness index and gold futures prices, respectively. Table 1 depicts the summarized statistics of the data.

4 Empirical Findings

Table 2 summarizes full sample results for $h = 1$. The estimated coefficients of MRV, MRV_w and MRV_M are always significant and have a positive sign. The estimated coefficients of RKU and RSK are significant and negative (see also Mei et al. 2017). The estimated coefficient of investor happiness, HA, is highly significant and has a negative sign. The negative sign of the estimated coefficient is expected as it signals that more happiness reduces the price pressure on gold given its inverted asymmetric reaction to positive and negative shocks documented in earlier empirical research (Baur 2012). As result, observed gold realized volatility decreases. The estimated coefficients of investor happiness, HA, are also negative but no longer significant for the two longer forecast horizons ($h = 5, 22$; results are not reported for the sake of brevity).

– Please include Table 2 about here. –

Table 3 summarizes the results of a comparison of out-of-sample forecast accuracy (HAR-RV model vs. HAR-RV-HA model) for three different lengths of the rolling-estimation window, three different forecast horizons, and two loss functions (linear and quadratic). The test results for the short and the medium forecast horizons, $h = 1$ and $h = 5$, are significant in all cases. The test results for the long forecast horizon ($h = 22$) are significant for two out of three lengths of the rolling-estimation window provided we assume a linear loss function. In sum, the results for the short and the medium forecast horizons suggest that investor happiness helps to improve accuracy of forecasts of realized volatility of gold returns, while the results for the long forecast horizon are mixed. In other words, the effect of investor happiness on forecasts of realized volatility dies out as the forecast horizon increases.

– Please include Tables 3 and 4 about here. –

Table 4 summarizes the results of some robustness checks. We consider three robustness checks. First, we add realized kurtosis to the HAR-RV/HAR-RV-HA models. Second, we add realized skewness to the HAR-RV/HAR-RV-HA models. Third, we consider a recursive estimation window. Results are consistent with the results we report in Table 3.

As an additional robustness check, we study a model that features a measure of volatility jumps of gold returns, the importance of which has been outlined by Demirer et al. (2019). Findings (summarized in Table A1 at the end of the paper) corroborate the results reported in Table 3. This, of course, was to be expected given that *MRV* is a jump-robust estimator of realized volatility.[3]

5 Concluding Remarks

We apply variants of the popular HAR-RV model to study whether a search-based measure of investor happiness helps to predict the daily realized volatility of gold returns both in sample and out of sample, as estimated from intraday data. Our in-sample results show that realized volatility is negatively linked to investor happiness, suggesting that more happiness reduces the price pressure on gold given its inverted asymmetric reaction to positive and negative shocks (Baur 2012). As for our out-of-sample results, we find that investor happiness significantly improves the accuracy of forecasts of realized volatility at short- and medium-run forecast horizons. This finding is robust to reasonable changes in the specification of the HAR-RV model.

[3] As yet another robustness check, we studied a model that features changes in investor happiness (defined as the first difference of the log of investor happiness). Findings (not reported, but available upon request from the authors) again are in line with the results reported in Table 3.

References

Amaya, D., Christoffersen, P., Jacobs, K., and Vasquez, A. (2015). Does realized skewness predict the cross-section of equity returns? Journal Financial Economics 118, 135−167.

Andersen, T.G., Dobrev, D., and Schaumburg, E. (2012). Jump-robust volatility estimation using nearest neighbor truncation. Journal of Econometrics 169, 75−93.

Asai, M. Gupta, R., and McAleer, M. (Forthcoming). Forecasting Volatility and co-volatility of crude oil and gold futures: Effects of leverage, jumps, spillovers, and geopolitical risks. International Journal of Forecasting.

Asai, M. Gupta, R., and McAleer, M. (2019). The Impact of Jumps and Leverage in Forecasting the Co-Volatility of Oil and Gold Futures. Energies 12, 3379.

Baker, M., and Wurgler, J. (2006). Investor sentiment and the cross-section of stock returns. Journal of Finance 61, 1645−1680.

Baker, M., and Wurgler, J. (2007). Investor sentiment in the stock market. Journal of Economic Perspectives 21, 129−152.

Balcilar, M. Bonato, M., Demirer, R., and Gupta, R. (2017). The effect of investor sentiment on gold market return dynamics: Evidence from a nonparametric causality-in-quantiles approach. Resources Policy 51, 77−84.

Balcilar, M., Gupta, R., and Kyei, C. (2018). Predicting stock returns and volatility with investor sentiment indices: A reconsideration using a nonparametric causality-in-quantiles test. Bulletin of Economic Research 70, 74−87.

Bathia, D., and Bredin, D. (2013). An examination of investor sentiment effect in G7 stock market returns. European Journal of Finance 19, 909−937.

Bathia, D., Bredin, D., and Nitzsche, D. (2016). International sentiment spillovers in equity returns. International Journal of Finance and Economics 21, 332−359.

Baur, D.G. (2012). Asymmetric volatility in the gold market. Journal of Alternative Investments 14, 26−38.

Baur, D.G., and Lucey, B.M. (2010) Is gold a hedge or a safe haven? An analysis of stocks, bonds and gold. Financial Review 45, 217−229.

Baur, D.G., and McDermott, T.K. (2010). Is gold a safe haven? International evidence. Journal of Banking & Finance 34, 1886−1898.

Beckmann, J., Berger, T., and Czudaj, R. (2019). Gold price dynamics and the role of uncertainty. Quantitative Finance, 19, 663−681.

Bollerslev, T., and Ghysels, E. (1996). Periodic autoregressive conditional heteroscedasticity. Journal of Business and Economics Statistics, 14, 139−151.

Bouoiyour, J., Selmi, R., and Wohar, M.E. (2018). Measuring the response of gold prices to uncertainty: An analysis beyond the mean. Economic Modelling 75, 105−116.

Campbell, J.Y. (2008). Viewpoint: estimating the equity premium. Canadian Journal of Economics 41, 1−21.

Corsi, F. (2009). A simple approximate long-memory model of realized volatility. Journal of Financial Economics 7, 174−196.

Da, Z., Engelberg, J., Gao, P. 2015. The Sum of All FEARS Investor Sentiment and Asset Prices. Review of Financial Studies 28, 1−32.

Demirer, R.,Gkillas, K., Gupta, R., and Pierdzioch, C. (2019). Time-varying risk aversion and realized gold volatility. North American Journal of Economics and Finance 50, 101048.

Diebold, F. X., and Mariano, R. S. (1995). Comparing predictive accuracy. Journal of Business and Economic Statistics 13, 253−263.

Fang, L., Honghai, Y., and Xiao, W. (2018). Forecasting gold futures market volatility using macroeconomic variables in the United States. Economic Modelling 72, 249−259.

García, D. (2013). Sentiment during recessions. Journal of Finance 68, 1267−1300.

Gkillas, K., Gupta, R., and Pierdzioch, C. (2019). Forecasting realized gold volatility: Is there a role of geopolitical risks? Finance Research Letters. DOI: `https://doi.org/10.1016/j.frl.2019.08.028`.

Harvey, D., Leybourne, S., and Newbold, P. (1997). Testing the equality of prediction mean squared errors. International Journal of Forecasting 13, 281−291.

Hyndman, R.J. (2017). forecast: Forecasting functions for time series and linear models. R package version 8.0, URL: `http://github.com/robjhyndman/forecast`.

Hyndman, R.J., and Khandakar, Y (2008). Automatic time series forecasting: the forecast package for R. Journal of Statistical Software 26, 1−22.

Mei, D., Liu, J., Ma, F., and Chen, W. (2017). Forecasting stock market volatility: Do realized skewness and kurtosis help?. Physica A 481, 153−159.

Pierdzioch, C., Risse, M., and Rohloff, S. (2016). A boosting approach to forecasting the volatility of gold-price fluctuations under flexible loss. Resources Policy 47, 95−107.

R Core Team (2019). R: A language and environment for statistical computing, Vienna, Austria: R Foundation for Statistical Computing. URL http://www.R-project.org/. R version 3.3.3.

Reboredo, J.C., and Ugolini, A. (2018). The impact of Twitter sentiment on renewable energy stocks. Energy Economics 76, 153−169.

You, W., Guo, Y., and Cheng, P. (2017). Twitter's daily happiness sentiment and the predictability of stock returns. Finance Research Letters 23, 58−64.

Zhang, B. (2018). Economic Policy Uncertainty and Investor Sentiment: linear and nonlinear causality analysis. Applied Economics Letters 26, 1264−1268.

Zhang, W., Li, X., Shen, D., and Teglio, A. (2016). Daily happiness and stock returns: Some international evidence. Physica A 460, 201−209.

Zhang, W., Wang, P., Li, X., and Shen, D. (2018). Twitter's daily happiness sentiment and international stock returns: Evidence from linear and nonlinear causality tests. Journal of Behavioral and Experimental Finance, 18, 50−53.

Table 1: Summary Statistics

Statistic	MRV	HA
Min	0.001	5.840
Mean	0.107	6.025
Median	0.062	6.031
Max	2.799	6.357

Note: MRV was multiplied by the factor 10^3. Number of observations = 2704. The full-sample contemporaneous (that is, for $h = 0$) correlation of MRV and HA is -0.069.

Table 2: Full Sample Results

results.table	Intercept	MRV	MRV_w	MRV_m	HA	RKU	RSK	Adj. R2
R-RV	1.7515	4.0685	3.7045	3.6795	–	–	–	0.5300
p-value	0.0799	0.0000	0.0002	0.0002	–	–	–	–
HAR-RV-HA	3.8751	4.0450	3.3866	3.3318	-3.8436	–	–	0.5335
p-value	0.0001	0.0001	0.0007	0.0009	0.0001	–	–	–
HAR-RV-HA-RKU	3.8642	4.0142	3.2925	3.3500	-3.8202	-2.4439	–	0.5340
p-value	0.0001	0.0001	0.0010	0.0008	0.0001	0.0145	–	–
HAR-RV-HA-RSK	3.7980	4.0545	3.5333	3.6798	-3.7662	–	-2.2024	0.5338
p-value	0.0001	0.0001	0.0004	0.0002	0.0002	–	0.0276	–
HAR-RV-HA-RKU-RSK	3.9548	3.9143	3.1083	3.2414	-3.9100	-2.3084	-2.3423	0.5343
p-value	0.0001	0.0001	0.0019	0.0012	0.0001	0.0210	0.0192	–

Note: p-values were computed based on Newey-West robust standard errors. Estimated coefficients were scaled by their estimated standard error. Adj. R2 = adjusted coefficient of determination. Forecast horizon: $h = 1$.

Table 3: Out-of-Sample Results (HAR-RV vs. HAR-RV-HA Model)

Rolling window	$h = 1$	$h = 5$	$h = 22$
		L1 loss	
1300	0.0000	0.0054	0.1873
1400	0.0000	0.0001	0.0485
1500	0.0000	0.0000	0.0247
		L2 loss	
1300	0.0000	0.0212	0.4968
1400	0.0000	0.0006	0.2215
1500	0.0000	0.0005	0.1294

Note: p-values of the modified Diebold-Mariano test under the assumption of a linear (L1 loss) and a quadratic (L2 loss) function. Null hypothesis: the series of forecasts from the HAR-RV vs. HAR-RV-HA models are equally accurate. Alternative hypothesis: the forecasts from the HAR-RV-HA model are more accurate.

Table 4: Out-of-Sample Results (Robustness Checks)

Specification window	$h=1$	$h=5$	$h=22$
HAR-RV-RKU vs. HAR-RV-RKU-HA (rolling)	0.0000	0.0008	0.2364
HAR-RV-RSK vs. HAR-RV-RKU-HA vs. (rolling)	0.0000	0.0006	0.2227
HAR-RV vs. HAR-RV-HA (recursive)	0.0000	0.0502	0.3787

Note: p-values of the modified Diebold-Mariano test under the assumption of a quadratic (L2 loss) function. Null hypothesis: the series of forecasts from the HAR-RV vs. HAR-RV-HA models are equally accurate. Alternative hypothesis: the forecasts from the HAR-RV model extended to include HA are more accurate. Length of the rolling-estimation window / the initialisation period used for the recursive estimation window: 1400 observations.

Appendix

Table A1: Out-of-Sample Results (HAR-RV-JUMP vs. HAR-RV-JUMP-HA Model)

Rolling window	$h=1$	$h=5$	$h=22$
		L1 loss	
1300	0.0000	0.0145	0.1888
1400	0.0000	0.0006	0.0531
1500	0.0000	0.0004	0.0278
		L2 loss	
1300	0.0000	0.0215	0.4892
1400	0.0000	0.0007	0.2191
1500	0.0000	0.0009	0.1310

Note: p-values of the modified Diebold-Mariano test under the assumption of a linear (L1 loss) and a quadratic (L2 loss) function. Null hypothesis: the series of forecasts from the HAR-RV-JUMP vs. HAR-RV-JUMP-HA models are equally accurate. Alternative hypothesis: the forecasts from the HAR-RV-JUMP-HA model are more accurate.