Griffith UNIVERSITY
Queensland, Australia

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Author

Todorova, Neda, Soucek, Michael

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Overnight information flow and realized volatility forecasting

Neda Todorova[a], Michael Souček[b]

[a] *Corresponding author*
Griffith Business School, Griffith University
170 Kessels Road, Nathan, Queensland 4111, Australia
Email: n.todorova@griffith.edu.au
Phone: +61 7 3735 7219, Fax: +61 7 3735 3719
[b] *Europa-University Viadrina Frankfurt (Oder), Germany, Email: soucek@europa-uni.de.*

Abstract

This study compares various approaches for incorporating the overnight information flow for forecasting realized volatility of the Australian index ASX 200 and seven very liquid Australian shares from March 2007 to January 2014. The analysis shows that considering overnight information separately rather than adding it to the daily realized volatility estimates leads consistently to better out-of-sample results despite the higher number of involved parameters. A novel, very promising approach is to combine the assets' own overnight returns with realized volatility estimates of related assets from other markets for which intraday data is available while the Australian exchange is closed.

Keywords: Forecasting of realized volatility; Overnight information flow; Australian equity market.

JEL Classification: C5, G1, G15.

1. Introduction

The information flow in financial markets is continuous, but major stock exchanges are often open for trading solely for a limited number of hours per day. The increasing availability of intraday data for various assets allows for precise volatility estimation for the open market period. There are different approaches of considering overnight returns for volatility estimation and forecasting. The squared overnight returns can be merely added to the intraday return based realized volatility measure (Blair et al. 2001), taken into account by scaling procedures (e.g. Hansen and Lunde 2005, Martens 2002, Koopman et al. 2004) or their weight relative to the daily realized volatility can be optimised (Hansen and Lunde 2005). However, there is still no consensus about how it is optimal to treat overnight returns when calculating and forecasting realized volatility in markets where trading does not take place 24 hours a day (Ahoniemi and Lanne 2013). Nevertheless, this is an issue of major importance especially for smaller markets which are closed while a large portion of highly relevant information arrives from the large US and European markets. This study runs a horse race on the forecasting accuracy of different approaches for taking the overnight information flow into account for the Australian equity market. The Australian Stock Exchange ASX with a six-hour trading day starting at 10:00 a.m. Eastern Standard Time (24:00 GMT) to 4:00 p.m. is an excellent example of a market where trading takes place only during the night time of the major US and European markets and is correspondingly closed when these are open.

Research has been already done using intraday data of the Australian market addressing the problem of the different nature of the overnight returns. In an empirical study of high frequency equity data over the period January 1993-July 2002, Bertram (2004) establishes that the overnight process is discrete and recommends modelling the intraday volatility process and the overnight jump process separately, but does not address forecasting issues at all. Kalev et al. (2004) focus on public company announcements as a proxy for information flow and investigate the information-volatility relation under the GARCH framework for five Australian stocks from 1995 to 2000 by including the overnight jump into the first intraday interval of the day. Mian and Adam (2001) investigate the behaviour of volatility for intraday high frequency returns of the ASX equity index from 1993 to 1996 and omit the overnight returns completely. Thus, neither of these studies explicitly addresses the questions of whether or how it is optimal to include the overnight returns for the purposes of forecasting realized volatility.

This question has been raised in the case of other markets. Ahoniemi and Lanne (2013) consider the scaling procedure of Martens (2002) and Koopman et al. (2004) as well as the optimally weighted squared overnight return proposed by Hansen and Lunde (2005) and find that the latter is more accurate in-sample for the S&P 500 index but not for individual stocks. Moreover, they show that accounting for overnight returns may affect the choice of the best performing forecasting model. Blanc et al. (2014) decompose the daily volatility of 280 constituents of the S&P-500 index into overnight and intraday contributions within an ARCH framework and find that the overnight and intraday returns exhibit a very different behaviour, in the sense that while historical intraday returns affect both future intraday as well as overnight volatilities, historical overnight returns have a negligible effect on future intraday volatilities. Making use of the specific characteristics of the NASDAQ markets, Chen et al. (2012) use realized volatilities based on after-hours high frequency stock returns to predict one-step ahead stock volatility by inserting into a GARCH setting information from the whole after hours period, the preopen and the post-close variance, as well as the overnight squared return for 30 stocks. Chen et al. (2012) find that the inclusion of the preopen time can notably improve the out-of-sample predictability of the next day volatility while the post-close time and overnight squared returns have less predictive power. Tsiakas (2008) applies a stochastic volatility model which discerns between the nontrading periods of weeknights, weekends, holidays and long weekends, and allows for asymmetric effects of overnight news, to six European and US stock indexes and documents a substantial predictive ability of financial information accumulated during nontrading hours. Taylor (2007) goes one step further and makes use of high-frequency S&P 500 overnight futures volatility to predict S&P 500 stocks volatility showing that overnight information flow has a significant impact on the volatility of daytime traded equities.

This paper extends extant literature in two important directions. First, we run a comprehensive comparison among various approaches of treating overnight returns by applying them in the heterogeneous autoregressive (HAR) model to forecast one-step ahead realized volatility in the case of the leading Australian equity index ASX 200 and seven very liquid Australian stocks. In addition, we are the first to proxy the overnight information flow by the volatility of the MSCI World real time index realized over time periods when the Australian Stock Exchange (ASX) is closed. For most of the considered assets, this approach leads to a substantial enhancement of the forecasting power.

The question of how it is optimal to treat the overnight returns for the Australian market for forecasting purposes is of significant importance as for some of the assets under consideration, the ratio between the volatility during active to closed market time is around one on average, which indicates that 50% of the volatility occurs while the market is closed. For comparison, Hansen and Lunde (2005) document an average of 4 for the same ratio for the 30 equities of DJIA, meaning that only 20% of the volatility emerges during inactive market periods for the US stock market.

The article is arranged as follows. The next section presents the methodology of the study. Subsequent sections describe the data and the out-of-sample results of rolling estimates. The final section concludes.

2. Methodology

2.1. Realized volatility

To measure the daily quadratic variation using intraday data we employ a realized volatility measure. Realized volatility in its original form, as proposed by Andersen and Bollerslev (1998) is based on the intraday futures' prices $P_{t,i}$ observed at time intervals of fixed length. The resultant continuous intraday returns are

$$r_{t,i} = 100 \ln \left(\frac{P_{t,i}}{P_{t,i-1}} \right) \text{ for } i > 0, \tag{1}$$

with the first index t denoting the day of observation $t = 1, 2, \ldots, T$. The index i denotes the time of observation on a particular day $i = 0, 1, 2, \ldots, I$ (I+1 prices in total). The realized volatility on a trading day t is estimated by finding the total of the squared intraday returns, $\sum_{i=1}^{I} r_{t,i}^2$.

To account for the fact that the price process may be contaminated by market microstructure noise, which in turn may cause the realized volatility to be a biased and inconsistent estimator of the nonobservable volatility, we follow the kernel-based approach in Hansen and Lunde (2006) and make following adjustment,

$$RV_t = \sum_{i=1}^{I} r_{t,i}^2 + 2 \sum_{j=1}^{q} \left(1 - \frac{j}{q+1} \right) \sum_{i=1}^{I-j} r_{t,i}\, r_{t,i+j}. \tag{2}$$

This estimator exhibits the convenient feature of providing always positive values for realized volatility.[1] We calculate the realized volatility based on 5-minute returns and the number of autocovariances q covers 30-minute window lengths (q = 6).

2.2. Overnight information flow and realized volatility

Similarly to Hansen and Lunde (2005), we define the close-to-open return as $r_{ON,t} = 100 \ln\left(\frac{P_{t+1,1}}{P_{t,I+1}}\right)$ and the open-to-close return as $r_{d,t} = 100 \ln\left(\frac{P_{t,I+1}}{P_{t,1}}\right)$ such that $r_t = 100 \ln\left(\frac{P_{t+1,1}}{P_{t,1}}\right) = r_{d,t} + r_{ON,t}$. In this study, for forecasting purposes, we use as overnight return the jump from today t to the next day $t+1$, as we are interested in extracting the information of the overnight period after the market of the assets under consideration is closed.[2]

First, we follow the approach of Blair et al. (2001) which is broadly used in literature and incorporate the overnight return to simply adding it to the realized volatility of day t,

$$RV_t^{ON} = RV_t + r_{ON,t}^2. \tag{3}$$

Second, we apply the estimator of Hansen and Lunde (2005),

$$RV_t^{SC} = \hat{\delta} \cdot RV_t, \tag{4}$$

which estimates the volatility of a whole day by scaling the realized volatility estimated for the open market time by the factor[3]

$$\hat{\delta} = \frac{\sum_{i=1}^{T}(r_t - \bar{r})}{\sum_{i=1}^{T} RV_t}. \tag{5}$$

In this study, we calculate a rolling scaling factor based on the most recent 1,500 trading days. Using a scaling factor based on the whole sample period would result in incorporating information in forecasting procedures which is not available at the moment of building the

[1]Barndorff-Nielsen et al. (2008) discuss the asymptotic properties of the kernel-based estimator in Hansen and Lunde (2006).

[2]Strictly speaking, by including information on the overnight returns the forecasts can only be done once the first price of the new day has been established.

[3]We also used a similar scaling factor, as proposed by Martens (2002) and Koopman et al. (2004),

$$\hat{\delta} = \frac{\sum_{i=1}^{T}(r_{d,t}^2 + r_{ON,t}^2)}{\sum_{i=1}^{T} r_{d,t}^2},$$

with no notable difference in the results.

forecasts.

Third, we use the approach of Hansen and Lunde (2005) who optimally weight the squared overnight return and the sum of squared intraday returns. They solve the optimisation problem for the variance of the target estimator,

$$\min_{\omega \in \Omega} E[RV_t^{HL}(\omega) - IV_t]^2 \tag{6}$$

with $\omega \in R^2$,

$$RV_t^{HL} = \omega_1 r^2_{ON,t} + \omega_2 RV_t, \tag{7}$$

which for the class of conditionally unbiased estimators that are linear RV_t and $r^2_{ON,t}$, can be shown to be equal to

$$\min_{\omega_1,\omega_2} \mathrm{var}(\omega_1 r^2_{ON,t} + \omega_2 RV_t), \quad \text{s.t.} \quad \omega_1\mu_1 + \omega_2\mu_2 = \mu_0, \tag{8}$$

where μ_1, μ_2 and μ_0 denote the expectations of the overnight squared return r^2_{ON}, the realized volatility RV_t and their sum $RV_t + r^2_{ON,t}$, respectively. The solution of (8) is given by

$$\omega_1^* = (1-\varphi)\frac{\mu_0}{\mu_1} \quad \text{and} \quad \omega_2^* = \varphi\frac{\mu_0}{\mu_2}, \tag{9}$$

where

$$\varphi = \frac{\mu_2^2\eta_1^2 - \mu_1\mu_2\eta_{12}}{\mu_2^2\eta_1^2 + \mu_1^2\eta_2^2 - 2\mu_1\mu_2\eta_{12}} \tag{10}$$

and $\eta_1^2 = \mathrm{var}(r^2_{ON,t})$, $\eta_2^2 = \mathrm{var}(RV_t^2)$ and $\eta_{12}^2 = \mathrm{cov}(r^2_{ON,t}, RV_t)$.

Last, new to literature, we proxy the information flow during the non-trading hours of the Australian exchange by using the realized volatility of another asset and more specifically, the MSCI World real time index. There is a daily record of the MSCI World real time index almost around the clock. We apply a realized volatility estimate, labelled RV_t^{MSCI}, established with intraday returns available in the period between the Australian stock market's close of day t (6:00 am GMT) and before the opening on day $t+1$, adjusted for microstructure noise according to (2).[4]

[4]The original data record of MSCI is in US$. In order to avoid additional volatility emerging from the forex markets, we do not incorporate foreign exchange rate effects when calculating returns of the MSCI World (all other assets' prices are in AUD).

2.3. Forecasting models

We seek to identify the best specification of overnight returns for forecasting the one-day ahead realized volatility during the open market time by comparing eight HAR-type models. The first four include the plain realized volatilities (without overnight returns) and the realized volatilities adjusted to incorporate the overnight information, as in (3), (4) and (7), respectively. These models can be summarized as

$$RV_{t+1} = \alpha_0 + \alpha_1 X_t + \alpha_2 X_{t-4,t} + \alpha_3 X_{t-21,t} + \epsilon_{t+1}, \tag{11}$$

with X being the open-market time realized volatility RV (*model 1*), the open-market realized volatility plus the overnight return RV^{ON} (*model 2*), the open-market realized volatility scaled up to a volatility over the whole day according to the optimisation approach of Hansen and Lunde (2005) RV^{HL} (*model 3*) or the scaling estimator of Hansen and Lunde (2005) RV^{SC} (*model 4*). $X_{t-4,t}$ and $X_{t-21,t}$ are the normalized sums of the previous week's and month's realized volatilities, respectively.
Furthermore, we investigate the contribution of overnight information to enhancing the forecasting power of the HAR model by incorporating this information on a stand-alone basis. This is motivated by the results of Bertram (2004) who recommends modelling the intraday volatility process and the overnight jump process separately due to their completely different nature. We consider following extensions of the plain HAR-RV model,[5]

$$RV_{t+1} = \alpha_0 + \alpha_1 RV_t + \alpha_2 RV_{t-4,t} + \alpha_3 RV_{t-21,t} + \beta Y_t + \epsilon_{t+1}, \tag{12}$$

where Y_t is either the very last night's squared overnight return $r^2_{ON,t}$ only (*model 5*) or the vector of the last night's, week's and month's overnight returns ($r^2_{ON,t}$, $r^2_{ON,t-4,t}$, $r^2_{ON,t-21,t}$) as *model 6*.[6] *Model 7* inserts in Y_t one term only: the realized volatility of the MSCI World index RV_t^{MSCI} over the partition of the last trading day t when the Australian stock market is closed already. This way of "bridging" the closed market time for one asset by using the realized volatility of a proxy of the global economy is new to literature. Finally, *model 8*

[5]In the following, results for the realized variance specification are reported. Similar results emerge when using the square root of the considered estimates. The logarithmic specification has not been chosen due to the fact that there is a number of cases of zero overnight returns.

[6]$r^2_{ON,t-4,t}$ and $r^2_{ON,t-21,t}$ are again established as normalized sums up to day t.

combines *model 6* and *model 7* by including $r^2_{ON,t}$, $r^2_{ON,t-4,t}$, $r^2_{ON,t-21,t}$ as well as the the realized volatility of the MSCI World index RV_t^{MSCI} immediately preceding the open of day $t+1$, $Y_t = (r^2_{ON,t}, r^2_{ON,t-4,t}, r^2_{ON,t-21,t}, RV_t^{MSCI})$.

3. Data

Transaction prices are obtained from the Thomson Reuters Tick History data base of the Securities Industry Research Centre of Australasia (Sirca). The data pertain to the spot index S&P/ASX 200 (in the following ASX 200) and seven of its largest constituents. The sample period for forecasting is restricted by the data availability of the real time MSCI World Index for which intraday records can be downloaded for periods after March 4, 2007. The previous 1,500 trading days for which data is available for the Australian assets are used for calculation of the scaling procedures (4) and (7). The period over which rolling one-step-ahead estimates are established is from the March 4, 2007 to January 31, 2014, a total of 1,852 trading days, with the first 500 observations used as a rolling window. These price data cover the full six-hour trading day at the ASX starting from 10:00 a.m. Eastern Standard Time (24:00 GMT) to 4:00 p.m. The stocks were chosen to give wide market coverage in terms of sector representation. An important criterion for the stock selection was that they are not listed at another major exchange with open market time deviating from the Australian market.[7] The considered stocks are Telstra (TLS) from the area of telecommunication services, Commonwealth bank (CBA) and Westpac (WBC) from the bank sector, Woolworths (WOW) as a representative of the food and staples retailing, Newcrest (NCM) from the mining and Woolside (WPL) and Santos (STO) from the energy sector.

To begin with the quality of the daily transaction record, there is no consensus about the treatment of outliers in high-frequency data. Possible ways to handle outliers are to delete or adjust them. Their impact on volatility can also be separately considered. Brownlees and Gallo (2006) discuss filtering techniques based on rolling windows and the definition of thresholds for the size of single price movements. However, the categorization of individual data points as outliers may be a challenging task, and might lead to distortions. Ait-Sahalia and Mykland (2009), for example, caution about raw data cleaning procedures which smooth the data set and alter its autocorrelation structure which may in turn influence the properties

[7] For this reason, stocks for example like Rio Tinto and BHP were excluded.

of the noise process. Ait-Sahalia et al. (2011) identify a price observation as an outlier when the return from one transaction to the next that is larger in magnitude than an arbitrary cut-off is instantaneously followed by a return of the same magnitude but of the opposite sign. However, the essential question at this point is "how large is large". Hansen and Lunde (2005) exclude the seven largest observations of the squared overnight return and the three largest RV_t from their estimation of optimal weights. Fleming and Kirby (2011) exclude days in which either RV_t or $r_{ON,t}$ is among the largest 0.5% of the observations for a given stock. These two studies proceed in this way in order not to obtain negative weights ω_1 for the overnight returns which may potentially result in negative volatility estimates.[8] Deleting extreme observations for forecasting purposes with time series models may result in omitting important information about the volatility dynamics. For this reason, in the seldom cases when φ is estimated as higher than 1, it is set to 1 resulting in the weights $\omega_1^* = 0$ and $\omega_2^* = \frac{\mu_0}{\mu_2}$.

Table 1 shows basic statistics of the overnight returns $r_{ON,t}$ and the returns of the whole day r_t, the plain open-market realized volatility as well as its versions extended to span a day of 24 hours, (3), (4) and (7), respectively. Furthermore, characteristics of the measures μ_2/μ_1, φ, $\frac{\eta_{12}}{\eta_1\eta_2}$, ω_1 and ω_2, relevant for the calculation of RV_t^{HL} are reported as well. It is interesting to see that the realized volatility of the broad equity index is much lower on average than that of the individual stocks. The overall much smoother nature of the ASX 200 is also evident at the return level. Its highest and lowest returns over night and over the whole day (24 h) exhibit a substantially lower magnitude than the individual stocks. While the correlation $\eta_{12}/(\eta_1\eta_2)$ between overnight and open-market volatility is comparable to the values established by Hansen and Lunde (2005), the relation between overnight and open market volatility is quite different to this study and across equity index and individual stocks. Hansen and Lunde (2005) report volatility ratios μ_2/μ_1 of around 4 for individual stocks. While the ratio for ASX 200 is around 3 on average meaning that 25% of the volatility emerges overnight, the price dynamics of all stocks exhibits a much higher variation arising during the night period. The corresponding average ratio varies between 0.91 and 2.07 across the stocks under consideration providing eminent evidence of the substantial influence of overnight periods and the highly practically

[8] It can easily be shown that φ is higher than 1 when $\frac{\mu_2\eta_1}{\mu_1\eta_2}\text{corr}(r^2_{ON,t}, RV_t) > 1$ which occurs empirically in seldom cases but is possible. Due to the high variation of the overnight returns of the given data set, for five out the seven stocks there are very few cases when φ becomes higher than 1 and ω_1 becomes negative, correspondingly.

relevant need of their accurate modelling for forecasting purposes for the Australian market. Another interesting observation is that by construction, the standard deviation of RV_t^{HL} is always lower than that of RV_t^{ON}. RV_t^{ON} provides in most of the cases the highest average volatility estimate for the whole day. Note that the averages of RV_t^{ON} and RV_t^{HL} are different despite the relation $\omega_1\mu_1+\omega_2\mu_2 = \mu_0$ because the weighting parameters ω_1 and ω_2 are estimated on a rolling basis.

4. Results

The volatility forecasts are generated using the parameter sets obtained from a rolling fixed-window approach using the 500 latest observations. To evaluate the predictive performance of the various specifications we compute the R^2 statistic from the Mincer-Zarnowitz regressions of observed realized volatility on the corresponding one-step ahead forecasts. In addition to the R^2 statistic, we also report the mean error (ME), the mean absolute error (MAE), the mean relative error (MRE) and the root mean squared error (RMSE). As indicated by Corsi et al. (2008), the RMSE may be of particular interest for risk management purposes since it assigns more weight to larger forecast deviations. The results are reported in Table 2 and the best results obtained per asset and evaluation criterion are printed bold.

The major findings can be summarized as follows: First, there is no model which consistently outperforms all others. However, except in the case of CBA, when the mean error (ME) is minimal with RV^{HL} (*model 3*), all best performing rolling estimates are generated by models considering the overnight information separately from the realized volatility based on intraday data from the open market time. For NCM highest predictive power in terms of an R^2 is achieved with a HAR model including the last night's, week's and month's squared returns (*model 6*) while for CBA, using solely the realized volatility of the MSCI World yields the highest R^2. For ASX 200 and the remaining five companies, the highest explanatory power in terms of an R^2 is achieved by inserting both a realized volatility proxy of another asset which can be seen as a representative for the global equity markets as well as a HAR-type extension in terms of the own historical overnight returns. This is a surprising result as the extended HAR models (12) entail more parameters than (11) and are hence prone to a more serious parameter uncertainty problem than a simple HAR model, which may in turn adversely affect their forecasting performance. However, it appears that the incremental informational content inherent in the overnight periods conclusively overcompensates this parameter uncertainty. Moreover, the superiority of *model 8* which includes both historical overnight returns and RV_t^{MSCI} is intriguing as, strictly seen, the overnight period between the close of day t and the opening of day $t+1$ is covered twice (by $r^2_{ON,t}$ and RV_t^{MSCI}). Apparently, RV_t^{MSCI} contains a different information set than the history of the own overnight returns. As a result, the difference between the R^2 of *model 8* as opposed to *model 6* and *7* is quite pronounced, especially in the case of ASX 200, STO, WBA, WOW and WPL. In total, it appears that including overnight information into a HAR model for the Australian equity market is able to enhance the explanatory power of forecasts by almost 10% for the ASX 200 and up to 13.3% for individual equities. Note that in most of the cases, this superiority is achieved without any notable deterioration of the given loss functions.

Comparing the suitability of the plain open-market realized volatility RV_t (*model 1*) with its extended versions RV_t^{ON}, RV_t^{SC} and RV_t^{HL} as predictors (*models 2-4*) does not allow for identifying a clear winner. Doubtlessly, overnight returns contain important information for the one-step ahead realized volatility, however it is difficult to say which estimator provides most useful information. While adding the squared overnight return to the open-market realized volatility without any smoothing (RV_t^{ON}, *model 2*) seems to have quite a distorting effect in some cases (CBA, TLS), it appears to have the most explanatory power in terms of R^2 for ASX 200, NCM, WBC, WOW and WPL. Again, this supports our finding that the overnight information flow should be taken into account separately that the daytime realized volatility.

5. Conclusion

This paper compares different approaches of modelling the information flow arising during the closed market time for enhancing the predictive power of the standard volatility forecasting HAR model for the Australian market. The assets under consideration are characterised by a much lower open to closed market volatility ratio (mostly between 1 and 2 on average), indicating that up to 50% of the volatility arises during the time when the market is closed, compared to only 20% for US equities, as established by Hansen and Lunde (2005). This shows the major importance of an adequate approach for treating the overnight information flow for the Australian market. The results conclusively show that considering the overnight returns separately from the open market realized volatility consistently contributes to enhancing the forecasting accuracy and predictive power of rolling one-step ahead forecasts. A novel approach which performs quite well is to combine the asset's own overnight returns with a proxy of the overnight information flow by the corresponding partition of the daily realized volatility of another asset which is likely to reflect the development of the relevant market. Using the MSCI World real time index for this purpose works well for the ASX 200 and the majority of stocks under consideration. Future research may explore the potential for example of an international commodity price index for forecasting realized volatility of companies of the energy or mining sector for further enhancements.

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Tables

Table 1: Descriptive statistics

	Mean	SD	Min	Max	Mean	SD	Min	Max	Mean	SD	Min	Max
	ASX 200				CBA				NCM			
$r_{ON,t}$	0.02	0.54	-3.34	4.67	0.02	1.30	-12.74	6.94	0.04	1.99	-14.38	13.17
r_t	-0.01	1.07	-5.22	5.76	0.02	1.87	-8.69	11.88	-0.05	2.78	-17.04	21.44
RV_t	12.38	7.43	2.55	66.26	16.85	10.39	3.22	109.21	24.34	13.78	2.65	150.96
RV_t^{ON}	14.27	8.80	3.33	99.43	22.84	17.19	4.43	209.61	35.49	22.82	2.69	229.44
RV_t^{SC}	14.70	8.84	3.03	77.87	24.59	15.00	4.26	159.26	37.23	20.84	4.13	227.21
RV_t^{HL}	14.38	8.42	3.43	76.84	23.69	14.50	4.07	151.41	35.86	19.89	3.49	200.11
$\frac{\mu_2}{\mu_1}$	3.04	0.63	2.70	5.41	1.05	0.29	0.89	1.80	0.91	0.14	0.73	1.23
φ	0.92	0.05	0.77	1.12	0.94	0.03	0.85	1.09	0.79	0.03	0.70	0.95
$\frac{\eta_{12}}{\eta_1\eta_2}$	0.40	0.13	0.03	0.67	0.32	0.05	0.14	0.53	0.27	0.06	0.12	0.39
ω_1	0.35	0.30	0.00	1.32	0.13	0.06	0.00	0.40	0.41	0.10	0.10	0.67
ω_2	1.23	0.11	0.93	1.34	1.88	0.18	1.34	2.10	1.68	0.17	1.27	1.95
	STO				TLS				WBC			
$r_{ON,t}$	0.07	1.56	-11.72	10.11	0.06	0.87	-8.00	6.59	0.05	1.30	-8.95	6.84
r_t	0.02	2.19	-12.77	11.33	0.01	1.42	-11.20	8.46	0.01	1.90	-9.80	12.98
RV_t	23.82	12.88	4.77	124.24	16.30	6.36	4.79	59.71	18.55	10.09	3.68	96.31
RV_t^{ON}	30.98	19.61	4.77	187.25	19.73	10.39	5.40	128.11	24.98	15.77	3.68	146.52
RV_t^{SC}	30.79	16.54	6.23	160.53	21.03	8.23	6.18	78.21	25.64	13.81	5.29	134.04
RV_t^{HL}	31.86	16.96	6.19	156.50	20.59	7.98	6.17	75.69	25.30	13.49	4.83	127.65
$\frac{\mu_2}{\mu_1}$	1.27	0.19	1.14	1.82	1.68	0.12	1.54	2.02	1.22	0.29	1.01	1.98
φ	0.92	0.01	0.89	0.97	0.99	0.01	0.96	1.02	0.90	0.04	0.76	1.09
$\frac{\eta_{12}}{\eta_1\eta_2}$	0.26	0.06	0.10	0.36	0.18	0.06	0.05	0.34	0.38	0.07	0.17	0.59
ω_1	0.19	0.03	0.08	0.23	0.03	0.03	0.00	0.13	0.23	0.10	0.00	0.70
ω_2	1.65	0.07	1.46	1.73	1.58	0.05	1.43	1.64	1.66	0.15	1.15	1.91
	WOW				WPL							
$r_{ON,t}$	0.05	0.84	-5.02	6.44	0.13	1.42	-10.48	11.55				
r_t	0.01	1.29	-5.78	7.58	0.00	2.04	-14.17	10.78				
RV_t	15.46	8.59	3.42	90.26	19.47	11.07	4.02	101.70				
RV_t^{ON}	19.03	11.33	4.35	106.95	26.44	17.69	4.51	193.33				
RV_t^{SC}	18.04	10.04	3.97	103.70	28.43	16.06	5.80	152.67				
RV_t^{HL}	18.98	10.26	4.29	109.69	27.41	15.28	5.70	143.86				
$\frac{\mu_2}{\mu_1}$	2.07	0.34	1.70	2.99	1.05	0.21	0.90	1.66				
φ	0.90	0.02	0.87	1.02	0.95	0.08	0.44	1.09				
$\frac{\eta_{12}}{\eta_1\eta_2}$	0.33	0.07	0.15	0.54	0.36	0.08	0.11	0.55				
ω_1	0.30	0.07	0.00	0.50	0.12	0.21	0.00	1.47				
ω_2	1.35	0.06	1.17	1.48	1.89	0.26	0.72	2.09				

Note: $r_{ON,t}$ and r_t denote the overnight returns and the return realized over the whole day in per cent, respectively. RV_t is the annualized volatility realized over open market times only. RV_t^{ON} adds the squared overnight return to RV_t. RV_t^{SC} and RV_t^{HL} are established following (4) and (7) respectively. μ_1 and μ_2 denote the expectations of the overnight squared return r_{ON}^2 and the realized volatility RV_t. η_1^2, η_2^2 and η_{12} are the variance of the squared overnight returns, the variance of the realized variances and the covariance between them, respectively. φ, ω_1 and ω_2 are estimated according to (10) and (9).

Table 2: One-step-ahead forecast evaluation

	ME	MRE	MAB	RMSE	R^2	ME	MRE	MAB	RMSE	R^2
			ASX 200					CBA		
Model 1	0.052	0.339	0.815	0.783	0.166	0.110	0.499	0.602	0.874	0.424
Model 2	0.046	0.324	0.753	0.786	0.179	0.125	0.538	0.687	0.898	0.389
Model 3	0.046	0.333	0.776	0.783	0.167	0.370	0.677	0.876	1.103	0.395
Model 4	0.053	0.339	0.819	0.782	0.167	0.144	0.513	0.631	0.887	0.422
Model 5	**0.034**	**0.309**	**0.662**	0.776	0.204	0.102	0.495	0.592	0.867	0.429
Model 6	0.037	0.327	0.665	0.776	0.209	**0.089**	**0.492**	**0.562**	0.861	0.436
Model 7	0.065	0.336	0.744	0.754	0.233	0.114	0.503	0.567	**0.848**	**0.467**
Model 8	0.057	0.325	0.673	**0.742**	**0.263**	0.133	0.518	0.576	0.858	0.464
			NCM					STO		
Model 1	0.023	1.199	0.716	2.682	0.161	0.171	1.056	0.680	1.954	0.223
Model 2	-0.043	1.153	0.649	2.601	0.209	0.220	1.110	0.708	1.979	0.224
Model 3	**0.004**	1.170	0.677	2.626	0.194	0.198	1.060	0.675	1.933	0.245
Model 4	0.074	1.220	0.747	2.690	0.159	0.201	1.075	0.702	1.965	0.219
Model 5	0.014	1.169	0.704	2.590	0.215	0.152	**1.046**	0.645	1.903	0.262
Model 6	-0.044	**1.133**	**0.620**	**2.562**	**0.232**	**0.123**	1.078	0.610	1.897	0.271
Model 7	0.133	1.285	0.775	2.754	0.136	0.187	1.069	0.657	1.905	0.268
Model 8	0.097	1.218	0.727	2.625	0.202	0.149	1.075	**0.607**	**1.869**	**0.297**
			TLS					WBC		
Model 1	0.097	0.472	0.435	0.804	0.282	0.106	0.622	0.579	0.990	0.298
Model 2	0.159	0.503	0.528	0.833	0.256	0.101	0.629	0.591	0.972	0.320
Model 3	0.104	0.473	0.439	0.804	0.285	0.133	0.627	0.589	0.983	0.319
Model 4	0.106	0.474	0.442	0.804	0.284	0.152	0.643	0.622	1.003	0.297
Model 5	0.091	0.463	0.417	0.803	0.286	0.104	0.620	0.570	0.983	0.308
Model 6	0.086	0.460	0.409	0.798	0.293	**0.087**	**0.612**	**0.545**	0.962	0.333
Model 7	0.085	0.467	0.414	0.795	0.295	0.100	0.623	0.549	0.960	0.348
Model 8	**0.076**	**0.457**	**0.390**	**0.791**	**0.303**	0.102	0.623	0.546	**0.957**	**0.352**
			WOW					WPL		
Model 1	0.090	0.408	0.749	0.759	0.097	0.090	0.744	0.764	1.886	0.117
Model 2	0.101	0.407	0.789	0.744	0.149	0.135	0.780	0.787	1.779	0.217
Model 3	0.097	0.406	0.750	0.748	0.125	0.128	0.759	0.790	1.890	0.118
Model 4	0.085	0.405	0.739	0.757	0.097	0.136	0.766	0.798	1.898	0.113
Model 5	**0.084**	**0.394**	0.710	**0.731**	0.163	0.072	0.755	0.675	1.771	0.221
Model 6	0.090	0.407	0.736	0.745	0.143	0.087	0.766	0.692	1.770	0.223
Model 7	0.096	0.415	0.721	0.764	0.113	**0.071**	**0.728**	0.672	1.827	0.173
Model 8	0.090	0.409	**0.681**	0.748	**0.157**	0.090	0.763	**0.647**	**1.740**	**0.250**

Note: R^2 is established with Mincer-Zarnowitz regressions of observed realized volatility on the corresponding one-step ahead forecasts. ME, MAE, MRE and RMSE label the mean error, the mean absolute error, the mean relative error and the root mean squared error, respectively. *Model 1* includes historical open-market time realized volatilities as independent variables. *Model 2*, *model 3* and *model 4* use historical volatilities established accroding to (3), (4) and (7), respectively. *Model 5* considers besides the open-market realized volatilities additionally the last night's squared overnight return. *Model 6* incorporates a HAR-type consideration for the historical last night's, week's and month's overnight returns. *Model 7* proxies the overnight development by using the volatility of the MSCI World real time index realized after the previous day's close of the Australian market. *Model 8* combines *model 6* and *model 7*. The results for the best individual forecasts per asset and criterion are printed bold.