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Forecasting stock volatility using after-hour information: Evidence from the Australian Stock Exchange

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ABSTRACT

Since markets generally do not trade during overnight period, volatility cannot be estimated on a high-frequency basis. We adopt a new forecasting approach by using squared overnight return, pre-open volatility of the same asset and realized volatilities of related assets from other markets, where intraday data is still available while the Australian Stock Exchange (ASX) is closed, to predict stock volatility. We use a number of different specifications of the Heterogeneous Autoregressive (HAR) model to identify an optimal way to incorporate this additional information. We evaluate the forecasting performance of 45 ASX 200 stocks, categorized in three groups based on their annual total trading volumes, three Global Industry Classification Standard (GICS) indices and the S&P/ASX 200 index using a rolling estimation method. Our empirical analysis of the ASX constituents confirms the usefulness of using pre-open volatility of the same asset and realized volatilities of related assets from other markets when the ASX is closed for forecasting future volatility. Furthermore, we find that the predictive power of overnight information for all stocks and indices is higher during the market opening period and declines gradually over the trading day. However, the decrement is steeper for active stocks, suggesting that the predictive power is higher for inactively traded stocks. Finally, we evaluate the economic significance of the augmented HAR model that includes realized volatilities of related assets from other markets, and we find that it provides significant utility gains to a typical mean-variance investor.

1. Introduction

Information relevant for investors accumulates around the clock, but stock exchanges are usually open only for a limited number of hours. A main advantage of having stock markets around the world is that there is almost always an open market in some part of the world. Due to the integration of global financial markets, information accumulated during one market closure is subsequently reflected in prices when that market reopens, and thus the overnight period/non-trading period is becoming a very important area for research. The existing literature highlights both the importance of non-trading hours and the fact that prices evolve in different ways during trading and non-trading hours. However, no consensus approach has yet emerged to address the issue of overnight period/non-trading period effect on the daytime volatility.

Modeling US and European stock markets, Tsiakas (2008) documents that information accumulated overnight contains substantial predictive ability[1]. Focusing on realized volatility, Martens (2002) models the dynamics of returns during non-trading hours differently from those during trading hours. The simplest approach, which is widely used in the literature, is to ignore the overnight period where only the intraday squared returns are summed (Andersen et al., 2001; Corsi, 2009; Wang et al., 2009). However, Hansen and Lunde (2006) argue that such an estimator is not a proper proxy of the true volatility as it does not span a full 24-hour period. Another solution is to calculate the overnight return by subtracting each day's close value from the next day's open, and to add this squared return as one equally-weighted factor in the sum of intraday returns (Blair et al., 2001; Martens, 2002). A third method is to calculate realized volatility by ignoring the overnight period, but then scale the resulting value upward so that the volatility estimate covers an entire 24-hour day (Koopman et al., 2005; Martens, 2002). Fourth, Hansen and Lunde (2005) derive a weighting scheme for the overnight returns and the sum of intraday returns.

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[1] Tseng et al. (2012) demonstrate similar results for the Taiwanese stock exchange using a Heterogeneous Autoregressive Model (HAR), finding that when overnight returns are incorporated into the model, the forecasting performance of realized volatility significantly improves for both in-sample and out-of-sample forecasts.

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Our study aims to improve the forecasting of stock market volatility by accounting for the non-trading period volatility, and takes the Australian Stock Exchange (ASX) as a specific case study. The implication is that as Australia is the first major market to be open by the rising sun followed by Japan and Hong Kong, the general behavior of the ASX will be mainly influenced by the overnight values since significant market shifting information might arrive from large markets such as the US and Europe while the Australian market is closed. Moreover, due to the fact that Australia is isolated from the rest of the major markets in the world in terms of its time zone, using Australia as a specific case study thus provides us with an interesting platform to analyze the overnight/non-trading period effect.

Our approach is to carry out one-day-ahead and seven-day-ahead forecasting analysis for realized volatility with squared overnight return, pre-open volatility, and the realized volatilities of related assets from other markets, where the intraday data is available while ASX is closed. We use the well specified Heterogeneous Autoregressive Model (HAR) introduced by Corsi (2009). The HAR model has a better forecasting performance for future volatility than GARCH-type models, which is the most widely used volatility modeling approach in the literature[2]. Andersen et al. (2006) state that the central improvement appears to come from the fact that GARCH models only use daily data while HAR models use much larger information set that is contained in intraday data. Therefore, the reasons of using HAR model in our study are two-fold. Firstly, it has a better forecasting performance on the future volatility; and secondly, HAR model can capture the long memory dynamics of volatility effectively yet in a simple and parsimonious manner. We construct 13 HAR models to include overnight information and we select the best model using the Diebold and Mariano (1995) pair-wise comparison test for non-nested models, the Clark and West (2007) modified test for nested models, and Theil's U statistic based on the MSFE (mean square forecasted error) criteria in our one-day- and seven-day-ahead rolling estimates. We use various in-sample sizes (i.e. 25%, 50% and 75% of the whole sample series) as additional robustness checks. We also exclude the Global Financial Crisis period (GFC) (2009–2012) to examine whether our results still hold in absence of this highly volatile period. It is evident that overnight price changes, together with the price series of other assets for which price data is available during the closed market time of the ASX, contain important information for predicting daytime volatility. Furthermore, the HAR model performs better when the additional information is added to the model on a stand-alone basis. Proxying the overnight information by squared (close-to-open) overnight returns leads to Theil's U statistic exceeding 1, confirming that this is a very noisy estimator. However, when the non-trading gap includes pre-open volatility only, i.e., 7:00 a.m. to 10:00 a.m. EST, Theil's U statistics lower than 1 are documented, suggesting that relevant information in the overnight period is inherent mostly in the pre-open time volatility. This observation is in line with Martens (2002) who suggests that the lack of predictive power of the overnight squared return is probably due to the noise associated with the calculation of squared returns. Moreover, Chen et al. (2012) and Barclay and Hendershott (2004) point out that this might also be due to the spillover effect and the possibility of the trading of informed market participants on private information that is yet to be released during the following regular hours. Furthermore, we also carry out an economic significance test by using a popular mean-variance trading strategy to assess the economic significance of our findings. It demonstrates that the utility gain is on average 4.3% per annum using a trading strategy based on the best forecasting model compared to a passive buy-and-hold trading strategy.

It is interesting to see how the non-trading gap of securities could be bridged by the after-hour information of a relevant security from another market. As our sample comprises companies of various industries (telecommunications, financials, industrials, materials, health care, energy, etc.), the MSCI world real time index, the AUD/USD series, the Goldman and Sachs Commodity Index (GSCI) and the Dow Jones Industrial Index (DJI) appear as promising proxies in capturing relevant information in the non-trading period of these assets. We find that intraday volatility of financial, telecommunication, industrial and consumer discretionary stocks in Australia can be more precisely forecasted when overnight information of the MSCI World real time index, AUD/USD series and DJI is incorporated. Hence, the after-hour information of these assets is a meaningful proxy to bridge the overnight period of the ASX for forecasting the next day's realized volatility. Furthermore, the GSCI and DJI series appear to contain useful information when making predictions for energy- and material-related stocks. Additionally, we document similar results for Australian stock indices as when using individual securities, the non-trading period of the financial and industrial indices can be bridged by the after-hour information of MSCI world real time index and DJI series, while the volatility of energy index (AXEJ) can be better forecast using after-hour information of GSCI and DJI. Moreover, we find that the predictive power of the squared overnight returns is highest at the market opening and declines gradually over the trading day, being higher for inactively and mid traded stocks than for actively traded stocks.

Our study contributes to the existing literature in the following ways. First, we consider two different ways of accumulating additional information to enhance the forecasting ability of the HAR model: namely, adding the information as the 73rd return and also on a stand-alone basis[3]. Second, we investigate 4 distinct assets whose after-hour information is available when the ASX is closed. The purpose of using different types of assets with different trading hours is to capture various types of information from the non-trading period of the ASX. This way of treating overnight/non-trading period information has not been examined so thoroughly yet in the previous literature. Finally, we perform an economic significance analysis and quantify the utility gains for an investor who opts for the extended model compared to the conventional HAR model.

The rest of the paper proceeds as follows. Section 2 briefly reviews volatility forecasting literature. Section 3 explains the data used in this study. The results of modeling and conditional volatility forecasting are provided in Section 4. Section 5 contains our empirical analysis. Finally, Section 6 concludes.

2. Literature review

Seasonality in terms of price changes is a heavily exhibited feature in the high frequency trading literature and reveals a substantial amount of information about the financial market's active trading hours, volume of trading activity, and development of the trading flow. Schmid (2009) states that the seasonal patterns of trading activity are associated with the inherent structure of the main worldwide financial market centers, for example, London, Tokyo and New York and more specifically, their opening and closing times. Accordingly, Dacorogna and Ebrary (2001) state that the financial market can be divided into three major trading sessions during which trading activity peaks in a day: East Asia, Europe and America. Usually these three trading sessions are referred to as the Tokyo, London and New York trading sessions as described in Table 1. Consequently, it is understood that when the trading hours of the market centers overlap, inevitably, the trading activity of the financial market increases as more traders participate in the market.

It is therefore evident that the Australian equity market, with a six-hour trading day starting at 10:00 a.m. until 4:00 p.m. local time, is

[2] Refer to Andersen et al. (2006) for a comprehensive literature survey on forecasting, using realized measures. The main finding is that even though their models under comparison is based on simple autoregressive structures such as the HAR, they provide much better results than GARCH-type models.

[3] As the daytime information is collected at five-minute frequency, the 6-hour trading period of the ASX thus has 72 five-minute intervals.