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Evaluating whether the A-VIX improves volatility forecasts in the Australian equity market

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Abstract: Understanding volatility is key to effective financial risk management. We investigate the efficacy of adding A-VIX to historical volatility based models which forecast volatility in the S&P/ASX 200. The A-VIX estimates the implied volatility of 30-day-ahead options. Volatility forecasting models from the GARCH and HAR frameworks are selected. Model performance is compared across the volatile COVID-19 period.

Keywords: *Realised volatility, VIX, A-VIX, GARCH, HAR*

1. INTRODUCTION

Volatility is a vital component in understanding the risk of financial assets. This research considers univariate models under the GARCH and HAR, and will include extensions to investigate the leverage effect in the Australian context. Further extending these models with the A-VIX will determine whether the implied volatility can improve predictive performance in one-day-ahead volatility forecasts. Realised volatility forecasts can then be used as inputs when managing financial risk, such as when estimating value at risk (Brooks and Persand 2003; Kambouroudis et al. 2021).

2. METHODOLOGY

The Chicago board of Exchange (CBOE) introduced the CBOE Volatility Index (VIX) in 1993. It initially captured the volatility implied by the Black-Scholes model interpolated from near at-the-money options on the OEX (S&P 100). In 2003 the formula was updated to use out-of-the-money calls and puts on the S&P 500 Index and a new formula which estimates the conditional risk-neutral expectation of the (annualised) return variance over the next 30 calendar days (Carr and Wu 2006). The A-VIX was introduced on 21st September 2010 using the later CBOE method and options on the ASX S&P 200 (S&P Dow Jones Indices 2025).

Chosen volatility models must be able to capture persistance in volatility of asset returns series (Crato and de Lima 1994; Ding et al. 1993). Considered models capture the leverage effect, where falling returns and increasing volatility are observed together (Black 1976). The generalised autrogressive conditional heteroscedasticity (GARCH) family serve as baseline historical volatility forecasting models, and can be written as:

$$r_t = \mu_t + \epsilon_t \tag{1}$$

$$\epsilon_t = z_t \sigma_t \tag{2}$$

$$\sigma_t^2 = \alpha_0 + \alpha_1 \epsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2 + \gamma_1 I_{t-1} \epsilon_{t-1}^2 + \sum_{i=1}^{X} \lambda_i x_{i,t-1} \tag{3}$$

Where $z_t \sim N(0,1)$ and restrictions $\alpha_0 > 0, \alpha_1 \geq 0$, $\beta_1 \geq 0$, $\gamma_1 \geq 0$, $\lambda_i \geq 0$ are imposed to ensure the variance is positive. The indicator variable I_{t-1} takes the value of 1 where $\epsilon_{t-1} < 0$ and 0 otherwise. The α and β coefficients capture volatility persistence (Engle 1982, Bollerslev 1986), the γ_1 coefficient captures the leverage effect (Glosten et al. 1993). λ coefficients allow numerous positive exogenous variables to be included in the variance equation. Exogenous variables of particular interest are the realised volatility estimate from Andersen and Bollerslev (1998), and the A-VIX. To complement the considered GARCH models, heterogenous autoregressive (HAR) models which directly utilise the realised variance estimate will be considered. Of particular interest is the semi-variance-HAR model of Patton and Sheppard (2015) which can be written as:

$$RV_t = \sum_{i=1}^{M} r_{t,i}^2 \tag{4}$$

$$RV_t^+ = \sum_{i=1}^{M} r_{t,i}^2 \times 1_{r_{t,i} \geq 0} \tag{5}$$

$$RV_t^- = \sum_{i=1}^{M} r_{t,i}^2 \times 1_{r_{t,i} < 0} \tag{6}$$

$$RV_t = c + \beta_1 RV_{t-1}^+ + \beta_2 RV_{t-1}^- + \beta_3 \left(\frac{1}{5}\sum_{i=1}^{5} RV_{t-i}\right) + \beta_4 \left(\frac{1}{22}\sum_{i=1}^{22} RV_{t-i}\right) + \epsilon_t \tag{7}$$

Where $r_{t,i}$ is the i-th intraday return of day t, $\epsilon_t \sim N(0, \sigma^2)$, and β coefficients and constant c will be estimated via ordinary least squares. The inclusion of the semi-variances allows the upside and downside risk to be modelled separately, and the leverage effect to be captured where $\beta_2 > \beta_1$. 5-minute intervals are used to calculate realised variance metrics following Anderson and Bollerslev (1998). The means of the last 5 and last 22 trading days capture the persistent weekly and monthly variance respectively. HAR models will be extended with the change in A-VIX following Xiao et al. (2021).

Daily open and close of the ASX S&P 200 and A-VIX are obtained from LSEG Workspace (LSEG 2025a). 5-minute prices of the ASX S&P 200 are obtained from LSEG Tick History (LSEG 2025b). Rolling windows of 2000 observations will be used when forecasting from GARCH and HAR models, with a starting in-sample period of 2000 observations from 10th September 2010 to 16th August 2018 and a 1675 observation out-sample period from 17th August 2018 to 28th March 2025.

Forecasts will be compared with the ex-post realised variance measured by equation 4. Models are compared using using the mean square error (MSE) and quasi likelihood (QLIKE) as they are robust to noise in the ex-post realised measure (Patton 2011). Following Anderson and Bollerslev (1998), a Mincer-Zarnowitz regression based on the ex-post measure will be employed and models compared based on the coefficient of determination, R^2.

3. CONCLUSIONS

Baseline models incorporating the leverage effect will be fitted and their appropriateness discussed. They will be compared with extended models incorporating the A-VIX. The significance/insignificance of the A-VIX term will be noted, and the model performance as measured by MSE, QLIKE and R^2 will be compared to baseline models. Closing comments will be made on potential reasons behind performance differences. Final modelling results are pending further honours work, and these results will be ready for the conference.

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