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This is the Published version of the following publication

Erdugan, Riza, Kulendran, Nada and Natoli, Riccardo (2019) Incorporating financial market volatility to improve forecasts of directional changes in Australian share market returns. Financial Markets and Portfolio Management, 33 (4). pp. 417-445. ISSN 1934-4554

The publisher's official version can be found at
https://link.springer.com/article/10.1007%2Fs11408-019-00338-z
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Financial Markets and Portfolio Management (2019) 33:417–445
https://doi.org/10.1007/s11408-019-00338-z

Incorporating financial market volatility to improve forecasts of directional changes in Australian share market returns

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Published online: 25 November 2019
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Abstract
This study examines whether incorporating volatility improves the forecast of directional changes in the returns of Australia's banking, industrial and resource sectors. This study first estimates a benchmark non-volatility logit regression model and assesses it against four estimated volatility logit models measured by mean absolute deviation, standard deviation, return squared (U^2) and range. An out-of-sample prediction performance, assessed by Brier's QPS statistic and hit ratio, confirms that volatility improves the prediction of directional changes of returns. A simple trading strategy is utilized to provide practical improvement in investors' market timing decisions.

Keywords Binary regression model · Volatility estimates · Marginal probability · Forecast comparison

JEL Classification G17

1 Introduction

The aim of this study is to identify whether incorporating volatility improves the forecast of directional changes in the returns of Australia's banking, industrial and resource sectors. In order to achieve this, a one-step-ahead forecasting model is developed. This study is important because it is the first attempt to undertake a forecast of the directional changes of asset returns incorporating volatility in an Australian setting. The economy of Australia is one of the largest capitalist economies in the world and a major exporter of resources. It is also an attractive destination for international

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investors with an equity market comprising the eighth largest in the world and the second largest in the Asia-Pacific.

As recent reviews by Benson et al. (2014, 2015) indicate, although there is not much work on forecasting directional change in asset returns, empirical investigations of the relation between stock return volatility and stock returns have a rich tradition. For example, Durack et al. (2004) use Australian data to test the premium-labor (PL) formulation of the Conditional Capital Asset Pricing Model (CCAPM) against Fama and French's (1993) three-factor model and arbitrage pricing theory (APT).[1] They provide evidence that there was evidence that the PL model could successfully describe the cross section of returns although improvement could occur by adding variables that have been shown to have explanatory power.

Other Australian research includes Bertram (2004), who conducts a study addressing the problem of the different nature of overnight returns. Using high-frequency equity data over the period from January 1993 to July 2002, Bertram recommends modelling separately the intraday volatility process and the overnight jump process. However, Bertram does not address any forecasting issues. In related studies, Kalev et al. (2004) employ public company announcements as a proxy for information flow while examining the information–volatility relation under the GARCH framework for five Australian stocks from 1995 to 2000, while Mian and Adam (2001) investigate the behavior of volatility for intraday high-frequency returns of the ASX equity index from 1993 to 1996. However, neither Kalev et al. (2004) nor Mian and Adam (2001) explicitly address the questions of whether or how it is optimal to include the overnight returns for the purposes of forecasting realized volatility.

While Taylor (2007) and Tsiakas (2008) incorporate overnight information flow to their respective assessments of volatility on asset returns, Chen et al. (2012) find that the inclusion of the preopen time can markedly improve the out-of-sample predictability of the next-day volatility forecast. Further, Anderson and Vahid (2007) develop univariate and multivariate forecasting models for historical volatility in Australian stocks and show that although the latter models outperform the former models, there was little difference between simple and sophisticated factor models.

Todorova and Soucek (2014) extend the extant literature by running a comprehensive comparison of various approaches of treating overnight returns. They use a heterogeneous autoregressive (HAR) model to forecast one-step ahead realized volatility on the ASX 200 and seven highly liquid Australian stocks. They find that running overnight returns separately from the open market realized volatility contributes to improved forecasting accuracy and predictive power of rolling one-step-ahead forecasts.

With respect to predicting the directional changes in asset returns, the importance of volatility has been emphasized by Bekiros and Georgoutsos (2008) and Christoffersen and Diebold (2006). Further, both risk-return analysis and the theory of investment under uncertainty provide a rationale for considering volatility in prediction. Past studies (Annaert et al. 2001) have found that volatility in stock returns and interest rates has a significant impact on future recession. As stated by Bekiros and Georgoutsos (2008,

[1] This work was primarily based on Jagannathan and Wang (1996), although Durack et al. (2004) extend the study by evaluating the influence of US market movements over Australian stock returns.

p. 398), ‘the intuition behind this relationship between volatility and asset return is that a higher volatility raises the probability of observing the negative return’. Christoffersen and Diebold (2006) show that sign probability forecasts are more sensitive to changes in volatility that occur due to random arrival of good and bad news. To measure volatility in asset return, there are two estimates: (1) implied volatilities from options and (2) historical volatility measures, which include the U^2 approach, STD approach, which is measured by 12-month average standard deviation, the MAD approach, which is measured by absolute deviation from the 12-month average return, and range, which is the difference between the highest and lowest market prices over a fixed sampling interval. Implied volatility is not considered in this study because the focus is to select the best historical measure for predicting the directional change in asset return.

The importance of international volatility is a key feature of this paper as there are numerous studies that provide evidence that movements in the US markets influence returns in other markets (see, for example, Eun and Shim 1989; Theodossiou and Lee 1993; Phylaktis 1997; Ghosh et al. 1999; Forbes and Rigobon 2002; Burdekin and Siklos 2012). From an Australian perspective, Ragunathan et al. (1999) find that although Australian and US returns are related, the relationship is sensitive to the stage of the business cycle. Durand et al. (2001) find that over 20% of the daily variance of the Australian market can be explained by variations in the US market and that Australian returns are Granger-caused by movements in the US market. According to Durand and Scott (2003), the strong US effect on the Australian market is most likely due to investors overreacting to US market movements. Given these findings, we examine the influence of US market movements over the cross section of returns in Australia.

To provide evidence of volatility transmission across countries, past studies have estimated the variance–covariance transmission mechanism between countries with the aid of ARCH and GARCH models (Gallo and Otranto 2008; Lee and Kim 1993; Engle et al. 1990; Forbes and Rigobon 2002). When the markets are integrated, unexpected movement in international financial markets may have an adverse effect on the local equity market’s volatility and hence on directional changes (Engle and Susmel 1993).

The significance of predicting directional changes in asset returns has been discussed in several financial papers. Leung et al. (2000, p. 174) state that ‘trading driven by a certain forecast with a small forecast error may not be as profitable as trading guided by an accurate prediction of the direction of movement (or sign of return)’. In addition to this, there is evidence from financial econometric studies (Lo and MacKinlay 1988; Leung et al. 2000) that financial asset returns are to some extent predictable (Leitch and Tanner 1991; Wagner et al. 1992; Pesaran and Timmerman 1995; Kuan and Liu 1995; Larsen and Wozniak 1995; Womack 1996; Gencay 1998; Leung et al. 2000; White 2000; Pesaran and Timmerman 2000; Cheung et al. 2003). Predictability in stock returns is not necessarily due to market inefficiency or overreaction from irrational investors, but rather to predictability in certain aggregate variables that are part of the information set. More specifically, macro-variables (such as interest rates or consumption growth) that to a certain extent determine stock returns are themselves predictable (Ferson and Harvey 1991; Leung et al. 2000).

Only a few previous studies have forecasted the directional changes of returns using the logit and probit models with economic variables (Leung et al. 2000; Anatolyev and Gospodinov 2010; Hong and Chung 2003; Rydberg and Shephard 2003). In recent years, Kauppi and Saikkenon (2008) estimate the binary dynamic probit model, which is further extended and used by Nyberg (2011). Kauppi and Saikkenon (2008) introduce dynamic binary probit models and then apply these to predict recessions in the USA and identify interest rate spread as an important predictor of US recessions. Further, they compare dynamic and static probit models and conclude that the dynamic model outperforms the static model. Another study of financial market volatility, which focuses on predicting recessions (Annaert et al. 2001), shows that interest rates and stock return volatility contribute significantly to forecasting future recessions. Annaert et al. (2001) also discuss the different methods of calculating the volatility for financial variables.

Although other studies have focused on excess returns rather than their magnitude (Nyberg 2011; Faust and Wright 2011; Campbell and Thompson 2008), this study focuses on the prediction of directional changes on asset returns. In order to assess whether volatility improves the forecast of directional changes in the Australian share market, this study selects three major Australian sector indices: banks, industrials and resources. These three sectors are the backbone of the Australian economy and are linked to international markets via international trade and investment. Fluctuations in these stock returns include, but are not limited to, movement in the domestic economic variables and unexpected movement in both the domestic and international financial market (share market and currency market) volatilities.

Studies on international directional predictability have been conducted by Christoffersen et al. (2007), Nyberg and Ponka (2016) and Ponka (2016) amongst others. Of these studies, Christoffersen et al. (2007) examine the direct connection between asset return volatility forecastability and asset return sign forecastability. The out-of-sample predictive performance verifies the importance of allowing for higher-ordered conditional moments. The study by Nyberg and Ponka (2016) assesses the benefits of predicting the signs of returns jointly focusing on the predictive power originating from the USA to foreign markets. Their results from both in-sample forecasting and out-of-sample forecasting show that the bivariate model outperforms the univariate models in seven out of ten markets. This suggests that it is not only lags of US returns that have predictive power, but also the predictive information from the USA to the other markets. In addition, Ponka (2016) examines the impact of real oil prices on the directional predictability of excess stock returns in the USA and ten other countries. Ponka's (2016) finding shows that oil prices are useful predictors of the direction of stock returns in a number of markets. The aforementioned studies point to the importance of international directional predictability in stock returns and the US impact on other markets. These findings also support Rapach et al. (2013) who show that lead–lag relationships are an important feature of international stock return predictability, with the USA generally playing a leading role.

The above studies highlight the fact that when financial markets are integrated, unexpected fluctuations in international market volatilities can create uncertainty in the local market return, which leads to more than one possible answer to the question of whether the return will change or convert into an expansion/contraction period in the next or a subsequent period. The next or subsequent period may be a day, week, month, quarter or year, and the focus of this study is to predict the next month's expansion/contraction period. When there is a volatile situation, risk and uncertainty inevitably arise. As Knight's (1921) seminal work shows, there is a distinction between risk and uncertainty. Risk exists when a probability based on past experience can be attached to an event, whereas uncertainty exists when there is no objective way to place a probability on that event. As such, this study seeks to predict the probability of the occurrence of a recovery (positive return) and the timing of recovery in the return via a binary logit model.

This study first estimates a logit regression model using only selected economic and financial variables. A one-step-ahead forecasting model is developed to predict the directional changes in the Australian share market. The non-inclusion of any market volatility denotes the benchmark model. A model incorporating domestic and international financial market volatilities is also estimated (along with the same selected economic and financial variables in the benchmark model) to assess the extent of the impact volatility has on forecasted asset return values. To select the best forecasting model and to identify the best measure of volatility between MAD, STD, U^2 and range, an out-of-sample prediction performance of the estimated models is assessed using Brier's QPS statistic and hit ratio. This study considers only the static binary model since the focus is to identify the importance of financial market volatility in predicting directional changes in asset return.

The rest of the paper is structured as follows: Section two discusses the forecasting models for predicting the directional changes in asset return. Section three explains the selection of the data used in this study and their sources. Section four discusses the methodology for modelling the static binary-dependent variable model. Section five provides the estimated model results, marginal probability analysis and forecast comparisons. Finally, section six concludes.

2 Forecasting models for predicting the directional changes in asset return

First, to demonstrate that the directional changes in asset return are predictable, this section introduces the Christoffersen et al.'s (2007) method, which is also discussed in Nyberg (2011). It assumes that the data generating process of r_t is:

$$r_t = \mu_t + \sigma_t \varepsilon_t \tag{1}$$

where r_t = asset return; μ_t = the conditional mean; σ_t = the conditional variance; and ε_t ~IID(0, 1), which is the conditional probability of a positive return, given the information set $\acute{\Omega}_{t-1}$, is:

$$\begin{aligned} P_{t-1}(r_t > 0) &= 1 - P_{t-1}(r_t \leq 0) \\ &= 1 - P_{t-1}(\varepsilon_t \leq -\mu_t/\sigma_t) \\ &= 1 - F_\varepsilon(-\mu_t/\sigma_t) \end{aligned} \tag{2}$$

where $F_\varepsilon(.)$ is the cumulative distribution function of the error term ε_t. If the conditional probability of positive return [Eq. (2)] varies with the information set $\acute{\Omega}_{t-1}$, then the sign of the return should be predictable. The next step in model building is to define the dependent variable that can be useful to predict the directional changes in the asset return. This is achieved via Eq. (3) below:

$$I_{it} = \mathrm{Ln}\left(\frac{S_{it}}{S_{it-1}}\right)_t \tag{3}$$

where I_{it} is the monthly return from the Australian share market at time t; $i =$ resource sector, industrial sector and banking sector; and S_{it} and S_{it-1} are the current and previous period share price indexes, respectively. The dependent variable I_{it} takes the value 1 when the return (r_{it}) is positive and zero otherwise. Hence:

$I_{it} = 1$, if $r_{it} > 0$ where return is positive, $i =$ resource sector, industrial sector, banking sector
$I_{it} = 0$, if $r_{it} \leq 0$ where return is zero or negative.

When the dependent variable is nominal (1/0), the OLS technique is not appropriate, but binary models such as the logit and probit regression models are capable of estimating the probability associated with the positive return in the asset return. Binary models can be estimated using the maximum likelihood method. The logit regression and probit regression models are different in the specification of the distribution of the error term (ε) in the regression model. If the cumulative distribution of the error term (ε) is logit, then the model is known as a logit regression model, and if the error term (ε) follows a normal distribution, it is a probit regression model. Since the cumulative normal and the logit distributions are very similar to each other except in the tail region, it is expected that the results will not be markedly different using these models unless the sample is large (Maddala 2001). Amemiya (1981) has established the relationship between the estimates of logit regression and probit regression. Despite their similarity, the logit regression model has two practical advantages. The first is its simplicity. The equation of the cumulative distribution function is very simple, while the normal cumulative distribution function involves an unevaluated integral. Second, it lends itself to easy interpretation. The inverse linearizing transformation for the logit model, $\Lambda^{-1}(p)$, is directly interpretable as log odds, while the inverse transformation of probit model, $\Phi^{-1}(p)$, does not have a direct interpretation. This study considers only the logit regression model, and the static logit regression forecasting model is given as:

$$p_{it} = \Lambda(.) = \Lambda(\omega + x_{t-k}\beta_i) \tag{4}$$

where $\Lambda(.)$ denotes the value of the logit cumulative distribution; k is the number of lags; and vector x'_{t-k} represents all the explanatory variables that are included in this model. P_{it} is the probability that the particular outcome of positive return occurs in time t for sector i ($i = 1$, resource sector; $i = 2$, industrial sector; $i = 3$, banking sector).

3 Data and sources

3.1 Selection of economic and financial variables

According to Chen et al. (1986), there is no satisfactory theory to argue that the relation between financial markets and the macroeconomic variables is entirely in one direction. However, there are two distinct ways of identifying the macroeconomic variables that influence asset prices. One way is to consider the asset valuation model, which consists of cash flow (in the numerator) and discount rate (in the denominator). Here, any macroeconomic variables that influence the cash flow and discount rate directly or indirectly influence the share market return as a whole. The second approach is the risk-and-return concept, where risk has two components: systematic and unsystematic risks, with rational investors more concerned about systematic risk which is related to market variables.

Typically, share prices are determined by fundamental economic variables such as interest rates, exchange rates and inflation rates. Many studies have been published about the relationship between share prices and fundamental economic variables in the USA, Japan and European countries (see, for example, Chen et al. 1986; Humpe and Macmillan 2009; Beenstock and Chan 1988; Mukherjee and Naka 1995). Within the Australian share market studies, Groenewold and Fraser (1997) find that the Australian share market is influenced by macroeconomic factors such as short-term interest rates, the inflation rate and the money growth rate. Chaudhuri and Smiles's (2004) study finds long-run relationships between the Australian real stock price index (ASX) and real gross domestic product (GDP), real private consumption, real money and real oil price. Kazi's (2008) study finds that bank interest rates, corporate profitability, dividend yield, industrial production and, to a lesser extent, global market movement all significantly influence the Australian share market return in the long run.

Based on past studies and investors' common intuition, the following set of economic and financial variables are identified as valid and justifiable independent variables to forecast directional changes in the asset return. The variables' measures in growth rate are: retail trade (RET), private sector non-residential building approvals (NRBA), money supply (M3), yield on 10-year bonds (TYBG), price earnings ratio (PEG), dividend yield (DIVG), total employed persons (EMP), RBA index of commodity prices of base metals (CPB), oil price (OIL), trade-weighted index (TWI), US share price index SP500 (SP5), Euro area composite leading indicator (CLIEU). These are discussed in the remaining subsections in this section.

Monthly data is obtained from the DX database [Reserve Bank of Australia (RBA) Bulletin, OECD main economic indicators and the International Monetary Fund (IMF) international financial statistics] from the period from December 1979 to October 2018. Three major sectors' share price indices: banks (BAN), resources (RES) and industrials (IND) are considered as dependent variables.

3.2 Economic output

Although Australian GDP is the most comprehensive measure of economic output to explain share market return, monthly data on GDP are not available. The following Australian monthly indicators, RET and NRBA, are considered as significant proxies to measure the effect of GDP on the share market return. The expected sign is positive, and RET represents a significant factor for the industrial sector, whereas NRBA (non-residential building approvals) is a significant indicator for the banking sector.

To measure the effects of international economic output on Australian share prices, this study considers certain economic indicators from the USA, China and the Euro area that have a positive impact on Australian share market return. The SP500 index is a commonly used indicator for global economic growth, which can have a positive impact on Australian share prices. It is widely used as a tracking index by fund managers including Australia compared to other global equity indices such as MSCI, NYSE, NASDAQ and FTSE100. In addition, the composite leading indicator CLIEU from Europe should also have positive impacts on resources and industrial share market returns. Europe is a major trading partner of Australia, with Australia exporting resources, industrial and agricultural commodities and services such as tourism.

3.3 Capital market variables

Interest rates have two different effects on stock prices. First, it can affect firms as a cost factor. Higher interest rates mean higher costs and lower profits for the firm. Second, the interest rate is used as a discount factor in the net present value (NPV) model, where higher interest rates mean a lower NPV of the investment. Although interest rates affect all three sectors, the effect of interest rates on the banking sector is more significant because it increases/decreases the profit margin of the banking sector. To measure the effects of interest rates, this study identifies TYBG, which is the yield on 10-year bonds, as a significant indicator. Further, this study also includes share price dividend yield (DIVG) and price earnings ratio (PEG) as useful predictors for predicting future return (Pierson et al. 2015).

In addition, the variable M3 is included as it represents the availability of funds for firms and investors, which can have positive effects on share prices. For example, higher money supply implies that more credit is available to investors which can improve economic activity and create higher demand for goods and services and result in higher share prices.

3.4 Labor market variables

According to the Reserve Bank of Australia (RBA), the non-farm wages income share was 54.7% in the September quarter 2013, which implies that labor costs comprised approximately 55% of the total costs of firms in Australia. The expected relationship between stock returns and labor costs is negative because when labor costs are higher profit is lower. To measure the impact of labor costs on Australian share prices, the variable EMP is used.

3.5 Commodity prices

The effect of commodity prices on the share prices of the banking, industrial and resource sector varies. In the resources sector, commodities are considered as output, and therefore, the expected relationship between commodity prices and stock return is positive. In the case of the industrial sector, commodities are considered as intermediate input, or a factor of production, which affects the cost of production. The expected relationship between industrial sector share prices and commodity prices is negative. Commodity prices may affect banking sector share prices through the expansion/contraction of overall economic activity. If there is a high demand for commodities, this will increase overall economic activity, which may have a positive impact on banking sector share prices. The following commodity price index CPB is thus included.

Energy prices may affect all sectors in the Australian economy. Higher oil price (OIL) means a higher cost of living and production, which leads to higher costs for firms and lower demand for goods and services and ultimately lower profits. The expected relationship between OIL and bank and industrial sectors' stock returns is negative, whereas, since OIL is the output in the resources sector, the expected sign is positive.

3.6 Exchange rate

The banking, industrial and resources sectors are all exposed to exchange rate risk due to their international business activities. However, these sectors can manage the exchange rate risk through hedging. Shamsuddin (2009) examines the relationship between foreign exchange risk and Australian bank share prices and finds that the exchange rate parameter is positive and highly significant for the bank portfolio, indicating that an appreciation of the Australian dollar against the US dollar exerts a positive influence on bank stock returns. To measure the impact of the Australian dollar on Australian share prices, the TWI is considered. The TWI is the weighted average value of the Australian dollar against the currencies of the major Australian trading partners, with the weights being determined by the trading share of the countries.

3.7 International volatility

Having identified the link between international volatility and Australian asset returns, this study includes SP5 volatility and TWI volatility to predict the directional changes of selected share market returns in Australia. The plots of SP5 volatility measured in U^2, STD, MAD and range are given in Fig. 1. In comparison, both the MAD and STD measures exhibit smooth plots compared to U^2 and range because they are given in average values. Since high volatility creates more uncertainty which means more risk,

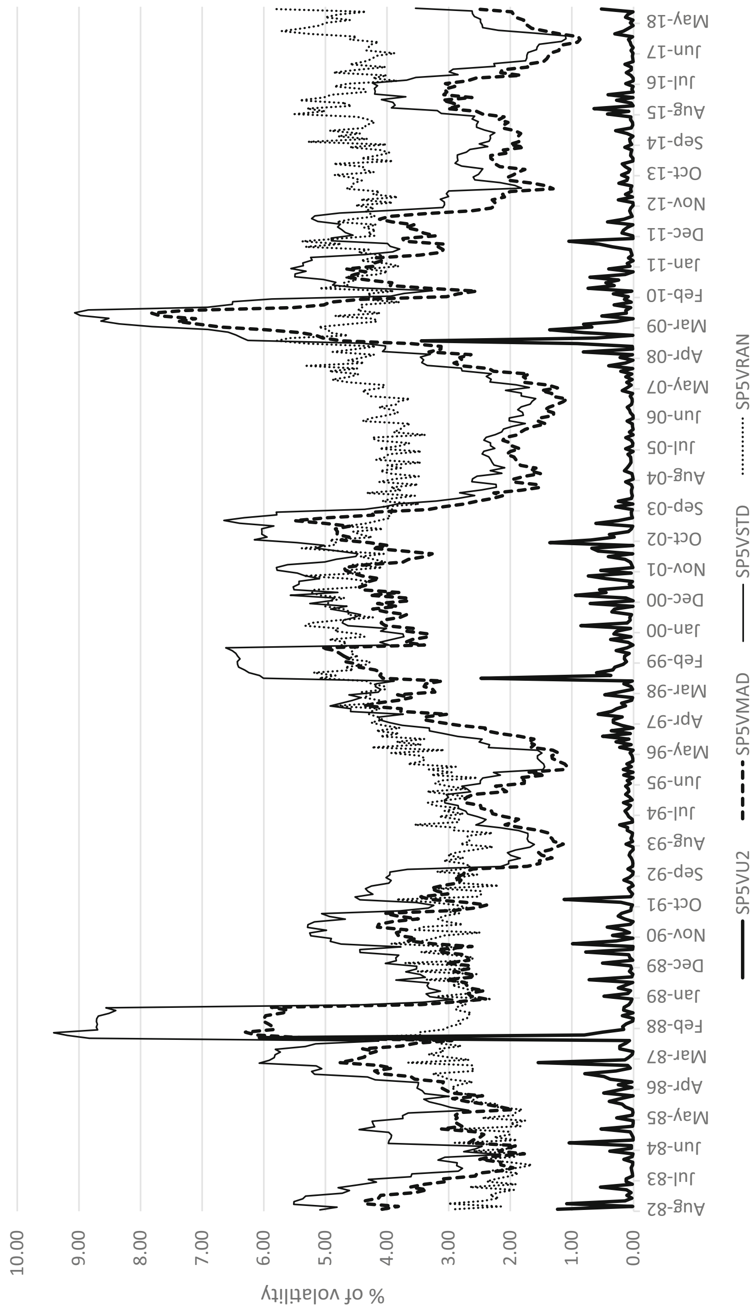

Fig. 1 Percentage of volatilities of SP500 measured in U^2, MAD, STD and range

the expected impact of U^2 and range on directional changes in asset return is higher than the MAD and STD measures.

4 Methodology

We estimate logit regression models with the relevant growth rates of the economic and financial variables, index volatilities, SP5 volatility and TWI volatility. First, the identified positive/negative returns are mapped into 1/0 variables, where 1 represents a positive return and 0 represents a negative return. Second, the logit regression models are estimated using monthly data for the period from August 1982 to October 2018. A dummy variable is included in the model to capture the 1987 stock market crash, but it is not significant. The estimated models are: (i) logit regression with economic and financial variables—excluding volatility; (ii) logit regression with economic and financial variables, volatilities of indices, SP500 index, and TWI measured by U^2; (iii) logit regression with economic and financial variables and volatilities of indices, SP500 index, and TWI measured by MAD; (iv) logit regression with economic and financial variables and volatilities of indices, SP500 index and TWI measured by STD; and (v) logit regression with economic and financial variables and volatilities of indices, SP500 index and TWI measured by range. Logit regression models are estimated using EViews (v.9.0) Huber–White options for robust standard errors (quasi-maximum likelihood standard errors). The results of the one-step-ahead estimated logit regression models for each sector are presented in Table 1.

To confirm there is no multicollinearity, the correlation matrix of the significant variables is reported in Table 2. The estimated models are considered valid since the likelihood ratio (LR) statistics are significant at the 5% level. Only correlations that are significant at the 5% level are reported in Table 1. The estimated McFadden R^2 cannot be interpreted like R^2 in general linear model. The former has the property which lies between zero and one with values from 0.20 to 0.40 indicating a highly satisfactory model fit. The optimal lag length for the estimated model, reported in square brackets, is obtained by using the Schwarz Bayesian criterion (SBC) beginning with a maximum lag length of 12. The use of different time lag lengths is incorporated to determine at which point volatility is significant. For forecasting purposes, significantly longer lags are included even though they may not have any meaningful interpretation.

5 Results

5.1 Descriptive statistics

Table 3 shows the summary descriptive statistics for the monthly logarithmic growth rates of the variables.

Table 1 Results of the estimated binary logit models, August 1982–October 2018

Variable	Banks	SE	Res	SE	Indus	SE
Economic variable model						
C	0.216	0.176	− 0.105	0.167	0.109	0.213
SP5	0.134	0.035	0.101	0.032	0.252	0.044
TWI			0.127	0.043		
$\mathrm{TWI}_{[-2]}$	0.099	0.044				
$\mathrm{TWI}_{(-11)}$					− 0.087*	0.045
$\mathrm{RET}_{[-3]}$					0.302	0.125
OIL			0.047	0.016		
$\mathrm{OIL}_{[-8]}$	0.034	0.016				
CPB			0.048*	0.029		
$\mathrm{CPB}_{[-4]}$	0.052*	0.027			0.061	0.032
M3			0.253*	0.153		
$\mathrm{M3}_{[-7]}$	0.289	0.140				
NRBA	0.007*	0.004				
$\mathrm{NRBA}_{[-4]}$			0.009	0.003		
EMP						
$\mathrm{EMP}_{[-9]}$	− 0.774	0.380			− 0.926	0.479
TYBG	− 0.055*	0.029			− 0.085	0.035
$\mathrm{TYBG}_{[-8]}$			0.050*	0.026		
PEG	0.088	0.028	0.081	0.032	0.195	0.040
DIVG	− 0.172	0.038	− 0.137	0.043	− 0.189	0.049
$\mathrm{CLIEU}_{[-1]}$					2.793	1.314
R^2	0.272		0.239		0.427	
AIC	1.033		1.094		0.811	
SBC	1.137		1.188		0.915	
HQC	1.074		1.131		0.852	
LR	158.80		142.54		244.99	
PLR	0.000		0.000		0.000	
LL	− 211.6		− 225.9		− 163.8	
QPS	0.448		0.390		0.254	
Economic variable model + U^2						
C	0.253	0.192	− 0.076	0.178	0.129	0.229
SP5	0.139	0.035	0.108	0.034	0.289	0.048
TWI			0.165	0.048		
$\mathrm{TWI}_{[-2]}$	0.077*	0.042				
$\mathrm{TWI}_{[-6]}$					− 0.083*	0.050
$\mathrm{RET}_{[-3]}$					0.300	0.131
OIL			0.051	0.016		

Table 1 continued

Variable	Banks	SE	Res	SE	Indus	SE
$OIL_{[-8]}$	0.033	0.017				
$CPB_{[-1]}$			0.048*	0.027		
$CPB_{[-4]}$	0.045*	0.027			0.070	0.034
M3			0.273*	0.155		
$M3_{[-2]}$					0.585	0.197
$M3_{[-7]}$	0.244*	0.143				
$NRBA_{[-1]}$	− 0.008*	0.004				
$NRBA_{[-4]}$			0.011	0.003		
$EMP_{[-9]}$	− 0.825	0.373			− 1.146	0.531
TYBG	− 0.059	0.030			− 0.109	0.035
$TYBG_{[-8]}$			0.051	0.026		
PEG	0.087	0.028	0.083	0.032	0.206	0.042
DIVG	− 0.174	0.038	− 0.136	0.043	− 0.207	0.052
$CLIEU_{[-1]}$					2.437	1.224
$SP5VU_{[-2]}$	− 0.548	0.267			− 1.246	0.336
$SP5VU_{[-4]}$			− 0.932	0.405		
R^2	0.286		0.260		0.462	
AIC	1.023		1.075		0.774	
SBC	1.146		1.187		0.896	
HQC	1.072		1.119		0.822	
LR	166.8		155.64		265.0	
PLR	0.000		0.000		0.000	
LL	− 207.6		− 221.3		− 153.8	
QPS	0.442		0.389		0.265	
Economic variable model + MAD						
C	0.895	0.432	− 0.105	0.159	0.902	0.396
SP5	0.136	0.034	0.101	0.034	0.251	0.044
TWI			0.127	0.043		
$TWI_{[-2]}$	0.110	0.045				
$TWI_{[-6]}$					− 0.080*	0.048
$RET_{[-3]}$					0.300	0.129
OIL			0.047	0.016		
$OIL_{[-2]}$	− 0.026*	0.015				
CPB			0.048*	0.029		
$CPB_{[-4]}$	0.053*	0.027			0.059*	0.031
M3			0.253*	0.153		
$M3_{[-2]}$					0.526	0.192
$M3_{[-10]}$	0.319*	0.170				
NRBA						
$NRBA_{[-1]}$	− 0.008	0.004				

Table 1 continued

Variable	Banks	SE	Res	SE	Indus	SE
$NRBA_{[-4]}$			0.009	0.003		
EMP						
$EMP_{[-9]}$	− 0.736	0.365			− 0.907*	0.506
TYBG	− 0.056	0.029			− 0.095	0.034
$TYBG_{[-8]}$			0.050*	0.026		
PEG	0.090	0.028	0.081	0.032	0.204	0.039
DIVG	− 0.166	0.038	− 0.137	0.043	− 0.198	0.048
$CLIEU_{[-1]}$					3.306	1.295
BANVM						
$BANVM_{[-5]}$	− 0.168*	0.095				
$SP5VM_{[-2]}$					− 0.268	0.122
R^2	0.278		0.239		0.437	
AIC	1.030		1.094		0.803	
SBC	1.143		1.188		0.916	
HQC	1.075		1.131		0.847	
LR	162.04		142.54		250.43	
PLR	0.000		0.000		0.000	
LL	− 210.06		− 225.88		− 161.09	
QPS	0.422		0.390		0.28	
Economic variable model + STD						
C	0.816	0.407	0.751	0.336	1.279	0.471
SP5	0.129	0.034	0.102	0.034	0.278	0.048
TWI			0.139	0.045		
$TWI_{[-2]}$	0.091	0.042				
$TWI_{[-6]}$					− 0.095*	0.052
$RET_{[-3]}$					0.223	0.114
OIL			0.046	0.016		
$OIL_{[-8]}$	0.029*	0.017			− 0.044	0.018
CPB			0.049*	0.029		
$CPB_{[-4]}$	0.052*	0.027			0.056*	0.033
$M3_{[-2]}$					0.584	0.204
$M3_{[-10]}$	0.310	0.161				
NRBA						
$NRBA_{[-1]}$	− 0.008*	0.004				
$NRBA_{[-4]}$			0.008	0.003		
EMP					− 1.148	0.458
$EMP_{[-9]}$	− 0.727	0.376				
TYBG	− 0.052*	0.029			− 0.103	0.044
$TYBG_{[-8]}$			0.055	0.025		
PEG	0.090	0.028	0.089	0.032	0.177	0.038

Table 1 continued

Variable	Banks	SE	Res	SE	Indus	SE
DIVG	− 0.173	0.037	− 0.125	0.042	− 0.187	0.050
$CLIEU_{[-1]}$					3.744	1.398
$BANVS_{[-7]}$	− 0.115*	0.067				
$TWIVS_{[-10]}$			− 0.253	0.124		
$SP5VS_{[-2]}$					− 0.267	0.101
R^2	0.280		0.242		0.447	
AIC	1.027		1.091		0.795	
SBC	1.140		1.185		0.924	
HQC	1.072		1.128		0.846	
LR	163.38		144.05		213.11	
PLR	0.000		0.000		0.000	
LL	− 209.39		− 225.12		− 131.55	
QPS	0.422		0.384		0.301	
Economic variable model + RANGE						
C	− 2.282	0.905	− 3.127	1.032	7.970	2.401
SP5	0.151	0.036	0.127	0.042	0.289	0.068
TWI			0.169	0.054		
$TWI_{[-2]}$	0.089*	0.049				
$RET_{[-3]}$					0.695	0.172
OIL			0.052	0.018		
$OIL_{[-2]}$	− 0.031	0.016				
$CPB_{[-4]}$	0.055	0.028				
$M3_{[-6]}$					− 0.483*	0.259
$M3_{[-10]}$	0.373	0.169				
$NRBA_{[-1]}$	− 0.009	0.005				
$NRBA_{[-4]}$			0.008	0.004		
$EMP_{[-8]}$					1.846	0.806
$EMP_{[-9]}$	− 0.677*	0.372				
TYBG	− 0.052*	0.030			− 0.079	0.040
$TYBG_{[-8]}$			0.057	0.028		
PEG	0.093	0.029	0.084	0.032	0.187	0.066
DIVG	− 0.164	0.037	− 0.102	0.040	− 0.126	0.064
$WBCVR_{[-2]}$	− 0.423	0.216				
SP5VR					− 1.907	0.537
$USDVR_{[-10]}$			− 0.920	0.296		
$TCLVR_{[-8]}$					− 0.796	0.332
R^2	0.289		0.241		0.465	
AIC	1.020		1.102		0.793	
SBC	1.143		1.207		0.928	
HQC	1.069		1.144		0.847	

Table 1 continued

Variable	Banks	SE	Res	SE	Indus	SE
LR	168.46		123.74		163.70	
PLR	0.000		0.000		0.000	
LL	− 206.8		− 194.9		− 94.2	
QPS	0.417		0.366		0.401	

This table shows the results of the estimated binary logit models over the period from August 1982 to October 2018 of the following variables: BANVM, volatility of banks index measured by the mean absolute deviation; BANVS, volatility of banks index measured by the standard deviation; CLIEU, Euro area composite leading indicator; CPB, RBA index of commodity prices of base metals; DIVG, growth rate of dividend yield of ASX; EMP, total employed persons; INDVM, volatility of industrials index measured by the mean absolute deviation; M3, money supply; NRBA, private sector non-residential building approvals; OIL, oil price; PEG, growth rate of price earnings ratio of ASX; RET, retail trade; SP5, US share price index SP500; SP5VM, volatility of the US share price index SP500 measured by the mean absolute deviation; SP5VS, volatility of the US share price index SP500 measured by the standard deviation; SP5VU, volatility of the US share price index SP500 measured by the squared growth rate; TCLVR, volatility of the Transurban Limited share (TCL) price measured by range; TWI, trade-weighted index; TWIVS, volatility of the TWI measured by the standard deviation; TWIVU, volatility of the TWI measured by the squared growth rate; TYBG, yield on 10-year bonds; USDVR, volatility of the US dollar measured by range; WBCVR, volatility of the Westpac Banking Corporation (WBC) measured by range; R^2, McFadden R^2; AIC, Akaike information criterion; SBC, Schwarz criterion; LR, likelihood ratio statistic; PLR, probability of the LR test statistics; LL, log likelihood statistics; QPS, quadratic probability score

* denotes significance at the 10% level. All other variables are significant at the 5% level of significance

5.2 Estimated model results

Table 1 shows the results of the estimated models for the banking, industrial and resource sectors with statistically significant economic and financial variables and SP5 volatility and TWI volatility measured in U^2, MAD, STD and range. The SP5 volatility and TWI volatility measured in U^2 are statistically significant for the banking, resource and industrial sectors. SP5 volatility has a negative sign. When volatility is measured by MAD and STD, SP5 volatility is only statistically significant in the industrial sector and has a negative sign. TWI volatility measured by STD is only statistically significant in the resources sector. The results of the SP5 and TWI volatilities in the models confirm that volatilities (international and domestic) are important for predicting the directional changes in the banking, industrial and resource sector returns. Further, the SP5 result provides evidence for a direct international volatility effect on Australian stock prices.

The impact of economic and financial variables on the directional changes in the banking, resources and industrial returns varies by sector. Statistically significant variables in the banking sector models are: SP5, TWI, TYBG, OIL, CPB, M3, NRBA, TYBG, PEG and DIVG and EMP, each with their expected signs. Statistically significant variables in the resources sector models are: SP5, TWI, M3, OIL, CPB, NRBA, TYBG, PEG and DIVG, each with their expected signs. Statistically significant variables in the industrial sector models are: SP5, TWI, CPB, RET, EMP, TYBG, PEG, DIVG and CLIEU, each with their expected signs.

Table 2 Correlation matrix of significant variables, August 1982–October 2018

	BANVM	BANVS	CLIEU	CPB	DIVG	EMP	INDVM	M3	NRBA	OIL	PEG	RET	SP5	SP5VM	SP5VS	SP5VU	TCLVR	TWI	TWIVS	TYBG	USDVR	WBCVR
BANVM	1.00																					
BANVS	0.94	1.00																				
CLIEU	0.05	0.09	1.00																			
CPB	− 0.05	0.00	0.30	1.00																		
DIVG	0.03	0.06	− 0.16	0.02	1.00																	
EMP	− 0.03	0.00	0.08	0.10	0.02	1.00																
INDVM	0.82	0.90	0.14	0.04	0.05	0.02	1.00															
M3	− 0.02	0.00	− 0.07	− 0.05	0.09	0.12	0.02	1.00														
NRBA	− 0.01	0.00	0.03	− 0.01	− 0.06	0.02	0.01	− 0.09	1.00													
OIL	− 0.09	− 0.08	0.16	0.21	− 0.05	− 0.01	− 0.08	− 0.04	0.05	1.00												
PEG	− 0.02	− 0.03	0.12	0.01	− 0.64	− 0.03	− 0.01	− 0.04	0.00	0.12	1.00											
RET	− 0.01	0.01	0.01	− 0.05	0.02	− 0.05	0.01	0.07	0.09	0.03	0.00	1.00										
SP5	− 0.07	− 0.08	0.21	0.00	− 0.47	0.05	− 0.06	− 0.06	− 0.04	0.04	0.48	0.06	1.00									
SP5VM	0.59	0.61	0.05	0.00	0.00	− 0.08	0.60	0.01	0.01	− 0.01	0.06	0.03	− 0.01	1.00								
SP5VS	0.59	0.65	0.02	0.00	0.02	− 0.08	0.65	0.02	0.01	− 0.02	0.04	0.04	− 0.03	0.98	1.00							
SP5VU	0.21	0.23	− 0.18	0.02	0.36	0.00	0.25	0.03	0.02	− 0.05	− 0.34	− 0.02	− 0.27	0.30	0.33	1.00						
TCLVR	0.06	0.08	− 0.08	− 0.04	0.06	0.02	0.05	− 0.01	− 0.07	0.08	− 0.06	0.05	− 0.10	0.02	0.00	− 0.08	1.00					
TWI	− 0.02	0.01	0.18	− 0.06	− 0.28	− 0.05	0.02	− 0.03	0.02	0.16	0.27	0.06	0.28	0.08	0.07	− 0.24	0.07	1.00				
TWIVS	0.51	0.44	− 0.04	− 0.11	− 0.06	0.09	0.38	0.06	− 0.01	− 0.02	0.06	0.02	0.00	0.42	0.38	0.17	0.05	0.00	1.00			
TYBG	− 0.01	0.02	0.24	0.22	0.11	− 0.02	0.01	− 0.04	0.02	0.27	− 0.10	0.03	− 0.02	− 0.01	− 0.01	0.03	0.05	0.01	0.00	1.00		
USDVR	0.22	0.20	− 0.13	− 0.13	0.18	0.00	0.12	0.14	− 0.02	− 0.05	− 0.11	0.00	− 0.19	0.22	0.20	0.25	0.16	− 0.16	0.27	− 0.03	1.00	
WBCVR	− 0.04	− 0.04	− 0.05	− 0.07	0.09	0.02	− 0.12	− 0.08	0.02	0.00	− 0.07	− 0.05	− 0.11	0.03	0.00	0.09	0.31	0.00	0.11	− 0.04	0.47	1.00

This table shows the correlation between the following variables over the period from August 1982 to October 2018: BANVM, volatility of banks index measured by the mean absolute deviation; BANVS, volatility of banks index measured by the standard deviation; CLIEU, Euro area composite leading indicator; CPB, RBA index of commodity prices of base metals; DIVG, growth rate of dividend yield of ASX; EMP, total employed persons; INDVM, volatility of industrials index measured by the mean absolute deviation; M3, money supply; NRBA, private sector non-residential building approvals; OIL, oil price; PEG, growth rate of price earnings ratio of ASX; RET, retail trade; SP5, US share price index SP500; SP5VM, volatility of the US share price index SP500 measured by the mean absolute deviation; SP5VS, volatility of the US share price index SP500 measured by the standard deviation; SP5VU, volatility of the US share price index SP500 measured by the squared growth rate; TCLVR, volatility of the Transurban Limited share (TCL) price measured by range; TWI, trade-weighted index; TWIVS, volatility of the TWI measured by the standard deviation; TYBG, yield on 10-year bonds; USDVR, volatility of the US dollar measured by range; WBCVR, volatility of the Westpac Banking Corporation (WBC) measured by range

Table 3 Descriptive statistics: August 1982–October 2018

	Mean	Median	Maximum	Minimum	Std. Dev.	Skewness	Kurtosis	Probability	Sum	Sum Sq. Dev.
BANVM	3.75	3.63	7.20	1.48	1.22	0.36	2.53	0.01	1015.78	398.59
BANVS	4.85	4.73	9.08	1.76	1.53	0.27	2.59	0.07	1314.36	629.04
CLIEU	0.00	0.02	0.55	− 0.70	0.17	− 0.69	6.36	0.00	0.27	7.90
CPB	0.25	0.42	13.96	− 21.39	4.10	− 0.44	5.85	0.00	66.60	4543.88
DIVG	0.06	0.00	28.61	− 28.68	5.76	− 0.40	10.29	0.00	16.25	8958.4
EMP	0.16	0.13	0.92	− 0.63	0.24	0.00	3.08	0.96	42.61	15.85
INDVM	2.63	2.51	6.24	1.04	0.95	0.92	4.10	0.00	713.32	241.60
M3	0.71	0.64	3.47	− 2.99	0.74	− 0.09	6.34	0.00	191.31	149.31
NRBA	0.64	0.51	111.65	− 72.37	26.05	0.12	3.75	0.03	174.02	183269.90
OIL	0.50	1.77	20.14	− 31.18	8.42	− 0.82	4.34	0.00	136.09	19146.86
PEG	0.01	0.24	21.67	− 18.33	5.19	− 0.14	4.45	0.00	1.62	7286.39
RET	0.39	0.32	7.75	− 11.21	1.12	− 2.54	51.96	0.00	105.19	338.56
SP5	0.53	1.02	10.23	− 18.55	4.31	− 0.83	4.65	0.00	143.52	5017.8
SP5VM	3.02	2.91	7.82	0.86	1.37	0.80	3.63	0.00	819.12	504.51
SP5VR	4.40	4.35	5.82	3.07	0.47	0.34	3.22	0.05	1193.06	60.87
SP5VS	3.87	3.79	9.07	1.10	1.67	0.64	2.97	0.00	1047.46	749.47
SP5VU	0.19	0.06	3.44	0.00	0.34	5.15	41.99	0.00	50.94	30.66
TCLVR	− 0.83	− 0.82	0.66	− 3.32	0.65	− 0.79	4.40	0.00	− 226.23	114.45
TWI	0.03	0.00	6.34	− 14.76	2.66	− 0.81	5.96	0.00	8.60	1909.9
TWIVS	2.52	2.24	6.07	1.26	0.89	1.88	7.38	0.00	683.23	215.30
TYBG	− 0.44	− 0.69	17.82	− 16.29	4.68	0.12	4.13	0.00	− 118.99	5924.6
WBCVR	0.50	0.46	2.05	− 1.14	0.60	− 0.02	2.62	0.43	134.44	97.53
USDVR	− 3.32	− 3.38	− 1.60	− 4.31	0.46	0.49	3.39	0.00	− 900.86	56.66

This table presents descriptive statistics of the following variables: BANVM, volatility of banks index measured by the mean absolute deviation; BANVS, volatility of banks index measured by the standard deviation; CLIEU, Euro area composite leading indicator; CPB, RBA index of commodity prices of base metals; DIVG, growth rate of dividend yield of ASX; EMP, total employed persons; INDVM, volatility of industrials index measured by the mean absolute deviation; M3, money supply; NRBA, private sector non-residential building approvals; OIL, oil price; PEG, growth rate of price earnings ratio of ASX; RET, retail trade; SP5, US share price index SP500; SP5VM, volatility of the US share price index SP500 measured by the mean absolute deviation; SP5VR, volatility of the US share price index SP500 measured by range; SP5VS, volatility of the US share price index SP500 measured by the standard deviation; SP5VU, volatility of the US share price index SP500 measured by the squared growth rate; TCLVR, volatility of the Transurban Limited share (TCL) price measured by range; TWI, trade-weighted index; TWIVS, volatility of the TWI measured by the standard deviation; TYBG, yield on 10-year bonds; WBCVR, volatility of the Westpac Banking Corporation (WBC) measured by range; USDVR, volatility of the US dollar measured by range

TWI is statistically significant in the banking sector models, which confirms that an appreciation of the Australian dollar has a positive impact on directional changes in the banking index return, which supports Shamsuddin's (2009) study. TYBG is statistically significant and has a negative sign only for the banking and industrial sectors. This suggests that higher TYBG (i.e. high interest rates) can lead to higher funding costs and result in share price declines due to investor expectation. The NRBA is statistically significant and has a positive sign in the banking sector and resource sector. The positive sign reflects the fact that as more building approvals occur, the more economic activity increases, which has a positive impact on the banking and resource sectors.

The Euro area is an important trading partner for Australia which explains why CLIEU is statistically significant and has a positive sign in the industrial sector models. Retail price is statistically significant only in the industrial sector, because retailing and manufacturing stocks represent a large proportion of the industrial index. OIL is the output in the resource sectors and exhibits a positive sign in the resource models.

5.3 Marginal probability analysis

Table 4 provides the estimates of change in the probability of positive return (1) occurrence as a result of a 1% change in the economic and financial variables and SP5 and TWI volatilities. It can be measured by $\Delta p = \beta_j p_i(1 - p_i)$, where Δp is the change in probability, β_j is the estimated coefficient (Maddala 2001, p. 327; Pindyck and Rubinfeld 1998, p. 316). A single value cannot be assigned on the probability (p_i) to measure the impact of the explanatory variable on the probability. However, Pindyck and Rubinfeld (1998, p. 316) indicate that the most useful single value of p_i to choose for this interpretation is the sample mean value (Kulendran and Wong 2011). For the bank, industrial and resource sectors, the sample mean value of p_i was obtained by substituting the sample mean values of the growth rate of economic and financial variables as well as the SP5 and TWI volatilities in the estimated logit regressions.

A 1% increase in the growth rate of the SP5 will, on average, result in an increase in the probability of a positive return occurrence by 0.03 for the banking sector, 0.03 for the resources sector and 0.06 for the industrial sector. Marginal probability analysis shows that change in the growth rate of the SP5 will have more effect on the industrial sector followed by the banking and resource sectors. A 1% increase in SP5 volatilities measured by U^2 will result in a decrease in the probability of positive return occurrence by 0.14, 0.23 and 0.31 for the banking and industrial sectors, respectively. This implies that SP5 volatility has a greater effect on the industrial sector followed by the resources and banking sectors. When the volatility of the SP5 is measured by MAD and range the marginal probability for the industrial sector is 0.07 and 0.48, respectively. These findings show that the effect of SP5 volatility on the directional changes in the banking, resource and industrial sectors returns varies by sector and measures. The influence of the US stock market and its volatility measure support the findings of Rapach et al. (2013). It also supports Ponka (2016) and Nyberg and Ponka (2016) regarding the influence of international directional predictability in stock returns and the US impact on the Australian market. The variable CLIEU has the highest probability in

Table 4 Marginal probability estimate (change in probability due to 1% change in the growth rate of economic variables), August 1982–October 2018

Models	Variables																				
	SP5	TWI	TYBG	OIL	CPB	RET	PEG	DIVG	M3	NRBA	EMP	CLIEU	BANVS	INDVM	SP5VU	SP5VM	SP5VS	SP5VR	USDVR	WBCVR	TCLVR
Economic variables model																					
Banks	0.03	0.02	− 0.01	0.01	0.01		0.02	− 0.04	0.07	0.00	− 0.19										
Resources	0.03	0.03	0.01	0.01	0.01		0.02	− 0.03	0.06	0.00											
Industrials	0.06	− 0.02	− 0.02		0.02	0.08	0.05	− 0.05	0.13		− 0.23	0.70									
Economics variables + U^2																					
Banks	0.03	0.02	− 0.01	0.01	0.01		0.02	− 0.04	0.06	0.00	− 0.21				− 0.14						
Resources	0.03	0.04	0.01	0.01	0.01		0.02	− 0.03	0.07	0.00					− 0.23						
Industrials	0.07	− 0.02	− 0.03		0.02	0.08	0.05	− 0.05	0.15		− 0.29	0.61			− 0.31						
Economics variables + MAD																					
Banks	0.03	0.03	− 0.01	− 0.01	0.01		0.02	− 0.04	0.08	0.00	− 0.18			− 0.04							
Resources	0.03	0.03	0.01	0.01	0.01		0.02	− 0.03	0.06	0.00											
Industrials	0.06	− 0.02	− 0.02		0.01	0.08	0.05	− 0.05	0.13		− 0.23	0.83				− 0.07					
Economics variables + STD																					
Banks	0.03	0.02	− 0.01	0.01	0.01		0.02	− 0.04	0.08	0.00	− 0.18		− 0.03								
Resources	0.03	0.03	0.01	0.01	0.01		0.02	− 0.03		0.00											
Industrials	0.07	− 0.02	− 0.03		0.01	0.06	0.04	− 0.05	0.15		− 0.29	0.94					− 0.07				
Economics variables + RANGE																					
Banks	0.04	0.02	− 0.01	− 0.01	0.01		0.02	− 0.04	0.09	0.00	− 0.17									− 0.11	
Resources	0.03	0.04	0.01	0.01			0.02	− 0.03		0.00									− 0.23		
Industrials	0.07		− 0.02			0.17	0.05	− 0.03	− 0.12		0.46							− 0.48			− 0.20

This table shows the marginal probability estimates of the following variables over the period from August 1982 to October 2018 for the different industries and models: BANVS, volatility of banks index measured by the standard deviation; CLIEU, Euro area composite leading indicator; CPB, RBA index of commodity prices of base metals; DIVG, growth rate of dividend yield of ASX; EMP is total employed persons; INDVM, volatility of industrials index measured by the mean absolute deviation; M3, money supply; NRBA is private sector non-residential building approvals; OIL, oil price; PEG, growth rate of price earnings ratio of ASX; RET, retail trade; SP5, US share price index SP500; SP5VM, volatility of the US share price index SP500 measured by the mean absolute deviation; SP5VR, volatility of the US share price index SP500 measured by range; SP5VS, volatility of the US share price index SP500 measured by the standard deviation; SP5VU, volatility of the US share price index SP500 measured by the squared growth rate; TCLVR, volatility of the Transurban Limited share (TCL) price measured by range; TWI, trade-weighted index; TYBG, yield on 10-year bonds; USDVR, volatility of the US dollar measured by range; WBCVR, volatility of the Westpac Banking Corporation (WBC) measured by range the industrial sector models. Here, a 1% increase in the growth rate of Euro economic activity on average will result in an increase in the probability of positive return occurrence by 0.94.

5.4 Forecast comparison with hit ratio and quadratic probability score (QPS)

This section compares the forecasting performance of the aforementioned binary models: (i) logit regression with economic and financial variables—excluding volatility; (ii) logit regression with economic and financial variables, volatilities of indices, SP500 index and TWI measured by U^2; (iii) logit regression with economic and financial variables and volatilities of indices, SP500 index and TWI measured by MAD; (iv) logit regression with economic and financial variables and volatilities of indices, SP500 index and TWI measured by STD; and (v) logit regression with economic and financial variables and volatilities of indices, SP500 index and TWI measured by range. Within-sample and out-of-sample tests using the QPS score and the hit ratio, which measures the percentage of correctly predicted positive $I_{it} = 1$ and negative $I_{it} = 0$ returns, were conducted.

Models are estimated from August 1982 to December 2012 (within sample), and an out-of-sample forecasting performance is carried out for the period from January 2013 to October 2018 with hit ratio and QPS statistics. To estimate the QPS score from the estimated probability (π_E) and to identify positive and negative return periods, the following rule is considered: if the predicted probability is π_E>0.5, it is considered as positive return (1), whereas π_E<0.5 is considered as negative return (0). Directional change from a positive return to a negative return and the timing of the directional change can be identified when the probability changes from greater than 0.5 to less than 0.5 or vice versa. The risk associated with the negative return is $(1 - \pi_E)$. The forecasting performances of the models are assessed using the quadratic probability score:

$$\mathrm{QPS} = \frac{1}{T}\sum_{t-1}^{T} 2\left(\prod_{t} - I_t\right)^2 \tag{5}$$

where T = forecast period; Π_t is the time—t probability forecast of a positive return over the horizon; I_t equals 1 if a positive return occurs within the horizon and 0 otherwise. The QPS ranges from 0 to 2, with a score of 0 corresponding to perfect accuracy. Calculated hit ratios and the QPS statistics for the above models within-sample period from August 1982 to December 2012 and the out-of-sample period from January 2013 to October 2018 are given in Tables 5 and 6.

According to the hit ratio and QPS statistics, on average, the logit regression model with economic and financial variables and volatilities measured by U^2 has the highest hit ratio and MAD has the lowest QPS score based on out-of-sample testing. Kruskal–Wallis tests confirm that the differences between the measures are not statistically significant. Incorporating volatility provides better forecasts of the selected three sectors of the Australian share market.

Table 5 Forecasting accuracy in terms of the QPS statistics: within-sample period (August 1982–December 2012), out-of-sample period (January 2013–October 2018)

Model	QPS Logit							
	Banks		Resources		Industrials		Average	
	Within sample	Out of sample	Within sample	Out of sample	Within sample	Out of sample	Within sample	Out of sample
Economic variable	0.321	0.448	0.347	0.390	0.235	0.254	0.301	0.3641
Economic variable + volatility U^2	0.312	0.442	0.340	0.389	0.221	0.265	0.291	0.3652
Economic variable + volatility MAD	0.317	0.422	0.347	0.390	0.237	0.280	0.301	0.3641
Economic variable + volatility STD	0.315	0.422	0.347	0.384	0.237	0.301	0.300	0.3688
Economic variable + RANGE	0.311	0.417	0.352	0.366	0.229	0.401	0.297	0.3947

This table shows the QPS statistic for all models in the different industries, as well as the average, for within-sample and out-of-sample periods

Table 6 Forecasting accuracy in terms of hit ratios: within-sample period (August 1982–December 2012) and out-of-sample period (January 2013–October 2018)

Model	Hit ratios							
	Banks		Resources		Industrials		Average	
	Within sample	Out of sample	Within sample	Out of sample	Within sample	Out of sample	Within sample	Out of sample
Economic variable	59.0	61.4	62.5	58.6	67.3	57.1	62.9	59.0
Economic variable + volatility U^2	60.4	61.4	60.2	61.4	67.0	57.1	62.5	60.0
Economic variable + volatility MAD	60.4	58.6	62.5	58.6	65.9	57.1	62.9	58.1
Economic variable + volatility STD	61.2	58.6	61.6	57.1	66.5	55.7	63.1	57.1
Economic variable + RANGE	60.4	54.3	61.6	57.1	71.0	54.3	64.3	55.2

This table shows the hit ratio for all models in the different industries, as well as the average, for within-sample and out-of-sample periods

Table 7 Trading strategies—buy and hold (B&H)

	Banks	Resources	Industrials
Average	0.0072	0.0044	0.0062
Beta	0.8222	1.2020	0.8658
Standard deviation	0.0558	0.0713	0.0465
Buy and hold	0.0093 (+ Buy)	− 0.0150 (− Sell)	0.0480 (+ Buy)
VaR	0.0918	0.1173	0.0766
1-year T-bond	0.0088		

This table shows results of simple buy and hold trading strategies based on a Monte Carlo simulation of annualized returns. The value-at-risk (VaR) is calculated at the 5% level of significance

5.5 Market timing test

In keeping with Nyberg and Ponka (2016), Nyberg (2011), Leung et al. (2000) and Pesaran and Timmermann (1995), we consider simple trading strategies based on a Monte Carlo simulation carried out on the out-of-sample monthly actual return to forecast the annualized return for banks, resources and industry based on the assumption that the out-of-sample prediction is similar to the out-of-sample actual returns. The strategy is threefold: (1) If the predictive out-of-sample forecast provides a positive sign and the forecasted annualized return is positive and greater than the risk-free rate, then the investor should buy stock in that sector. (2) If the predictive out-of-sample forecast provides a negative sign and the forecasted annualized return is negative and less than the risk-free rate, then the investor should sell stock in that sector and rebalance holdings. (3) If there are mixed results from the predictive out-of-sample forecast and the forecasted annualized returns, then the investor should hold. The strategy would see the investor rebalance their holdings on a monthly basis based on the signals coming from the aforementioned strategy. A comparison measure (1-year T-bond) is employed to show how the strategy actually performs against a benchmark. The annualized average returns, the 1-year T-bond return and a value-at-risk (VaR), which is a measure of the risk of loss of investments, are presented in Table 7.

The simulated results show that both bank and industry sectors have a positive annualized return (0.0093 and 0.0480, respectively), while the resources sector has a negative annualized return (− 0.0150). Thus, having identified the sign from our simulation, if the predictive out-of-sample forecast for banks and industry is also positive and negative for resources, then the following trading strategy can be developed for an investor: rebalance holdings by buying bank and industry sector stocks and selling resources sector stocks. The findings also show that both bank and industry annualized returns (0.0993 and 0.0480) outperform the 1-year T-bond benchmark return (0.0088), while resources (− 0.0150) underperform in comparison. The VaR values confirm the findings insofar as they demonstrate that the riskiest asset to hold is resources (0.1173), which aligns with the strategy to rebalance holdings via reducing the resources component of the investment.

6 Conclusion

To determine whether incorporating volatility improves the forecast of the directional changes in the Australian banking, industrial and resources sector share price returns, this study first estimated a logit regression model with the growth rate of economic and financial variables (excluding volatility) as a benchmark model. This was followed by estimations of both the growth rate of economic and financial variables and the SP500 and trade-weighted index volatilities. To measure volatility, four different measures, U^2, STD, MAD and range, were considered. A within-sample and out-of-sample one-step-ahead forecasting performance of the models was assessed with hit ratio and QPS statistics.

In this study, the logit model with volatility measured by both U^2 and MAD provided better forecasts than the other models. However, Kruskal–Wallis tests showed that these results were not statistically significant. Nonetheless, this study found that SP500 and trade-weighted index volatilities are important for predicting the directional changes in the Australian banking, industrial and resources sector share price returns and confirm international volatility effects on Australian banking, industrial and resources sectors share prices. Although the U^2 and MAD measure seemed to have more accurately captured the impact of volatility compared to STD and range, resulting in better directional change forecasts, the overall findings are inconclusive. This is worthy of further investigation and is an area for further research.

Economic and financial variables that are statistically significant for predicting directional changes in the banking, industrial and resource sectors share price return vary by sectors. Economic and financial variables that are useful to predict the directional changes in the banking sector return are: SP500, trade-weighted index, yield on 10-year bonds, oil price, the RBA index of commodity prices of base metals, growth rate of price earnings ratio of ASX, growth rate of dividend yield of ASX, money supply, private sector non-residential building approvals and total employed persons in Australia.

The economic and financial variables that are useful to predict directional changes in the resource sector return are: SP500, trade-weighted index, money supply, yield on 10-year bonds, growth rate of price earnings ratio of the ASX, growth rate of dividend yield of ASX, oil price, the RBA index of commodity prices of base metals and private sector non-residential building approvals.

The economic and financial variables that are useful to predict directional change in industrial sector return are: SP500, trade-weighted index, yield on 10-year bonds, the RBA index of commodity prices of base metals, retail trade, growth rate of price earnings ratio of ASX, growth rate of dividend yield of ASX, total employed persons in Australia and composite leading indicator for Euro area.

The SP500 variable is significant in all three sectors. According to the marginal probability analysis, a 1% change in the growth rate of the SP500 will have a greater effect on the industrial sector, followed by the banking and resources sectors. In the banking sector models, growth in total employed persons in Australia has the highest marginal probability, followed by growth in money supply and growth in the SP500 and trade-weighted index. In the resource sector models, growth in money supply has the highest probability, followed by growth in money supply and growth in SP500 and growth rate of dividend yield of ASX. In the industrial sector model, growth of composite leading indicator for Euro area has the highest probability, followed by growth in total employed persons in Australia and growth in money supply. The impact of SP5 volatility has more effect on the industrial sector than the banking sector, but this impact varies by sector and measures.

The trade-weighted index variable has more impact on the resource sector than the banking sector, and trade-weighted index volatility has more impact on the industrial sector than the resources sector. The positive impact of trade-weighted index on the banking sector supports Shamsuddin's (2009) finding that appreciation of trade-weighted index exerts a positive impact on the directional changes in the banking sector returns. The positive impact of trade-weighted index on banking, resource and industrial sectors on banking and resource sectors is due to some factors such as strong demand for mineral resources; higher real interest rates in Australia compared to other countries; and a stable economy. These factors may have created a strong demand from international investors for both the Australian dollar and Australian shares.

The Australian economy has a statistically significant effect on the directional changes in the Australian banking sector return since growth in total employed persons in Australia has the highest marginal probability followed by growth in money supply. The European economy has a statistically significant effect on directional changes in the industrial sector share price return. This is demonstrated via the fact that the composite leading indicator for the EURO area has the highest marginal probability in the industrial sector models compared to all other economic and financial variables. This is not surprising, given that the industrial sector consists of service industries such as tourism of which Europe is a major inbound travel market. A simple trading strategy was utilized to provide practical improvement in investors' market timing decisions. A limitation of this study is the focus on monthly frequency data which is, in part, because selected economic variables are available only on a monthly basis. Areas of future research include the use of shorter frequency data, such as daily and weekly, as well as incorporating excess returns in the forecasting.

Acknowledgements We would like to thank the editor Markus Schmid and the anonymous referees for their constructive recommendations, which helped to improve the quality of this paper. In addition, we would like to thank the feedback received during prior drafts from colleagues Dr. Guneratne Wickremasinghe and Dr. Ranjtih Ihalanayake.

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