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Does the vector error correction model perform better than others in forecasting stock price? An application of residual income valuation theory

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ABSTRACT

This paper employs a multi-equation model approach to consider three statistic problems (heteroskedasticity, endogeneity and persistency), which are sources of bias and inefficiency in the predictive regression models. This paper applied the residual income valuation model (RIM) proposed by Ohlson (1995) to forecast stock prices for Taiwan three sectors. We compare relative forecasting accuracy of vector error correction model (VECM) with the vector autoregressive model (VAR) as well as OLS and RW models used in the prior studies. We conduct out-of-sample forecasting and employ two instruments to assess forecasting performance. Our empirical results suggest that the VECM statistically outperforms other three models in forecasting stock prices. When forecasting horizons extend longer, VECM produces smaller forecasting errors and performs substantially better than VAR, suggesting that the ability of VECM to improve VAR forecast accuracy is stronger with longer horizons. These findings imply that an error correction term (ECT) of the VECM contributes to improving forecast accuracy of stock prices. Our economic significance analyses and robustness tests for different data frequency are in favor of the superiority of VECM estimator.

1. Introduction

Accurate price forecasts can provide investors trading strategies with numerous profits to make appropriate decisions. The earlier studies demonstrated that the residual income valuation model (RIM) was more accurate in forecasting stock prices than the traditional dividend discount model (DDM) and the free cash flow model (Francis et al., 2000; Jiang and Lee, 2007; Lee, 2007; Penman and Sougiannis, 1998). However, the RIM has been found to generate large forecasting errors. Another group of studies tried to improve forecasting accuracy by exploring factors of the errors such as underestimated stock prices,[1] a misspecified theoretical RIM (Lundholm and O'Keefe, 2001; Morel, 2003; Sougiannis and Yaekura, 2001), empirical model specification (Tsay et al., 2008), and error term autocorrelation (Higgins, 2011). Because of a single-equation model for lack of sufficient information in Joseph (2003), Tsay et al. (2008) used a simultaneous-equations model (SEM) to improve forecasting accuracy. The SEM can present a feedback relationship and the interactions between explanatory variables. Inspired by Tsay et al. (2008), this study used a vector autoregressive model (VAR) similar to the SEM. VAR can identify complete interactions among variables by showing a lead–lag relationship among variables[2] (Tswei, 2013), and contain more valuation information to improve forecast accuracy. Nevertheless, VAR fails to display the long-term relationship among explanatory variables. This drawback prevents us from accurately forecasting prices for longer horizons. Therefore, we further adopted a vector error correction model (VECM) to conduct forecasting experiments.

We observed that prior studies applied time-series models, especially VECM, to forecast economic indicators, such as wage and payroll (LeSage, 1990),[3] exchange rates (Baharumshah et al., 2010; Reinton and Ongena, 1999; Rios and De Los, 2009),[4] housing prices (Das et al., 2011), the price (Ran et al., 2010), and S&P 500 stock price (Reboredo et al., 2012), and Taiwan economic indicators (Shen, 1996). These studies mostly uphold the superiority of VECM in out-of-sample forecasting. They addressed that VECM contains the cointegration relationship with an error correction term (ECT), which captures a long-run equilibrium relationship between forecasted variable and the explanatory variables. This advantage contributes to improving forecast accuracy. Evidences of

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[1] These studies include Frankel and Lee (1998), Dechow et al.(1999), Myers (1999), Sougiannis and Yaekura (2001), and Choi et al. (2006).

[2] A VAR model is composed of more than two single-regression equations, each of which includes more than two variables.

[3] LeSage (1990) estimated a VECM and forecast variables, e.g., man-hours, nominal wages, and prices, which were further used to construct a forecast of payrolls.

[4] Following Meese and Rogoff (1983) and Reinton and Ongena (1999) compared the predictive ability of monetary models, e.g., flexible- and stick-price models (Bilson, 1981; Dornbusch, 1976; Frankel and Lee, 1998), with a random walk model of spot exchange rates in Norwegian markets.

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the cointegrating among stock prices, book value and residual income as well as earnings were found in the previous studies (Campbell and Shiller, 1987; Qi et al., 2000; Jiang and Lee, 2005, 2007; Lee, 2007; Tswei, 2013); these works further uphold valuation and forecasting ability of the RIM.

Westerlund and Narayan (2015) point out that the forecasting regression may face a number of potential issues, including heteroskedasticity, predictor endogeneity and persistency. In stock return predictability literature, forecasting regression model using an ordinary least square (OLS) is the most commonly used estimator; however, it ignores three statistical problems, such as heteroskedasticity, predictor endogeneity and persistency (Phan et al., 2015a), which result in biased coefficients and inefficiency in the predictive regression models.[5] In response to this, recent studies propose a FGLS approach for out-of-sample forecasting and find that FGLS outperforms OLS and bias-adjusted OLS (AOLS) in predicting stock returns. The advantage of FGLS is that it accounts for not only endogeneity and persistency of the predictor, but also the heteroskedasticity in the predictive regression model (Phan et al., 2015a; Westerlund and Narayan, 2012, 2015). Motivated by these studies, this paper first conducts forecasting model diagnostics for controlling three issues. Our results show that the null of no ARCH is rejected in OLS model for two predictors. By contrast, the null of no heteroskedasticity could not be rejected in VAR and VECM. With regard to predictor endogeneity, our results suggest that the null of no endogeneity is rejected for all predictors in OLS whereas the null could not be rejected in VAR and VECM. In sum, our evidences show that first, no heteroskedasticity exists in VAR and VECM residuals while heteroskedasticity exists in OLS. Second, there is no endogeneity in two predictors of VAR and VECM whereas endogeneity exists in the predictors of OLS. Our evidences imply that compared with OLS single-equation model, the multi-equation model approach seem to mitigate the problems of heteroskedasticity and predictor endogeneity. Regarding persistency, two predictors (book value and earnings) should be first differenced for the unit root behavior when we used them to estimate the VAR and VECM. Motivated by these evidences, different from the FGLS single-equation model used by above-mentioned literature, this paper employs multi-equation models such as VAR and VECM. We want to ask whether the multi-equation model outperform single-equation model in forecasting power of stock prices?

Based on the above analyses, we observe that the four aspects in existing studies require to be further explored and thus induce our four motivations. First, recent studies conclude that GLS accounts for three statistical problems and outperforms OLS in return-predictability. In this paper, preliminary model diagnostics find that heteroskedasticity and endogeneity exist in OLS whereas two issues do not exist in VAR and VECM. Two predictors can be first differenced to control the persistency problem. The preliminary evidence seem to guide us to turn another direction; one can use multi-equation models to implement forecasting experiments rather than GLS because VAR and VECM can mitigate three problems and have their specific advantages, which have been mentioned in first paragraphs. Second, current evidences on the forecasting ability of RIM are mixed. Certain studies confirm that the RIM is more accurate in forecasting stock prices than the traditional model, whereas others studies proposed some factors of large errors in applying RIM to forecast. The divergence in existing literatures motivates us to look for an approach to improve forecasting power of RIM. We thus use book value and earnings in the RIM as predictor variables. Third, RIM-based studies generally applied single-equation regression model and cross-section data to forecast stock prices (Higgins, 2011; Joseph, 2003); few employed the multi-equation time series methodology and longitudinal data to improve forecast accuracy of stock prices. This gap induces us to use a multi-equation approach to conduct out-of-sample forecasting.

Fourth, in the literature, the importance of data frequency has been explored commonly. Induced by this, we use different frequency data (monthly, quarterly, annual) to conduct robustness tests for three reasons. First, in the existing studies, the conclusion whether data frequency is dependent are divergent. Some studies favor that forecasting performance is data frequency-dependent. However, some scholars find that the number of factors that determine returns is not at all data frequency-dependent (Huang and Jo, 1995). Second, in a strand of literature favoring data frequency-dependent, the use of high frequency data produces greater evidence of return predictability than low frequency data (Bollerslev and Wright, 2001; Elton et al., 2010; Maheu and McCurdy, 2011; Narayan et al., 2013; Phan et al., 2015a,b); by contrast, some studies based on out-of-sample forecasting of stock returns use low-frequency data such as annual data (Goyal and Welch, 2003), quarterly data (Rapach et al., 2010), or monthly data (Narayan and Bannigidadmath, 2015; Westerlund and Narayan, 2012). Third, the literature dictates the choice of data frequency for different purposes. For instance, to determine expected inflation and short rates, quarterly data may be used by policy makers. Because visitor arrival figures are released monthly, tourism industries focus on monthly forecasts of stock returns (Phan et al., 2015a,b). Narayan et al. (2013) use daily and monthly data to examine commodity spot market return predictability. To investigate why data frequency-dependent matter in determining returns, Huang and Jo (1995) use daily, weekly, and monthly data.

In response to above motivations, this paper makes four contributions to the previous literature on forecasting stock prices. First, to control three statistic problems (heteroskedasticity, endogeneity and persistency), this paper employs a multi-equation model (VAR, VECM) approach in forecasting and provides some evidences on the superiority of VECM, different from single-equation GLS model widely used in return-predictive studies (Narayan and Bannigidadmath, 2015; Phan et al., 2015a; Westerlund and Narayan, 2012, 2015; Westerlund et al., 2015; Narayan, et al, 2014a,b, 2015). Second, different from using financial ratios such as DP, DY, EP, DE and oil price as the predictors in return-predictive studies, this paper uses accounting figures: book value and earnings as predictors based on the RIM because this paper aims to improve forecasting (or predictive) power of the RIM. Third, differing from RIM-based studies applying single-equation models and panel data (e.g., Higgins, 2011; Joseph, 2003), this paper adopts multi-equation time series models and longitudinal data to improve forecasting accuracy of the RIM. Our results suggest that compared to VAR and single-equation models (OLS, RW), VECM generates more accurate price forecasts, further confirming that an ECT can capture long-run information of accounting data, and contribute to improving forecasting power of the RIM. Fourth, our robustness-test results are not data frequency dependent in forecasting performance evaluation, different from the fact in existing literature that test results depend on data frequency (Narayan and Sharma, 2015; Phan et al., 2015a,b).

The aforementioned gaps in extant research motivated us to employ a time-series approach to improve forecasting ability of the RIM. This paper retrieved quarterly data of three Taiwanese stock sectors including composite stocks, electronic technology sector, and finance–insurance sector. We selected the sample periods of three variables (stock prices, book values, and earnings) spanning from 1986Q1 to 2013Q4. Based on the RIV theory, we modeled VAR, VECM, OLS and RW models to conduct out-of-sample forecasting. Two common instruments were used to assess forecasting performance. One is error statistics such as the root mean square error (RMSE), root mean squared percentage errors (RMSPE), mean absolute error (MAE), and mean absolute percentage error (MAPE). The other is the Diebold and Mariano (1995) (DM) test, which was used to evaluate the performance between any two of four time-series models.

[5] Many predictors are persistent and could lead to biased coefficients in predictive regressions if the innovation of predictor is correlated with return innovations (Nelson and Kim, 1993; Stambaugh, 1999). In addition, one of the well-known feature of financial time series data is that return is highly heteroskedastic, which is another source of bias and inefficiency in the predictive regression models (cite from Phan et al., 2015a).