ECONOMIC ANALYSIS & POLICY, VOL. 40 NO. 2, SEPTEMBER 2010

An Empirical Analysis of Real Activity and Stock Returns in an Emerging Market

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Abstract: The present paper analyzes the role of stock market returns as a predictor of real output for a fast-growing emerging market, Malaysia. In the analysis, forecasting equations for 1-, 2-, 4-, and 8-quarter forecasting horizons based on autoregressive distributed lags framework are adopted. From the estimation, we find evidence that stock market returns do contain predictive ability at short-forecasting horizons, especially at less than 4-quarter horizons. Estimating the forecasting models recursively, we note reduction of out-of-sample forecasting evaluation statistics, namely the mean absolute errors (MAE) and the mean squared forecast errors (MSFE), from those obtained from the simple autoregressive (AR) model. More importantly, the null hypothesis of equal predictive accuracy between the model with stock returns as a predictor and the AR model is rejected for the 1-quarter and 2-quarter forecasting horizons by the McCraken's (2007) out-of-sample-F statistics.

I. INTRODUCTION

The significance of anticipating future variations in real activities is well stated by the extensive number of empirical studies attempting to best forecast real output. Among many variables considered in the output forecasting exercises, financial prices particularly stock prices seem to be central. Indeed, there are early notable studies that document the predictive ability of stock prices for the US case. Among them include Fama (1981), Moore (1983), Fischer and Merton (1984), and Barro (1990). However, the extension by Aylward and Glen (2000) to emerging markets seems to yield weaker evidence. Arguably, the stock prices have an edge as a predictor of real activity since stock price data are readily available and, accordingly, cater the need to have a timely forecast. Moreover, they are in general accurately measured. By contrast, the data on rival output predictors such as money supply and other macroeconomic variables are available only with some lags and are normally subject to revisions. Perhaps, the major downside of stock prices is that they may contain too much noise. Moreover, as noted by

* I would like to express my thanks to an anonymous referee of the journal for useful comments on the paper's earlier draft. The remaining errors, however, remain my own responsibility.

Harvey (1989), the changes in stock prices may also reflect changes in firms' riskiness. These mean that their movements may have nothing to do with changing macroeconomic activity. In light of these, the analysis as to whether emerging stock markets normally characterized by relative high risk and volatility contains predictive ability for real output would be worth pursuing.

In this paper, we address the predictive ability of stock returns for real output growth for an emerging market, Malaysia. Compared to other emerging markets, the growth of Malaysia's stock market (i.e. Bourse Malaysia) is considered impressive. Parallel with a miraculous growth of more than a decade prior to the 1997/1998 Asian crisis, the size and liquidity of Bourse Malaysia had increased steadily as indicated by the value of turnover and market capitalization, respectively jumping up from RM29.5 billion and RM131.7 billion in 1990 to RM468.3 billion and RM806.8 billion in 1996 (Ibrahim, 2007, *Table 2*). The market index also had increased from 505.9 points to 1238.0 points over the same period. With this remarkable expansion, Demirguc-Kunt and Levine (1996) ranked Malaysia third in terms of the growth of market capitalization and the total value traded to GDP ratio among 44 developed and emerging markets over roughly the same period. However, typical of any emerging market, the stock market of Malaysia is characterized by relatively high volatility and is violently moved by crises such as the 1997/1998 financial crisis and, recently, the sub-prime crisis. In Malaysia, the belief in the predictive content of the stock market index is reflected by its inclusion in the index of leading indicators. However, given heightened market volatility or risk, the ability of the Malaysian market to anticipate future output seems to require empirical validation.

The forecasting experiment in the present paper is based on an autoregressive distributed lags model. Recursively estimating the model, we generate *h*-step-ahead forecasts for the periods of 1, 2, 4, and 8 quarters. The mean absolute errors (MAE) and mean squared forecasting errors (MSFE) are then calculated and benchmarked against its nested simple autoregressive (AR) model of output growth. Given the nested nature of the two alternative forecasting models, we apply McCraken's (2007) procedure to test whether the forecast errors from the two models are statistically different. In the next section, we briefly review related literature. Then, section 3 details the empirical approach. Data and results are presented in section 4. The final section concludes with the main findings and remarks.

II. RELATED LITERATURE

The standard stock valuation model posits that stock prices are essentially discounted expected future cash flows or earning to be received by firms. Since firms' earnings tend to be highly correlated with real income or real gross domestic product, it is believed that changes in stock prices reflect future directions of real activity. This forward-looking nature or leading role of stock price changes has received empirical attention from many studies, including Fama (1981), Moore (1983), Fischer and Merton (1984), Barro (1990), and more recently, Estrella and Mishkin (1998), Aylward and Glen (2000), Hassapis and Kalyvitis (2002), David et al. (2003), and Panopoulu (2007). These studies predominantly focus on the US market and other advanced markets. The exception is Aylward and Glen (2000), who extend the analysis to several emerging markets.

Examining the postwar US data, Fama (1981) notes a positive correlation between stock returns and subsequent GNP growth. Likewise, Moore (1983) documents evidence indicating the leading role of stock prices for the US business cycle for the period 1873-1975. The predictive role of stock returns is later reaffirmed by Fischer and Merton (1984) for the period 1950-1982 and Barro (1990) for the period 1891-1971. Comparing various financial variables as leading indicators, Fischer and Merton (1984) note that stock returns are the best predictor of future GNP growth. Similarly, Barro (1990) documents supportive evidence for significant predictive power of lagged stock returns for both investment and GNP variations. In a more recent article, Estrella and Mishkin (1998) compare the out-of-sample performance of various financial and macroeconomic indicators as predictors of U.S. recessions using data spanning from the first quarter of 1959 to the first quarter of 1995. Casting the analysis in a probit framework and simulating out-of-sample prediction of the U.S. recessions, they note the useful role of both stock prices and spreads in macroeconomic prediction. Indeed, the stock prices tend to perform well over one- to three-quarter forecasting horizons and even beat the spreads as a predictor of the US recessions for one-quarter ahead forecast.

With confirmative evidence of stock prices as an output predictor for the U.S. case, later studies have extended the analysis to other advanced markets. Hassapis and Kalyvitis (2002) empirically examine the causal link between output growth and real stock price changes for the G-7 countries. Estimating a bivariate vector autoregressive (VAR) model for each country, they find strong correlations between the two variables. More specifically, the simulated impulse-response functions from the estimated VAR indicate that unanticipated changes in both real stock prices and output exert significant impacts on future economic growth and market valuation of capital. Further, the directions of impacts are uniform across the countries and robust to the use of annual and quarterly data. The predictive ability of stock returns for real output is further substantiated by Panopoulou (2007) in the out-of-sample forecasting experiments comparing various financial indicators. According to Panapoulu (2007), on a country basis, the stock market return emerges as the single most powerful predictor. However, David et al. (2003) note that the out-of-sample forecasting performance of stock prices as well as yield spread tends to differ across countries examined, namely, Italy, the UK, US and Germany. Moreover, neither variable seems to be consistent in its predictive ability over the sample period from 1961 to 1996.

Among the listed studies, only Aylward and Glen (2000) extend the analysis to 15 emerging markets in addition to the G7 countries and Australia. Their analysis provides evidence supporting the leading role of stock price changes in some countries using annual data covering mostly 1951 to 1993. However, there exists substantial variations in the stock returns' explanatory power across countries. They also note that the results for the developed markets seem to be more encouraging than the emerging markets. Contradicting the previously mentioned studies on the out-of-sample forecast performance of stock returns, stock prices do not generally lead to improved forecasts of real output out of sample. The relatively scanty evidence for emerging markets, however, seem to require further evaluation, which we aim to contribute to the literature.

III. EMPIRICAL APPROACH

The paper employs a single-equation linear model as a basis for the forecasting experiment. More specifically, in line with existing studies (Aylward and Glen, 2000; David et al., 2003; and Panopoulu, 2007), the model takes the following autoregressive distributed lag (ADL) forms:

$$y_{t+h} = \alpha + \beta Crisis_t + \sum_{i=0}^{p} \theta_i y_{t-i} + \sum_{i=0}^{q} \phi_i r_{t-i} + \varepsilon_{t+1} \tag{1}$$

where y_{t+h} is the annualized growth of output over the next h quarters computed as $y_{t+h} = (400/h) \cdot (\ln Y_{t+h} - \text{h } Y_t)$, r is annualized stock return, and p and q are respectively the autoregressive and distributed lags orders. *Crisis* is the Asian crisis dummy variable that takes the value of 1 from 1997.Q3 and 1998.Q4 and 0 otherwise. It is incorporated in the regression when this time period is used in the estimation to account for independent influences of the crisis on real activity.

We also adopt the simple autoregressive model of real output growth by omitting the stock returns from equation (1) to generate benchmark forecasts. These models are estimated using the OLS estimation method. Note that, in computing output growth over more than 1 quarter, overlapping data are involved. This specification of the dependent variable induces autocorrelated error terms. Accordingly, we apply the Newey and West (1987) covariance matrix to ensure correct inferences.

Our forecasting experiment proceeds in the following ways. Following Panopoulu (2007), we first specify the autoregressive model for real output growth by using the Schwartz information criterion (SIC) to determine the autoregressive lag order, p. This is considered as a benchmark model. We then augment the AR model with stock returns to form the forecasting model with stock returns as the predictor. Again, the SIC is used to select the optimal distributed lags order, q. These two alternative models are then estimated recursively using quarterly data spanning from 1978.Q1 to 2008.Q4 to generate h-step-ahead forecasts for the periods of 1, 2, 4, and 8 quarters. In the empirical implementation, we take 1978.Q1 to 2003.Q4 to be our initial within sample estimation range while 2004.Q – 2008.Q4 (20 observations) as our out-of-sample forecasting period. The within-sample estimation period is then updated recursively by adding one observation at a time and holding the initial sample fixed. From this recursive estimation, we obtain 4 sets (i.e. corresponding to h = 1, 2, 4 and 8) of 20 out-of-sample forecasts for both models.

Based on these forecasts, we construct out-of-sample forecast evaluation statistics, namely, the mean absolute errors (MAE) and mean squared forecast errors (MSFE) for each forecasting horizon and each model as:

$$MAE = \frac{\sum_{i=1}^{n} | y_{t+h} - \hat{y}_{t+h} |}{n} \tag{2}$$

$$MSFE = \frac{\sum_{i=1}^{n} (y_{t+h} - \hat{y}_{t+h})^2}{n} \tag{3}$$

where $\hat{y}_{t+h}$ is the *h*-step-ahead forecast and *n* is the number of out-of-sample forecasts, which is 20 in our case. The potential improvement in forecasting output growth by basing on stock price changes is indicated by lower *MAE* and *MSFE* as compared to the benchmark model.

Finally, given the nested nature of the two alternative models, we apply McCraken (2007) OOS-F-test to test whether the *MSFE* of the model with the stock returns is significantly less than the *MSFE* of the benchmark model for one-step-ahead forecast. This F-statistic is recently applied by Panopoulou (2007) and is written as:

$$OOS-F = \frac{\sum_{i=1}^{n} (\varepsilon_{1,t}^2 - \varepsilon_{2,t}^2)}{n^{-1} \sum_{i=1}^{n} \varepsilon_{2,t}^2} \tag{4}$$

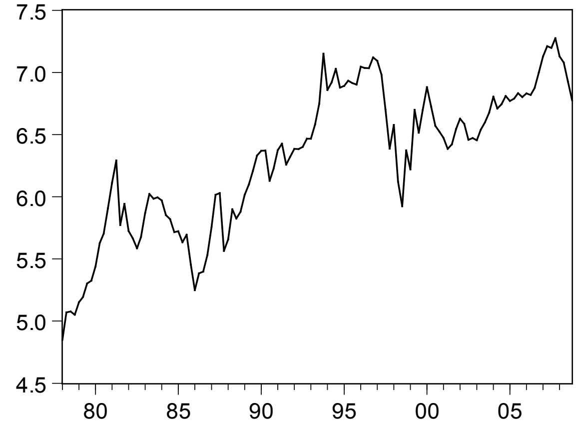
where ε_i is the forecast error of model *i* (*i* = benchmark AR model or ADL with stock returns). If there is no significant difference in the forecast accuracy of the two models, then the F statistic would essentially be closed to zero. The asymptotic critical values of this F test are tabulated in McCraken (2007).

IV. DATA AND RESULTS

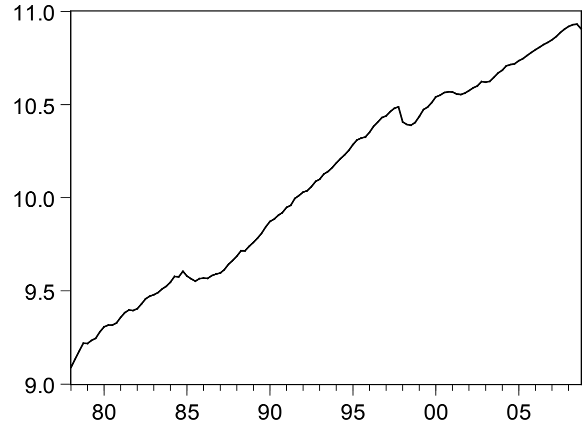
As noted, we use quarterly data spanning from 1978.Q1 to 2008.Q4, where observations from 2004.Q1 to 2008.Q4 are kept as out-of-sample observations. The real gross domestic product (GDP) is used to represent real activity. Since it is not seasonally adjusted, we apply first the Census X-12 procedure in EVIEWS to remove seasonal variations in the data. The stock price index is represented by the Kuala Lumpur composite index. The two series are expressed in natural logarithm. Then, the real output growth and stock returns are computed as logarithmic difference of the respective series. *Figure 1* plots the log level of both series. Over the 30-year time span, Malaysia has exhibited impressive output and stock market growth. Respectively, their annualized mean growth rates are 5.9% and 6.3%. From the graph, their movements seem to be in tandem. Both series have trended upward but with noticeable reduction around mid-1980s and 1997/1998, i.e. the years Malaysia experienced recession. However, as should be expected, the stock market index exhibits high variations relative to real output. The standard deviation of stock market return (63.5%) is 10 times higher than that of real output growth (6.2%).

As a preliminary assessment of stock returns as a predictor for real output, we compute the correlations between output growth over 1 quarter and overlapping 2 quarters, 4 quarters and 8 quarters and current and lagged stock market returns. These correlations are given in *Table 1*. As may be noted from the Table, current and once-lagged stock returns are significantly and positively related to future output growth up to 4-quarter horizon. Despite positive, the correlations turn insignificant beyond one-year period. These statistics are thus suggestive of the potential role of the stock market as a predictor for future growth over 1 year or less than 1 year. To further examine this, we estimate model 1 and present the results in *Table 2*.

Figure 1: Time Plots of Data Series



(a) The Kuala Lumpur Composite Index



(b) Real Gross Domestic Products

Table 1: Correlations between Output Growth and Current and Lagged Stock Returns

	Lagged Stock Return								
Output	0	1	2	3	4	5	6	7	8
y_{t+1}	0.305	0.262	0.225	0.059	0.027	-0.049	-0.037	-0.137	-0.123
y_{t+2}	0.314	0.293	0.169	0.058	-0.024	-0.062	-0.102	-0.145	-0.045
y_{t+4}	0.311	0.224	0.101	-0.001	-0.076	-0.126	-0.088	-0.070	0.049
y_{t+8}	0.160	0.062	0.012	-0.042	-0.013	-0.016	0.039	0.055	0.129

Note: the correlations in bold are significantly different from zero at 5% significance level.

Table 2: *h*-Quarter ahead forecast of Real Output Growth – 1978-2003

Coefficient	Forecast Horizons			
Estimates	1	2	4	8
a	4.687 (0.000)	5.519 (0.000)	5.501 (0.000)	5.795 (0.000)
b	-6.311 (0.064)	-7.065 (0.021)	-8.207 (0.010)	-3.310 (0.129)
q_0	0.260 (0.004)	0.086 (0.357)	0.126 (0.009)	0.035 (0.451)
f_0	0.019 (0.039)	0.019 (0.015)	0.014 (0.025)	0.008 (0.079)
f_1	--	0.019 (0.008)	--	--
Adj-R^2	0.2203	0.3168	0.3464	0.0817
F-Stats	10.511 (0.000)	12.477 (0.000)	18.316 (0.000)	3.7868 (0.013)

Notes: the model estimated is $y_{t+h} = \alpha + \beta Crisis_t + \sum_{i=0}^{p} \theta_i y_{t-i} + \sum_{i=0}^{q} \phi_i r_{t-i} + \varepsilon_{t+1}$.

Due to overlapping samples, the Newey-West (1987) covariance matrix is used. The autoregressive and distributed lags orders are based on SIC. The numbers in parentheses are p-values.

As can be noted from the Table, the autoregressive order 1 is selected by the SIC. Thus, the AR(1) model of output growth is our benchmark model. Augmenting the AR(1) with stock return, current stock return is included in all forecasting equations and once-lagged stock return in two-quarter-ahead forecasting equation on the basis of the SIC. The model explanatory power, i.e. the adjusted R^2, is satisfactory for one-quarter to four-quarter forecasting equations, reaching 34.6% for 4-quarter forecasting equation. It seems to be higher than those reported by Aylward and Glen (2000) for other emerging markets. The F statistics further support the model adequacy in explaining variations in output. The null hypothesis that all slope coefficients are jointly zero is rejected at better than 1% for forecasting horizon up to 4 quarters and at 5% for 8-quarter forecasting horizon. The estimated autoregressive coefficients are significant but small in magnitude, indicating slow adjustment speed of output growth. The stock return coefficients are all positive, reaffirming the noted positive correlations between output growth and stock returns. They are also significant at conventional levels of significance. These regression results tend to substantiate the ability of stock returns in anticipating future output growth over 1-year horizon. While the stock return remains significant at 10% in the 8-quarter-ahead forecasting equation, the model explanatory power drops substantially.

Note that the aforementioned statistics are essentially within sample statistics. Since within-sample goodness of fit needs not reflect the model ability to forecast out of sample, we simulate the forecasts of real output growth for the 4 forecasting horizons (i.e. 1, 2, 4 and 8 quarters) to further assess the ability of stock returns in predicting real output growth. The MAE and MSFE computed from the model as well as the benchmark AR model are presented in *Table 3*. From the Table, it is comforting to note that the significant predictive content of stock returns for output growth is robust to these out-of-sample statistics. More specifically, the model with stock returns outperforms the benchmark model for forecasting horizons up to again 4 quarters. The most improvement is in two-quarter forecasting equation. At 8-quarter forecasting horizon, however, the inclusion of stock returns makes forecasting worse. It needs to be noted that the lower forecast errors (MAE and MSFE) for longer forecasting horizons do not mean that the stock returns have better predictive content at longer horizons. These statistics are not comparable across *h*-step ahead forecasting equations since the dependent variables are not expressed in the same form. Moreover, given overlapping samples, the longer the horizons the smoother the output growth series. Accordingly, by construction, their forecast errors tend to be smaller the longer the horizons.

Table 3: Forecast Performance of Stock Returns

	Benchmark Model (A)		Model with Stock Return (B)		Ratio (B/A)	
Horizon	MAE	MSFE	MAE	MSFE	MAE	MSFE
1	2.3301	16.6402	2.0736	13.3126	0.890	0.800
2	1.6537	8.1524	1.3666	5.6731	0.826	0.695
4	1.2539	3.5920	1.1657	3.4894	0.930	0.971
8	0.4996	0.5323	0.5365	0.6475	1.074	1.216

Finally, to verify whether the forecast errors from 1-quarter, 2-quarter, and 4-quarter forecasting equations are significantly lower than those of the benchmark model, we compute McCraken's (2007) OOS-F statistics as given in (4). Respectively for the three (i.e. 1, 2, and 4) forecasting horizons, the statistic are 4.999, 8.740, and 0.588. Accordingly, significant improvements in the forecasts are evidenced at 1-quarter and 2-quarter horizons. The forecast errors from the 4-step ahead forecasting equation and the benchmark model, however, are not significantly different. In sum, the evidence that we gather suggests the predictive role of stock returns for real activity at short horizons, i.e. short-term forecasting.

V. CONCLUSION

Whether stock price changes reflect future real activity is investigated for an emerging market, Malaysia, using recursive estimation of autoregressive distributed lags forecasting equation for the period 1978-2008. The evidence we obtain seems overwhelmingly supportive of the stock returns as a leading indicator for output growth in Malaysia at short-horizon of less than 1 year. First, the preliminary correlation analysis indicates significant positive correlations between current and once-lagged stock price changes and subsequent GDP growth rates up to 4-quarter horizon. Second, as we move the forecasting horizon from 1-step ahead to 4-step ahead, we note incremental explanatory power of stock returns in the output-forecasting equations. Specifically, the explanatory power reaches 34.6%, which are comparable to those found for advanced markets and seem higher than the figures documented for several emerging markets. Third, the out-of-sample evaluation statistics suggest that stock returns do add incremental information for future output growth. Namely, the MAE and MSFE computed from the ADL model with stock returns as a predictor are lower than the simple AR benchmark model for 1-step, 2-step, and 4-step forecasting horizons. Finally, the McCraken's (2007) OOS-F statistics reject the null hypothesis of equal predictive accuracy between the ADL and AR models for 1-step and 2-step forecasts. In sum, despite being relatively volatile, the Malaysian stock market does have predictive ability for real output growth. However, as our evidence points out, its ability is limited only to only the short-run forecasts of at most 4 quarters ahead.

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