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GDP, Share Prices, and Share Returns: Australian and New Zealand Evidence

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Abstract

With the aim of predicting share market returns, many empirical studies have delved into how financial and macroeconomic variables can be used to forecast return variability. The aim of this paper is to examine whether the ratio of aggregate share price to GDP can capture the variation of future returns on the aggregate share market within Australia and New Zealand. Using quarterly and semi-annual data for the period 1991–2003 for New Zealand and for the period 1982–2006 for Australia, this study finds that the ratio of share price to GDP indeed captures a significant amount of the variation of returns on the New Zealand share market as well as the Australian share market; however, results for Australian data do vary, depending on the sample period. Results in this paper generally provide support for the theory behind previous papers, specifically that of Rangvid (2006).

Keywords: Predicting share market returns, forecast return variability, ratio of aggregate share price to GDP, Australia, New Zealand.
JEL Classification Codes: G00, G10

1. Introduction

Predicting share market returns using fundamental data has long been the subject of research in empirical finance. Following the lead of Fama and French (1988), there has been a large amount of evidence that financial ratios, such as dividend yield and price to earnings ratios, contain a significant amount of information about future share market returns (Campbell and Shiller 1989). However, this evidence had not persisted throughout the 1990s.

In searching for additional information as to how share prices will react in the future, it has been found that macroeconomic variables may contain information about future share returns that is not captured by financial ratios. In particular, Rangvid[1] (2006) finds that the ratio of share price to GDP captures more of the variation between future realised returns on the aggregate share market than price-earnings and price-dividend ratios.

This paper examines whether the price-to-GDP ratio can capture variations in future returns on the aggregate share markets of Australia and New Zealand. We will compare the forecasting power of price-to-GDP ratio with price-earnings and price-dividend ratios. Additionally, we will provide insight as to how the results found in previous studies compare for smaller and less liquid markets.

An important contribution of this research is the identification that the price-to-GDP ratio can predict variations within the aggregate share market. Using quarterly and semi-annual data, this study documents that the ratio of share price-to-GDP captures a significant proportion of the share returns and excess returns within Australia and New Zealand.

Australian results are time period dependent. Over long-time horizons, the price-output (*py)*-ratio predicts share returns well over the full sample and for the period 1982–1994. However, for sub-samples 1995–2006 and 1990–1999, both the price-earnings (*pe)*-ratio and price-dividends (*pd)*-ratios capture a greater fraction of share returns than the *py*-ratio. Australian results also show that, although for some periods the *py*-ratio is an excellent predictor of returns, it is not consistently better than either the *pe*-ratio or the *pd*-ratio.

New Zealand results provide stronger support for the findings reported by Rangvid (2006). A statistically significant relationship was found to exist between the price-to-GDP ratio and share returns. Within the New Zealand sample set, the price-to-GDP ratio captures more in the variation in returns than the price-dividend ratio and generally captures more of the variation of share returns than the variation in excess returns.

The remainder of this paper is organised into four sections. Section 2 presents a summary of related empirical evidence on predicting returns using financial ratios and macroeconomic variables. The theoretical motivation as to why the price-to-GDP ratio should predict returns is also provided. Data sets and sources of data used in this analysis along with the research design are described in Section 3, while Australian results and New Zealand results are presented separately in Section 4. The final section discusses some additional considerations in the analysis and presents concluding remarks.

2. Previous Literature

2.1. Predicting Returns with Financial Ratios

Initial evidence that fundamental data can be used to forecast share market returns is provided by Fama and French (1988). The authors' findings are twofold. First, share prices which are normalised by dividends or earnings can be used to capture time variation in expected returns. Second, dividend yield has more explanatory power. As a result of their findings, the authors conclude that the power of dividend yields to forecast share returns increases with the return horizon.

The literature also shows that dividend-price ratios can be used to predict future returns as demonstrated by Campbell and Shiller (1989). Making use of dividend ratios, they show that the dividend-price ratio is in effect a long-term expected real return on shares, contaminated by expected changes in real dividends. The Campbell-Shiller model expresses the log dividend-price ratio as the rational expectation of the present value of future dividend growth rates and discount rates.

[1] In a study of US data and G-7 data (for the period 1929–2003), Rangvid identified that the ratio of share price to GDP tracks a larger fraction of the variation over time in expected returns on the aggregate share market, capturing more of the variation than do price-earnings and price-dividend ratios and often also providing additional information about excess return.

Subsequently, Lamont (1998) finds that the information that dividends and earnings contain is mainly about short-run variation in expected returns, while price is the only relevant variable for forecasting long-horizon returns. By suggesting that dividends contain information about future returns and that earnings contain information, Lamont makes two broad deductions: Not only do dividends contain information about future returns because they help measure the value of future dividends, but earnings also contain information, as they are positively correlated with business conditions. Making use of quarterly earnings, which had previously been regarded as containing too much noise, Lamont demonstrated that information is contained in this data which provides important information about short-term movements in expected returns.

There is evidence indicating that, during the 1990s, the ability of dividend yields to predict share returns had deteriorated considerably. During the 1990s, movements in aggregate share prices, and consequently returns, were much different from what earnings and especially dividends would seem to have implied. This is demonstrated in Campbell and Shiller (2001), who examine the use of price-earnings ratios and dividend-price ratios as forecasting variables for the share market for an extensive sample of aggregate US data between 1871 and 2000 and aggregate quarterly data for 12 countries since 1970. Further, Ang and Bekaert (2001) examine whether dividend yield, earnings yield, and the short rate can predict share returns in France, Germany, Japan, the UK, and the US. Results support the proposition that the short rate is the only robust short-run predictor of excess returns. More recently, Goyal and Welch (2003) infer that dividend ratios have no predictive power, providing evidence to support their claims from prior to the 1990s. Further support for Goyal and Welch (2003) with respect to quantifying the lack of predictive power associated with dividend ratios is provided by Manzly, Santos, and Veronesi (2004). Making use of a general equilibrium model in which both investor preferences for risk and expectations of future dividend growth are time-varying, they explain the poor predictive performance of valuation ratios throughout the 1990s. The authors find that time-varying risk preferences cause the standard positive relationship between dividend yields and expected returns while, at the same time, the time-varying expected dividend growth induces a negative relationship between the two variables in equilibrium. These offsetting effects reduce the ability of the dividend yield to forecast future returns and essentially eliminate its ability to forecast dividend growth.

2.2. Using Macroeconomic Variables to Predict Share Returns

Chen, Roll, and Ross (1986) argue that the use of general economic state variables will influence the pricing of large share market aggregates. The authors use lagged macroeconomic variables and find that those that systematically affect share market returns include (i) the spread between long and short interest rates; (ii) expected and unexpected inflation; (iii) industrial production; and (iv) the spread between high- and low-grade bonds.

Evidence provided in the twenty-first century suggests that some macroeconomic variables contain information about futures returns over and above that of financial ratios, such as dividend yield. For example, Lettau and Ludvigson (2001) examine the role of fluctuations in the aggregate consumption-wealth ratio for predicting share returns, where aggregate wealth is defined as the sum of human and asset wealth. With human capital being an unobservable component of aggregate wealth, the authors argue that the important predictive components of the consumption-aggregate wealth ratio may be expressed in terms of the observables consumption, asset holdings, and current labour income. Findings show that short-term deviations from the common trend in consumption, asset holdings, and labour income combine as a strong univariate predictor of both raw share returns and excess share returns. Empirical evidence is provided to show that this *cay*-ratio predicts US excess returns well and captures a considerably larger fraction of the variation in expected returns than the price-dividend ratio and the dividend-earnings ratio. This result transpires despite growth rates of consumption, labour income, and asset holdings having a statistically insignificant relationship with future share returns.

Developing further the work of Lettau and Ludvigson (2001) by combining the *cay*-ratio with future labour income growth to predict share returns, Julliard (2004) finds that fluctuations in expected future labour income are a strong predictor of both real share returns and excess returns over a Treasury bill rate. Julliard (2004) finds that around one-third of the variance of returns is predictable over a one-year horizon when expected future labour growth rates and *cay* are jointly used as forecasting variables.

Earlier work by Cochrane (1991) relates the consumption-based asset model to a production-based asset model to examine forecasts of share returns by business-cycle-related variables and the association of share returns with subsequent economic activity. Cochrane (1991) shows that an investment-capital ratio predicts US returns.

In more recent times, there have been further developments in consumption-based assets models. Lettau and Ludvigson (2005) investigate a consumption-based present value relation that is a function of future dividend growth. Using data on aggregate consumption and measuring the dividend payments from aggregate wealth, they show that changing forecasts of dividend growth make an important contribution to fluctuations in the US share market. This contribution is significant despite the failure of the dividend-price ratio to uncover such variation. Subsequently, Santos and Veronesi (2006) extended the standard consumption-based asset pricing model. In their model, consumption is funded by labour income. The authors first show that changes in the fraction of consumption funded by labour income induce fluctuations in the expected excess return of the market portfolio and then that the ratio of labour income to consumption should forecast share returns at the aggregate level. This implication is then tested, and the results indicate that this labour income to consumption ratio is a strong predictor of US returns at long horizons.

Rangvid (2006) finds that the ratio of share prices to GDP captures a large fraction of the variation over time of future realised returns and as well as excess returns on the aggregate share market, both in-sample and out-of-sample. Rangvid (2006) uses annual data for the US over the period 1929–2003, as well as the international G-7 countries, and finds that the relationship between expected returns and the ratio of share prices to GDP is economically and statistically significant when measured over a long period of time. The ratio of share price to GDP is found to capture more of the variation of raw share returns than do price-earnings and price-dividend ratios and also provides additional information about excess returns.

The aim of this paper is to examine the roles of macroeconomic ratios, such as price-to-GDP ratio, in capturing the variations of aggregate share market returns in Australia and New Zealand. Rangvid's (2006) approach is adopted in this study.

2.3. Theoretical Motivation

The motivation for the tests carried out in Rangvid (2006), and subsequently for this paper, comes from the earlier work conducted by Campbell and Shiller (1989) which adopts a 'Dynamic Gordon model' and the general definition of returns to show that the price-dividend ratio can be written as

$$p_t - d_t = E_t \sum_{j=0}^{\infty} \rho^j (\Delta d_{t+1+j} - r_{t+1+j}) + \frac{k}{1-\rho} \tag{1}$$

where p_t is the log of the price of the share at period t, d_t is the log of the dividends that the shares pay out, r_{t+1} is the log return for the period t+1, Δ is the difference operator, and

$$k = \ln(1 + \exp^{\overline{p-d}}) - \rho(\overline{p-d}) \tag{2}$$

with $\overline{p-d}$ as the mean log price-dividend ratio and

$$\rho = \exp^{\overline{p-d}} / (1 + \exp^{\overline{p-d}}) < 1 \tag{3}$$

When Equation (1) is in terms of the aggregate share market, p_t measures the period t value of a share price index and d_t the period t value of the dividends paid out by the firms within the index.

Based on the definition of returns, a log-linear approximation, and the ruling out of bubbles, Equation (1) shows how the expectations of share market participants can be traced by the variation of the price-dividend ratio. 'If shares trade at a higher price for given dividends, Equation (1) shows that this is the case because share market participants expect future discount rates (the required returns on shares) to be low if the growth in dividends is relatively constant' (Campbell and Shiller 1989).

In response to recent empirical evidence that the power of the price-dividend ratio as a tool for predicting returns is not so strong, Rangvid (2006) analysed whether other fundamental factors, specifically GDP, could be used in combination with share prices to predict future movements in the aggregate share market. The author extends Equation (1) to include GDP by assuming that the non-stationary behaviour of dividends comes from output in the economy, $d_t = y_t + v_t$, where y_t is output, and v_t is a stationary disturbance term with a mean of zero. If the non-stationary part of dividends comes from output, Equation (1) can be written as

$$p_t - y_t = E_t \sum_{j=0}^{\infty} \rho^j (\Delta y_{t+1+j} - r_{t+1+j}) + \frac{k}{1-\rho} + v_t \tag{4}$$

One of the implications of Equation (4) is that the variation over time of the price-output ratio ($p_t - y_t$) should capture the variation over time in returns if output is not too volatile. Another implication of Equation (4) is that the price-output ratio should be an even better predictor of long-horizon returns, or returns over more than just a single period.

3. Data and Methodology

3.1. Data

The analysis is carried out using nominal gross domestic product (GDP henceforth) data from the Statistics New Zealand website[1] and from the Reserve Bank of Australia Statistics website[2] for the New Zealand and Australian studies, respectively. New Zealand GDP data are available quarterly from June 1987 to March 2006, while Australian GDP data is available quarterly from September 1959 to March 2006.

New Zealand share indices data for the NZSE40/NZX50 gross index were obtained from the University of Otago database and were limited to the period 1991–2003 at the time this study was conducted; for this reason, the New Zealand analysis is restricted to this period.[3] Dividend data for this sample period are obtained from the University of Otago database. There were insufficient earnings data for New Zealand,[2] so comparisons with the price-earnings ratio have been left out of the New Zealand results. Australian share indices data for the S&P/ASX 200 along with the associated price earnings ratios and dividend yields were obtained from the Reserve Bank of Australia.[4] This dataset is complete back to 1982, so the Australian sample covers the time period 1982–2006.

Historical data for the 90-day bank bill rates for New Zealand and Australia were obtained from the Reserve Bank of New Zealand website[5] and the Reserve Bank of Australia website,[6] respectively.

3.2. Methodology

The price-output ratio is calculated as $py_t = p_t - y_{t-1.}$ The price-dividend ratio is calculated as $pd_t = p_t - d_{t-1}$, and the price-earnings ratio as $pe_t = p_t - e_{t-1.}$ The subscript 't' is in quarters or half-years; p_t is the log of the price for period t of the NZSE40/NZX50 gross index for New Zealand or the S&P/ASX 200 in the Australian case; y_{t-1} is the log of the GDP for the period t-1 for either New Zealand or Australia; d_{t-1} is the log of the sum of dividends paid out over t-1 periods; and e_{t-1} is the log of earnings for the period t-1. The continuously compounded annual share return is denoted by $r_t = ln[(P_t+D_{t-1})/P_{t-1}]$. For the continuously compounded case, P_t is the value of the share price index in a given period, while P_{t-1} is the value of the share price index in the previous period. The log of excess returns is calculated as $er_t = r_t - i_t$, where i_t is the 90-day bank bill rate for quarterly data and the six-month government bond yield for semi-annual data. This traditional method of computing the excess return (er_t) will be compared with the method proposed in Rangvid (2006). Rangvid (2006) computes the log of excess returns as follows: $er_t^* = r_t - i_{t-1}$, where i_{t-1} is either the 90-day bank bill rate of the first month in the

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[2] There were too many missing data points and generally did not go back far enough.

previous quarter for quarterly data, or the six-month government bond yield for the previous six months for semi-annual data. The difference of the two approaches in computing er_t is due to the forward-looking nature of the ratios used in the analysis. The lagged interest rate i_{t-1} is used to coincide with the lagged macroeconomic variables, y_{t-1}, d_{t-1}, and e_{t-1}.

The analysis was conducted for quarterly and semi-annual data using both univariate and multivariate regressions of returns and excess returns on the lagged price-output, price-dividend, and price-earnings ratios. Regression models are fitted over the entire sample as well as for sub-samples.

The univariate regressions are of the form:

$$x_{t,t+k} = \alpha + \beta z_t + \varepsilon_t \qquad (5)$$

where α is a constant, and z_t indicates one of the predictor variables (*py, pd,* and *pe*). The multivariate regressions are of the form:

$$x_{t,t+k} = Z'_t \Psi + \varepsilon_t \qquad (6)$$

where Z_t is a column vector of predictor variables, and Ψ a column vector of coefficients. $x_{t,t+k}$ is the sum of either continuously compounded returns or excess returns (over risk-free rates) for the share index over the next k periods where k = 1, 2, …, 6. Quarterly/semi-annual/annual versions of the predictive regressions are run for k = 1, and then analysis for longer-horizon cumulative returns is carried out for k = 2, 3, …, 6. Longer-horizon regressions are run in an attempt to capture variations in expected returns that are not revealed in short-horizon regressions which may be a result of autocorrelation in returns. The regression models are fitted for sub-periods of five years as well as for the entire period in order to check the robustness of the model.

The summation of the long-horizon returns may result in overlapping variables. This may cause a bias towards the rejection of the null hypothesis of no predictive power. To allow for these potential biases, Newey-West *t*-statistics are used.

3.2.1. Residuals Analysis

Model (5) can be re-expressed as the following (using py_t as an example, where k = 1):

$$\ln P_{t+1} = \alpha + (\beta + 1)\ln P_t - \beta \ln Y_{t-1} + \varepsilon_t \qquad (7)$$

where the growth of a variable is compared with the base period values. As long as the ε_t's in Equation (5) are not auto-correlated and not correlated with the independent variables ($\ln P_t$ and $\ln Y_{t-1}$ in this case), the estimates are unbiased and consistent. The residuals are analysed to make sure that these assumptions are satisfied.

4. Results

4.1. Australian Evidence: Summary Statistics

Panel A of Tables 1 (a) and (b) gives the means and standard deviations of each series for the Australian quarterly and semi-annual data, respectively. The average annualised quarterly and semi-annual equity returns are approximately 14.04% and 13.9%, with standard deviations of 17.90% and 17.95%, respectively. The average annualised quarterly excess return is 5.18%, using the standard method for calculating excess returns, and 5.14%, using the lagged interest rate method. The corresponding average annualised semi-annual excess returns for these two methods are 4.72% and 4.49%, respectively. All three ratios have a greater volatility than returns for both quarterly and semi-annual data.

Table 1 (a): Quarterly
Summary Statistics
AUS data: Q4, 1982 - Q1,2006

	py	*pe*	*pd*	*r*	*er*	*er**
Panel A: Means and standard deviations						
Mean	-3.0595	2.8628	1.3823	0.1404	0.0518	0.0514
Std.	0.5798	0.3671	0.1836	0.1790	0.1784	0.1775
Panel B: Correlations						
py	1.0000					
pe	0.6494	1.0000				
pd	-0.5386	-0.6538	1.0000			
r	-0.1935	-0.1990	0.2355	1.0000		
er	-0.0990	-0.0961	0.1626	0.9921	1.0000	
*er**	-0.1023	-0.0997	0.1635	0.9922	0.9992	1.0000
Panel C: Univariate unit root and cointegration tests						
ADF	-3.80**	-2.05	-3.13*	-11.05**	-11.10**	-11.08**
PP	-3.80**	-2.05	-3.13*	-11.05**	-11.10**	-11.08**

Table 1(b): Semi-Annual
Summary Statistics
AUS data: 1983 - 2006

	py	*pe*	*pd*	*r*	*er*	*er**
Panel A: Means and standard deviations						
Mean	-3.7434	2.8664	1.3782	0.1390	0.0472	0.0449
Std.	0.5626	0.3563	0.1819	0.1795	0.1779	0.1758
Panel B: Correlations						
py	1.0000					
pe	0.6383	1.0000				
pd	-0.4899	-0.6058	1.0000			
r	-0.2739	-0.2384	0.2925	1.0000		
er	-0.1294	-0.0847	0.2022	0.9820	1.0000	
*er**	-0.1250	-0.0852	0.1954	0.9812	0.9975	1.0000
Panel C: Univariate unit root and cointegration tests						
ADF	-3.88**	-3.12*	-2.30	-7.67**	-7.77**	-7.62**
PP	-3.88**	3.12*	-2.30	-7.67**	-7.77**	-7.62**

Notes to Tables 1 (a) and (b): The first and second rows in Panel A displays the sample means and standard deviations for the price-GDP ratio (*py*), the price-earnings ratio (*pe*), the price-dividend ratio (*pd*), the quarterly return to equity (*r*), the traditional excess return ($er=r_t - i_t$) and excess return with lagged interest rates ($er^*=r_t - i_{t-1}$). Panel B presents the correlations between each series, while Panel C shows the results of the Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) tests for a unit root. The null hypothesis of each test is that the series is non-stationary, and the critical values are 2.58 at the 10% level and 3.51 at the 1% level. Significant statistics at the 1% level are indicated by ** and at the 5% level by *.

Panel B of Tables 1 (a) and (b) presents the correlations between each variable for the Australian quarterly and semi-annual data, respectively. The correlation between the price-earnings ratio and price-to-GDP ratio is over 0.63 for both data frequencies. The correlation between the price-dividend ratio and the price-to-GDP ratio is below -0.48 for both quarterly and semi-annual data, while the correlation between the *pe*-ratio and *pd*-ratio is the lowest in both cases. The correlation between returns and excess returns is quite high due to the low volatility of the associated interest rates.[3] The *py*-ratio has a slightly negative correlation with each return series.

The Australian results for the analysis of the residuals for each data frequency are presented in Appendix A. These show that the residuals do not suffer from serial correlation, nor are they correlated with the independent variables p_t and y_{t-1}. This indicates that the potential problems touched on in the note to Section 5 are of no significance, and therefore there are no problems with the specification of the model.

[3] 4.70% and 5.07% for the 90-day bank bill and the six-month bond, respectively.

4.2. Australian Evidence: Cointegration

As explained in Campbell and Shiller (1989), Lettau and Ludvigson (2001), and Rangvid (2006), a key statistical implication of a relation such as in Equation (4) is that, when returns and changes in output are covariance-stationary, the left-hand side of the equation should be covariance-stationary. That is, the output series, y_t, should cointegrate with the price series, p_t, such that the series $p_t - y_t$ is stationary. In testing for the hypothesis of stationarity, Panel C of Tables 1 (a) and (b) gives the results from the Augmented Dickey-Fuller (ADF) tests and the Phillips-Perron (PP) tests. For quarterly data, the null hypothesis of non-stationarity is rejected for all the returns series, the *py*-ratio, and the *pd*-ratio. This indicates that the *py*-ratio is stationary and implies that y_t cointegrates with p_t. The null hypothesis of a non-stationary price-earnings ratio cannot be rejected.[4] Given that both the *py*-ratio and the *pd*-ratio are both stationary, the theory behind equations (1) and (4) suggests that they should both be able to capture variations in future returns. For semi-annual data, non-stationarity cannot be rejected for the *pd*-ratio, which suggests that, for these data, the *py*-ratio and the *pe*-ratio should capture variations in future returns.

4.3. Australian Evidence: Predicting Returns

Tables 2 (a) and (b) report the univariate and multivariate regression results for Australian quarterly and semi-annual data, respectively. Panel A presents univariate regression results for share returns against the *py*-ratio, the *pe*-ratio, and the *pd*-ratio; Panel B reports results for traditional excess returns against the *py*-ratio, the *pe*-ratio, and the *pd*-ratio; while panel C shows results for excess returns using lagged interest rates against the *py*-ratio, the *pe*-ratio, and the *pd*-ratio. Panel D displays results for the multivariate regressions on share returns. For the multivariate regressions, only the most significant of the three return series is presented in each case, given that the focus of this paper is on the predictive power of each ratio individually; for both quarterly and semi-annual data, the multivariate results were best for share returns. Newey-West *t*-statistics are calculated to test for possible presence of autocorrelation and heteroskedasticity, which is particularly likely over longer horizons due to overlapping variables.

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[4] These statistics differ from Rangvid (2006) who finds that the null hypothesis of non-stationarity is rejected for the *py*-ratio and the *pe*-ratio, while the null hypothesis cannot be rejected for the *pd*-ratio.

Table 2(a): Quarterly
Full sample regressions of long-horizon cumulative returns

Horizon k:		1	2	3	4	5	6
Panel A: Stock return univariate regressions							
py	coef.	-0.02987	-0.05692	-0.07854	-0.09553	-0.10790	-0.12453
	t-stat.	(-1.90)	(-2.14)*	(-2.16)*	(-2.30)*	(-2.33)**	(-2.40)**
	R^2	**0.0374**	**0.0760**	**0.0981**	**0.1125**	**0.1243**	**0.1470**
pe		-0.04851	-0.07746	-0.09509	-0.10804	-0.11551	-0.12189
		(-1.96)*	(-1.63)	(-1.42)	(-1.37)	(-1.35)	(-1.33)
		0.0396	**0.0584**	**0.0618**	**0.0640**	**0.0655**	**0.0665**
pd		0.11485	0.18283	0.23759	0.27609	0.28675	0.29071
		(2.34)**	(1.44)	(1.56)	(1.68)	(1.63)	(1.52)
		0.0555	**0.0813**	**0.0963**	**0.1041**	**0.1004**	**0.0941**
Panel B: Excess return univariate regressions							
py		-0.01523	-0.02740	-0.03363	-0.03468	-0.03027	-0.03026
		(-0.96)	(-1.03)	(-0.93)	(-0.85)	(-0.69)	(-0.62)
		0.0098	**0.0180**	**0.0185**	**0.0152**	**0.0100**	**0.0088**
pe		-0.02334	-0.02725	-0.02026	-0.00917	0.00668	0.02206
		(-0.93)	(-0.61)	(-0.33)	(-0.13)	(0.09)	(0.26)
		0.0092	**0.0074**	**0.0029**	**0.0005**	**0.0002**	**0.0022**
pd		0.07899	0.11338	0.13793	0.14982	0.13762	0.12449
		(1.59)	(0.85)	(0.86)	(0.85)	(0.73)	(0.60)
		0.0264	**0.0320**	**0.0335**	**0.0315**	**0.0237**	**0.0175**
Panel C: Excess return univariate regressions*							
py		-0.01566	-0.02753	-0.03370	-0.03493	-0.03092	-0.03061
		(-0.99)	(-1.04)	(-0.93)	(-0.86)	(-0.70)	(-0.62)
		0.0105	**0.0183**	**0.0186**	**0.0155**	**0.0104**	**0.0090**
pe		-0.02409	-0.02772	-0.02023	-0.00846	0.00823	0.02551
		(-0.97)	(-0.62)	(-0.33)	(-0.12)	(0.10)	(0.30)
		0.0099	**0.0077**	**0.0029**	**0.0004**	**0.0003**	**0.0029**
pd		0.07902	0.11133	0.13277	0.14132	0.12564	0.10697
		(1.60)	(0.83)	(0.82)	(0.79)	(0.65)	(0.51)
		0.0267	**0.0311**	**0.0310**	**0.0280**	**0.0196**	**0.0129**
Panel D: Stock return multivariate regressions							
py		-0.01203	-0.03513	-0.05761	-0.07710	-0.09550	-0.12644
		(-0.57)	(-0.90)	(-1.07)	(-1.24)	(-1.43)	(-1.79)
pe		-0.00929	-0.00104	0.02028	0.03870	0.05054	0.07364
		(-0.25)	(-0.02)	(0.23)	(0.38)	(0.50)	(0.76)
pd		0.08224	0.12233	0.16882	0.20096	0.19916	0.18597
		(1.23)	(0.65)	(0.76)	(0.86)	(0.82)	(0.74)
		0.0624	**0.1021**	**0.1272**	**0.1437**	**0.1511**	**0.1693**

Notes: This table reports parameter estimates with t-statistics based on Newey-West standard errors, indicated below in parentheses, and R^2s indicated in bold. Panel A reports results from univariate regressions of quarterly and cumulative stock returns on the price-GDP ratio (*py*), the price-earnings ratio (*pe*), and the price-dividend ratio (*pd*). Panels B and C present results from univariate regressions of quarterly and cumulative excess returns on the price-output ratio (*py*), the price-earnings ratio (*pe*), and the price-dividend ratio (*pd*). Excess return* was calculated using lagged interest rates. Panel D gives results from multivariate regressions of returns on all three ratios. Significant statistics at the 1% level are indicated by ** and at the 5% level by *.

Table 2(b): Semi-Annual
Full sample regressions of long-horizon cumulative returns

Horizon *k*:		1	2	3	4	5	6
Panel A: Stock return univariate regressions							
py	coef.	-0.06178	-0.09497	-0.13027	-0.17876	-0.23724	-0.28603
	t-stat.	(-1.90)	(-1.96)*	(-1.97)*	(-2.13)*	(-2.48)**	(-2.84)**
	R^2	**0.0750**	**0.0969**	**0.1338**	**0.1942**	**0.2500**	**0.2919**
pe		-0.08490	-0.11815	-0.13604	-0.16486	-0.20424	-0.22566
		(-1.65)	(-1.24)	(-1.17)	(-1.20)	(-1.28)	(-1.33)
		0.0568	**0.0649**	**0.0677**	**0.0810**	**0.0952**	**0.0960**
pd		0.20412	0.28270	0.31297	0.35355	0.47115	0.58272
		(2.05)*	(1.30)	(1.18)	(1.25)	(1.48)	(1.75)
		0.0856	**0.0964**	**0.0927**	**0.0964**	**0.1308**	**0.1670**
Panel B: Excess return univariate regressions							
py		-0.02893	-0.02566	-0.02394	-0.03353	-0.05352	-0.06494
		(-0.88)	(-0.56)	(-0.39)	(-0.41)	(-0.55)	(-0.61)
		0.0167	**0.0072**	**0.0045**	**0.0067**	**0.0125**	**0.0147**
pe		-0.02990	-0.00983	0.01837	0.03202	0.02908	0.04071
		(-0.57)	(-0.12)	(0.18)	(0.26)	(0.21)	(0.28)
		0.0072	**0.0005**	**0.0012**	**0.0030**	**0.0019**	**0.0030**
pd		0.13988	0.16661	0.16999	0.19844	0.31350	0.42683
		(1.38)	(0.70)	(0.57)	(0.64)	(0.91)	(1.13)
		0.0409	**0.0342**	**0.0273**	**0.0299**	**0.0568**	**0.0873**
Panel C: Excess return univariate regressions*							
py		-0.02762	-0.02518	-0.02189	-0.03213	-0.05143	-0.06174
		(-0.85)	(-0.55)	(-0.34)	(-0.38)	(-0.51)	(-0.56)
		0.0156	**0.0070**	**0.0038**	**0.0061**	**0.0113**	**0.0128**
pe		-0.02971	-0.00742	0.02857	0.04752	0.04845	0.06265
		(-0.57)	(-0.09)	(0.27)	(0.37)	(0.33)	(0.41)
		0.0073	**0.0003**	**0.0030**	**0.0065**	**0.0051**	**0.0070**
pd		0.13356	0.14915	0.12881	0.14383	0.25082	0.36074
		(1.34)	(0.61)	(0.43)	(0.45)	(0.70)	(0.91)
		0.0382	**0.0275**	**0.0157**	**0.0155**	**0.0355**	**0.0603**
Panel D: Stock return multivariate regressions							
py		-0.03823	-0.06818	-0.12037	-0.20002	-0.28617	-0.36115
		(-0.89)	(-0.94)	(-1.28)	(-1.84)	(-2.29)*	(-2.51)**
pe		-0.00187	0.01328	0.05219	0.11361	0.19812	0.28914
		(-0.03)	(0.11)	(0.40)	(0.82)	(1.18)	(1.46)
pd		0.14397	0.19883	0.20425	0.21319	0.32253	0.44848
		(1.12)	(0.68)	(0.58)	(0.65)	(0.92)	(1.16)
		0.1080	**0.1301**	**0.1582**	**0.2196**	**0.2987**	**0.3742**

Notes: This table displays parameter estimates with *t*-statistics based on Newey-West standard errors, indicated below in parentheses, and R^2s indicated in bold. Panel A gives results from univariate regressions of semi-annual and cumulative stock returns on the price-GDP ratio (*py*), the price-earnings ratio (*pe*), and the price-dividend ratio (*pd*). Panels B and C give results from univariate regressions of semi-annual and cumulative excess returns on the price-output ratio (*py*), the price-earnings ratio (*pe*), and the price-dividend ratio (*pd*). Excess return* was calculated using lagged interest rates. Panel D gives results from multivariate regressions of stock returns on all three ratios. Significant statistics at the 1% level are indicated by ** and at the 5% level by *.

4.3.1. Quarterly Returns

In Table 2(a), for the regressions that use simple quarterly returns (where $k = 1$), the price-output ratio captures approximately 3.74% of the variation in quarterly Australian share returns and 0.98% and 1.05% of the variation of traditional excess returns and excess returns using lagged interest rates, respectively.[5]

In comparing the predictive power of the *py*-ratio with the *pe*-ratio and *pd*-ratio, both the *pe*-ratio and *pd*-ratio capture more of the variation in share returns than the *py*-ratio, while for excess returns the *pd*-ratio captures more of the variation than the *py*-ratio for both measures of excess return.[6] According to the theoretical model in Equation (4), positive deviations from py_t should decrease returns, and thus the coefficient on the *py*-ratio should be negative. In this case, the coefficient on the *py*-ratio is negative for both share returns and excess returns.

In the multivariate regression of quarterly ($k = 1$) share returns on the ratios, the multivariate regression captures more of the variation of share returns than any of the univariate regressions; however, none of the coefficients on the ratios are statistically significant.

4.3.2. Semi-annual Returns

As indicated in Table 2(b), for regressions that use simple semi-annual returns (where $k = 1$), the price-output ratio captures approximately 7.50% of the variation in semi-annual share returns and 1.67% and 1.56% of the variation of traditional excess returns and excess returns using lagged interest rates, respectively. For the share returns, the r-squares appear to be increasing towards significant levels in semi-annual than in quarterly analysis. The *py*-ratio captures more of the variation of both share returns and excess returns than the *pe*-ratio, but the *pd*-ratio captures more of the variation of share returns and excess returns than the *py*-ratio. Just as for quarterly returns, the coefficient on the *py*-ratio for share returns and excess returns is negative; however, for each return series, the coefficient is found to be insignificant.

In the multivariate regression of semi-annual ($k = 1$) share returns on the ratios, again the multivariate regression captures more of the variation of excess returns than any of the univariate regressions; however, none of the coefficients on the ratios are statistically significant.

4.3.3. Long-Horizon Returns

For longer-horizon regressions (where $k = 2…5$), the *py*-ratio captures more and more variation in cumulative share returns as the horizon increases,[7] for both quarterly and semi-annual data, and the *t*-statistics also increase as the horizon increases, as displayed in Tables 2(a) and 2(b). For quarterly data, the *py*-ratio captures 11.25% of the variation in fourth-quarterly ($k = 4$) cumulative share returns and increases to 14.70% for sixth-quarterly (1.5 years) cumulative share returns. The *t*-statistic in the sixth-quarterly cumulative regression is significant at the 1% confidence level. For semi-annual data, the *py*-ratio captures 19.42% of the variation in the fourth-semi-annual ($k = 4$) cumulative share returns and increases to 29.19% for the sixth-semi-annual (three years) cumulative share returns. The *t*-statistic in the sixth-semi-annual cumulative regression is also significant at the 1% confidence level.

In comparing the *py*-ratio to the *pe*-ratio and *pd*-ratio, the results show that, over long-horizons, the *py*-ratio captures more of the variation of share returns than both of the traditional ratios. However, the *pd*-ratio captures more of the variation of excess returns at every horizon and for both measures of

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5 These results are well below the predictive power in Rangvid's (2006) study which documents the price-output ratio capturing 15% of the variation in annual US share returns and 8% of the variation in excess returns. Such comparison may not be appropriate, though, for Rangvid (2006) uses annual and not quarterly returns.

6 This is different from Rangvid's (2006) study which finds that the *py*-ratio captures a much greater percentage of variation than both the *pe*-ratio and the *pd*-ratio.

7 These results are in line with Rangvid's (2006) study, which also finds that the *py*-ratio captures more of the variation in cumulative returns as the horizon increases, and, at the same time, the *t*-statistics also increase as the horizon increases.

excess return. The *py*-ratio captures movements in share returns better than it captures movements in excess returns for both quarterly and semi-annual data.[8]

4.3.4. Sub-sample Quarterly Results

Section 4.3.3 reports that the *py*-ratio contains information about future returns for the full Australian sample period, 1982–2006. This section examines the sub-periods of Q4, 1982–Q4, 1994 and Q1, 1995–Q1, 2006. The reason for using these sub-samples is that they approximately split the full sample into two equally sized sub-samples while maintaining more than 30 observations in each sample to allow for the assumption of normality to hold via the central limit theorem.

For the period Q4, 1982–Q4, 1994, the results for the *py*-ratio predicting share returns at long horizons are strong; as shown in Table 3, the *py*-ratio captures a significantly higher fraction of the variation in share returns than for the entire sample. For simple quarterly returns, (where $k = 1$) the *py*-ratio captures approximately 10.70% of the variation of share returns, which then increases greatly at longer horizons, capturing 38% of the sixth-quarterly cumulative return. For this sub-sample, neither the *pe*-ratio nor the *pd*-ratio captures nearly as much of the variation in share returns. Similarly, the estimates for excess returns also show that the *py*-ratio is a far better predictor than both the *pe*- and *pd*-ratios for this sub-sample. Overall, the *py*-ratio captures more of the variation in share returns than both measures of excess return for this sub-sample.

[8] These results are consistent with those from Rangvid (2006), which document that the *py*-ratio is a better predictor of share returns than excess returns.

Table 3: Quarterly
Subsample regressions of long-horizon cumulative returns
AUS data: Q4, 1982-Q4, 1994

Horizon k:		1	2	3	4	5	6
Stock Returns							
py	coef.	-0.08945	-0.16957	-0.23375	-0.28005	-0.30851	-0.34199
	t-stat	(-2.37)**	(-2.95)**	(-3.38)**	(-3.67)**	(-3.66)**	(-3.53)**
	R^2	**0.1070**	**0.2135**	**0.2790**	**0.3194**	**0.3480**	**0.3812**
pe		-0.05015	-0.07258	-0.08602	-0.09603	-0.10144	-0.10616
		(-1.25)	(-0.98)	(-0.86)	(-0.84)	(-0.86)	(-0.91)
		0.0324	**0.0386**	**0.0383**	**0.0391**	**0.0403**	**0.0403**
pd		0.11527	0.18116	0.23203	0.25073	0.23282	0.19114
		(1.53)	(1.05)	(1.21)	(1.27)	(1.10)	(0.77)
		0.0475	**0.0667**	**0.0769**	**0.0730**	**0.0573**	**0.0340**
Excess Returns							
py		-0.07692	-0.14506	-0.19739	-0.23175	-0.24775	-0.27023
		(-2.02)*	(-2.45)**	(-2.74)**	(-2.98)**	(-2.96)**	(-2.79)**
		0.0797	**0.1603**	**0.2056**	**0.2256**	**0.2309**	**0.2399**
pe		-0.02877	-0.02996	-0.02298	-0.01392	-0.00208	0.00753
		(-0.71)	(-0.42)	(-0.24)	(-0.13)	(-0.02)	(0.07)
		0.0107	**0.0067**	**0.0028**	**0.0008**	**0.0000**	**0.0002**
pd		0.09259	0.13872	0.17507	0.18559	0.16754	0.13991
		(1.22)	(0.79)	(0.88)	(0.89)	(0.74)	(0.52)
		0.0309	**0.0401**	**0.0453**	**0.0412**	**0.0305**	**0.0184**
*Excess Returns**							
py		-0.07885	-0.14692	-0.19992	-0.23571	-0.25399	-0.27731
		(-2.09)*	(-2.51)**	(-2.80)**	(-2.81)**	(-3.02)**	(-2.86)**
		0.0848	**0.1659**	**0.2110**	**0.2334**	**0.2407**	**0.2516**
pe		-0.03020	-0.03143	-0.02410	-0.01433	-0.00157	0.01009
		(-0.75)	(-0.44)	(-0.25)	(-0.13)	(-0.01)	(0.09)
		0.0120	**0.0075**	**0.0031**	**0.0009**	**0.0000**	**0.0004**
pd		0.09292	0.13664	0.16922	0.17555	0.15296	0.11795
		(1.24)	(0.77)	(0.84)	(0.83)	(0.67)	(0.43)
		0.0315	**0.0393**	**0.0423**	**0.0369**	**0.0252**	**0.0130**

Notes: This table presents results from regressions of future cumulative returns and excess returns on the price-GDP ratio (*py*), the price-earnings ratio (*pe*), and the price-dividend ratio (*pd*), for the period Q4 1982 – Q4 1994. The table shows parameter estimates with t-statistics based on Newey-West standard errors, indicated below in parentheses, and R^2s indicated in bold. Significant statistics at the 1% level are indicated by ** and at the 5% level by *.

The results for the period Q1, 1995–Q1, 2006, as displayed in Table 4, indicate that the *pd*-ratio clearly captures the greatest proportion of variation in both share returns and excess returns, while the *pe*-ratio has significant predictive power for both measures of excess return and especially so for share returns. All estimates for *pe* and *pd* are significant at the 1% level. The estimates for *py* ratios are not significant for this sub-period, and the r-squares are very low.

Table 4: Quarterly
Subsample regressions of long-horizon cumulative returns
AUS data: Q1, 1995-Q1, 2006

Horizon *k*:		1	2	3	4	5	6
Stock Returns							
py	coef.	-0.01384	-0.01176	0.00022	-0.00581	-0.02082	-0.04614
	t-stat	(-0.43)	(-0.25)	(0.00)	(-0.06)	(-0.16)	(-0.29)
	R^2	**0.0041**	**0.0017**	**0.0000**	**0.0001**	**0.0012**	**0.0047**
pe		-0.10551	-0.20066	-0.25471	-0.30056	-0.31592	-0.26001
		(-2.53)**	(-3.60)**	(-3.88)**	(-3.81)**	(-3.76)**	(-2.85)**
		0.1269	**0.2761**	**0.2877**	**0.2639**	**0.2077**	**0.1113**
pd		0.24808	0.37016	0.47132	0.66534	0.81471	0.90347
		(2.87)**	(3.57)**	(3.60)**	(4.31)**	(4.67)**	(5.18)**
		0.1575	**0.2238**	**0.2481**	**0.3458**	**0.3949**	**0.4242**
Excess Returns							
py		-0.01088	-0.00525	0.01125	0.01012	0.00080	-0.01698
		(-0.34)	(-0.12)	(0.17)	(0.11)	(0.01)	(-0.13)
		0.0026	**0.0003**	**0.0009**	**0.0005**	**0.0000**	**0.0009**
pe		-0.09943	-0.18906	-0.23793	-0.27880	-0.28932	-0.22936
		(-2.38)**	(-3.38)**	(-3.56)**	(-3.44)**	(-3.33)**	(-2.50)**
		0.1137	**0.2512**	**0.2615**	**0.2385**	**0.1849**	**0.0932**
pd		0.23954	0.35316	0.44617	0.63300	0.77551	0.85958
		(2.77)**	(3.45)**	(3.43)**	(4.14)**	(4.52)**	(5.09)**
		0.1482	**0.2087**	**0.2315**	**0.3287**	**0.3797**	**0.4133**
*Excess Returns**							
py		-0.00978	-0.00322	0.01413	0.01411	0.00619	-0.01217
		(-0.30)	(-0.07)	(0.21)	(0.15)	(0.05)	(-0.08)
		0.0021	**0.0001**	**0.0015**	**0.0009**	**0.0001**	**0.0004**
pe		-0.09792	-0.18665	-0.23464	-0.27455	-0.28403	-0.22147
		(-2.34)**	(-3.33)**	(-3.49)**	(-3.36)**	(-3.21)**	(-2.36)**
		0.1104	**0.2450**	**0.2536**	**0.2307**	**0.1772**	**0.0864**
pd		0.23732	0.35099	0.44354	0.62957	0.77178	0.85375
		(2.74)**	(3.40)**	(3.38)**	(4.07)**	(4.44)**	(4.95)**
		0.1455	**0.2064**	**0.2282**	**0.3243**	**0.3741**	**0.4052**

Notes: This table presents results from regressions of future cumulative returns and excess returns on the price-GDP ratio (*py*), the price-earnings ratio (*pe*), and the price-dividend ratio (*pd*), for the period Q1 1995–Q1 2006. The table shows parameter estimates with *t*-statistics based on Newey-West standard errors, indicated below in parentheses, and R^2s indicated in bold. ** and * indicate significant levels at 1% and 5%, respectively.

To examine whether the poor results for *py*-ratio for the Q1, 1995–Q1, 2006 sub-period are due to the 1990s, where the predictive power of financial ratios have previously been found to be poor predictors of returns, the sub-sample Q1, 1990–Q4, 1999 is also examined. Table 5 presents results for the period Q1, 1990–Q4, 1999. For this period, the regressions on share returns are insignificant and very low, relative to the other samples for each ratio. For excess returns, the results are even less encouraging, with the predictive power of the *py*-ratio shown to be insignificant. For this period, the *pe*-ratio is the best predictor of both share returns and excess returns.

Table 5: Quarterly
Subsample regressions of long-horizon cumulative returns
AUS data: Q1, 1990-Q4, 1999

Horizon *k*:		1	2	3	4	5	6
Stock Returns							
py	coef.	-0.00632	-0.01423	-0.04343	-0.08342	-0.08631	-0.07211
	t-stat	(-0.18)	(-0.22)	(-0.56)	(-1.04)	(-1.05)	(-1.00)
	R^2	**0.0008**	**0.0020**	**0.0136**	**0.0417**	**0.0430**	**0.0358**
pe		0.01565	0.05054	0.075504	0.068831	0.064335	0.05806
		(0.56)	(0.93)	(1.03)	(0.85)	(0.89)	(1.00)
		0.0083	**0.0428**	**0.0740**	**0.0543**	**0.0484**	**0.0494**
pd		0.0162	0.02513	0.063375	0.129304	0.124949	0.07615
		(0.34)	(0.24)	(0.56)	(1.26)	(1.25)	(0.80)
		0.0030	**0.0035**	**0.0171**	**0.0613**	**0.0572**	**0.0265**
Excess Returns							
py		0.01067	0.01789	0.00107	-0.02864	-0.02298	-0.00264
		(0.29)	(0.26)	(0.01)	(-0.32)	(-0.25)	(-0.03)
		0.0022	**0.0029**	**0.0000**	**0.0045**	**0.0027**	**0.0000**
pe		0.03021	0.07775	0.113016	0.114164	0.114987	0.1108
		(1.07)	(1.45)	(1.63)	(1.55)	(1.75)	(2.06)*
		0.0291	**0.0926**	**0.1491**	**0.1361**	**0.1378**	**0.1523**
pd		-0.01306	-0.02877	-0.00881	0.043744	0.030484	-0.02148
		(-0.26)	(-0.26)	(-0.07)	(0.37)	(0.26)	(-0.19)
		0.0018	**0.0042**	**0.0003**	**0.0064**	**0.0030**	**0.0018**
*Excess Returns**							
py		0.01396	0.02468	0.01099	-0.01570	-0.00754	0.14697
		(0.38)	(0.35)	(0.13)	(-0.17)	(-0.08)	(0.17)
		0.0039	**0.0054**	**0.0008**	**0.0014**	**0.0003**	**0.0013**
pe		0.03185	0.08142	0.118773	0.122225	0.125526	0.12411
		(1.13)	(1.53)	(1.75)	(1.73)	(2.00)*	(2.42)**
		0.0326	**0.1017**	**0.1657**	**0.1580**	**0.1651**	**0.1901**
pd		-0.01815	-0.03974	-0.02558	0.021143	0.002787	-0.05334
		(-0.37)	(-0.36)	(-0.20)	(0.18)	(0.02)	(-0.46)
		0.0036	**0.0080**	**0.0025**	**0.0015**	**0.0000**	**0.0110**

Notes: This table presents results from regressions of future cumulative returns and excess returns on the price-GDP ratio (*py*), the price-earnings ratio (*pe*), and the price-dividend ratio (*pd*), for the period Q1 1990–Q4 1999. The table shows parameter estimates with *t*-statistics based on Newey-West standard errors, indicated below in parentheses, and R^2s indicated in bold. Significant statistics at the 1% level are indicated by ** and at the 5% level by *.

Overall, for the Australian data, the *py*-ratio captures movements in share returns reasonably well at long horizons for the full samples of both quarterly and semi-annual data, as well as the first sub-sample of quarterly data. Over the full samples and for both data frequencies, the *py*-ratio captures more of the variation in share returns than either the *pe*-ratio or the *pd*-ratio over long horizons, whereas for excess returns, *pd*-ratio is the only ratio of the three to have significant predictive power. The predictive power of the *py*-ratios of both share returns and excess returns is below those of the *pe*- and *pd*-ratios for the period Q1, 1995–Q1, 2006, as well as for the 1990s sub-sample. In general, given that the findings vary depending largely on the sample period, the Australian data do not show consistent results that *py*-ratio can in fact capture a greater fraction of share returns than the *pe*-ratio and the *pd*-ratio, as was documented in Rangvid (2006).

4.4. Australian Evidence: Additional Analysis

4.4.1. Py-ratio and Interest Rate Prediction for Australia

From the Australian samples used in this paper, it was found that the *py*-ratio captures more of the variation of share returns than excess returns over a single period as well as at long horizons. Excess returns are simply the share return minus the risk-free rate, and to compare how the predictive power of the *py*-ratio differs for excess returns and share returns, it is interesting to examine the relationship between the *py*-ratio and interest rates.

Table 6 shows that the *py*-ratio has a highly significant relationship with future cumulative interest rates for the full sample and for the period 1990–1999. For the periods 1982–1994 and 1995–2006, the results are not as strong, but the relationship between the *py*-ratio and future cumulative interest rates is still significant.[9]

[9] Rangvid (2006) believes that Equation (2) relates the *py*-ratio to future share returns (which are the sum of excess returns and the risk-free rate), but not necessarily to excess returns on their own. Rangvid also finds that the coefficient of the *py*-ratio is negative (for regressions on future cumulative returns), and so implies that a negative share to the *py*-ratio should be associated with higher interest rates and with higher share returns in the future (as implied from negative coefficients on the regressions using returns). So, in terms of predicting excess returns, these will have offsetting effects. Rangvid finds that the *pe*-ratio and *pd*-ratio do not predict interest rates, and so these offsetting effects are not present with these variables.

Table 6: AUS Quarterly
Regressions of cumulative interest rates (90-day bank bills) on *py, pe, and pd*

Horizon *k*:		1	2	3	4	5	6
Q4, 1982 - Q1, 2006							
py	coef.	-0.01464	-0.02952	-0.04491	-0.06084	-0.07763	-0.09427
	t-stat	(-11.16)**	(-6.67)**	(-6.65)**	(-6.81)**	(-7.13)**	(-7.43)**
	R^2	**0.5727**	**0.5826**	**0.5925**	**0.6039**	**0.6200**	**0.6306**
pe		-0.02517	-0.05021	-0.07483	-0.09887	-0.12219	-0.14395
		(-14.02)**	(-6.92)**	(-7.06)**	(-7.17)**	(-7.24)**	(-7.18)**
		0.6789	**0.6989**	**0.7075**	**0.7090**	**0.7057**	**0.6946**
pd		0.03586	0.06945	0.09966	0.12627	0.14914	0.16623
		(6.99)**	(3.87)**	(3.65)**	(3.41)**	(3.17)**	(2.90)**
		0.3444	**0.3342**	**0.3129**	**0.2880**	**0.2615**	**0.2303**
Q4, 1982 - Q4, 1994							
py		-0.01254	-0.02451	-0.03636	-0.04830	-0.06076	-0.07175
		(-3.78)**	(-2.59)**	(-2.47)**	(-2.44)**	(-2.44)**	(-2.33)**
		0.2335	**0.2304**	**0.2274**	**0.2276**	**0.2320**	**0.2246**
pe		-0.02138	-0.04262	-0.06034	-0.08211	-0.09937	-0.11369
		(-9.42)**	(-6.80)**	(-7.14)**	(-7.57)**	(-7.88)**	(-7.75)**
		0.6538	**0.6873**	**0.6931**	**0.6856**	**0.6639**	**0.6180**
pd		0.02268	0.04244	0.05696	0.06514	0.06527	0.05123
		(3.47)**	(2.24)*	(2.02)*	(1.74)	(1.39)	(0.90)
		0.2044	**0.1891**	**0.1562**	**0.1180**	**0.0774**	**0.0327**
Q1, 1995 - Q1, 2006							
py		-0.00297	-0.00651	-0.01103	-0.01593	-0.02163	-0.02646
		(-2.26)*	(-1.29)	(-1.40)	(-1.47)	(-1.60)	(-1.70)
		0.1043	**0.1240**	**0.1538**	**0.1799**	**0.2162**	**0.2450**
pe		-0.00608	-0.01160	-0.01677	-0.02176	-0.02660	-0.03065
		(-3.65)**	(-2.21)*	(-2.18)*	(-2.17)*	(-2.21)*	(-2.17)*
		0.2321	**0.2227**	**0.2210**	**0.2255**	**0.2379**	**0.2431**
pd		0.00854	0.01699	0.02515	0.03234	0.03921	0.04389
		(2.24)*	(1.35)	(1.44)	(1.51)	(1.61)	(1.67)
		0.1027	**0.1137**	**0.1251**	**0.1332**	**0.1478**	**0.1574**
Q1, 1990 - Q4, 1999							
py		-0.01700	-0.03212	-0.04449	-0.05478	-0.06333	-0.06947
		(-6.00)**	(-3.45)**	(-3.32)**	(-3.19)**	(-3.11)**	(-3.04)**
		0.4867	**0.4804**	**0.4609**	**0.4356**	**0.4162**	**0.3992**
pe		-0.01456	-0.02721	-0.03751	-0.04533	-0.05065	-0.05274
		(-7.25)**	(-3.19)**	(-3.28)**	(-3.31)**	(-3.22)**	(-3.05)**
		0.5807	**0.5916**	**0.5908**	**0.5708**	**0.5388**	**0.4892**
pd		0.02926	0.05390	0.07219	0.08556	0.09447	0.09763
		(12.01)**	(6.70)**	(5.81)**	(4.82)**	(4.10)**	(3.56)**
		0.7916	**0.7694**	**0.7179**	**0.6511**	**0.5878**	**0.5227**

Notes: This table reports results from the regressions of future cumulative short interest rates (90-day bank bills) on the price-GDP ratio, the price-earnings ratio (*pe*), and the price-dividend ratio (*pd*) for the full sample period Q4 1982–Q1 2006, as well as the sub-samples Q4 1982–Q4 1994, Q1 1995–Q1 2006, and Q1 1990–Q4 1999. The table shows parameter estimates with *t*-statistics based on Newey-West standard errors, indicated below in parentheses, and R^2s indicated in bold. Significant statistics at the 1% level are indicated by ** and at the 5% level by *.

The results for Australian data in this paper appear to be consistent with this explanation for the *py*-ratio, given the negative coefficients on these variables for each sample period, and the *py*-ratio is documented to be a better predictor of share returns than excess returns. In terms of the *pe*- and *pd*-ratios, the *pe*-ratio generally has the greatest power at predicting interest rates for each sample period apart from the period 1990–1999, where the *pd*-ratio has the strongest relationship with interest rates.

4.5. New Zealand Evidence: Summary Statistics

The means and standard deviations of each series for the New Zealand quarterly and semi-annual data are presented in Panel A of Tables 7 (a) and (b). The average annualised quarterly and semi-annual equity returns are approximately 10.08% and 5.04%, with standard deviations of 14.33% and 10.41%, respectively. The average annualised quarterly excess return is 3.24% under the standard method and 3.20% using the lagged interest rate method, whereas the estimate for average annualised semi-annual excess returns are 1.66% and 1.61%, respectively, using the standard and lagged interest rate methods. As is the case with the Australian results, both the *py*-ratio and the *pd*-ratio have greater volatilities than those for returns for both quarterly and semi-annual data.

Table 7(a): Quarterly
Summary Statistics
NZ data: Q3, 1991-Q4, 2003

	py	*pd*	*r*	*er*	*er**
Panel A: Means and standard deviations					
Mean	-2.1062	1.7769	0.1008	0.0324	0.0320
Std.	0.2101	0.6988	0.1433	0.1451	0.1448
Panel B: Correlations					
py	1.0000				
pd	0.3914	1.0000			
r	-0.2425	-0.1431	1.0000		
er	-0.2289	-0.1347	0.9986	1.0000	
*er**	-0.2266	-0.1327	0.9986	0.9996	1.0000
Panel C: Univariate unit root and cointegration tests					
ADF	-2.60*	-7.28**	-7.67**	-7.50**	-7.53**
PP	-2.60*	-7.28**	-7.67**	-7.50**	-7.53**

Table 7(b): Semi-Annual
Summary Statistics
NZ data: 1991 - 2003

	py	*pd*	*r*	*er*	*er**
Panel A: Means and standard deviations					
Mean	-2.8122	2.1823	0.0504	0.0166	0.0161
Std.	0.2179	0.5143	0.1041	0.1054	0.1066
Panel B: Correlations					
py	1.0000				
pd	0.3596	1.0000			
r	-0.3422	0.0742	1.0000		
er	-0.2187	0.1717	0.8760	1.0000	
*er**	-0.1722	0.1600	0.8989	0.9269	1.0000
Panel C: Univariate unit root and cointegration tests					
ADF	-2.42	-9.26**	-5.35**	-4.17**	-4.46**
PP	-2.42	-9.26**	-5.35**	-4.17**	-4.46**

Notes to Tables 1 (a) and (b): Row one in Panel A displays the sample means and row two gives the standard deviations for the price-GDP ratio (*py*), the price-dividend ratio (*pd*), the quarterly return to equity (*r*), the traditional excess return (*er*) and excess return with lagged interest rates (*er**). Panel B shows the correlations between each series. Panel C gives the results of the Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) tests for a unit root. The null hypothesis of each test is that the series is non-stationary, and the critical values are 2.58 at the 10% level and 3.51 at the 1% level. Significant statistics at the 1% level are indicated by ** and at the 5% level by *.

The correlations between each variable for the New Zealand quarterly and semi-annual data are shown in Panel B of Tables 7 (a) and (b). The correlations between the *pd*- ratio and the *py*-ratio are close to 0.4 for both quarterly and semi-annual data. The correlation between returns and excess returns is very high[10] as a result of the low volatility of the interest rates. The *py*-ratio has a significantly negative correlation with returns and excess returns.

The New Zealand results for the analysis of the residuals for each data frequency are presented in Appendix B. Just as with the Australian data, these show that the residuals do not suffer from serial correlation, nor are they correlated with the independent variables p_t and y_{t-1}. This again indicates that the potential problems discussed in Section 3.2.1 are of no significance, and therefore there are no problems with the specification of the model.

4.6. New Zealand Evidence: Cointegration

The results from the Augmented Dickey-Fuller (ADF) tests and the Phillips-Perron (PP) tests are reported in Panel C of Tables 7 (a) and (b). For both quarterly and semi-annual data, the null hypothesis of non-stationarity is rejected for all the returns series, as well as the *pd*-ratio. For semi-annual data, non-stationarity cannot be rejected for the *py*-ratio, and, for the quarterly analysis, it is marginally rejected. This indicates that the *py*-ratio may be non-stationary and implies that y_t is not cointegrated with p_t. So, given that the *pd*-ratio is stationary while the *py*-ratio is non-stationary, the theory behind equations (1) and (4) suggests that perhaps the *pd*-ratio should be the better variable of the two at capturing variations in future returns.

[10] Approximately 4.04% for the 90-day bank bill and 3.38% for the six-month bond.

4.7. New Zealand Evidence: Predicting Returns

Tables 8 (a) and (b) report the univariate and multivariate regression results for New Zealand quarterly and semi-annual data, respectively. Panel A presents results for returns against the *py*-ratio and the *pd*-ratio; Panels B and C show results for traditional and lagged-interest-rates excess returns against the *py*-ratio and the *pd*-ratio. Panel D displays results for the multivariate regressions on share returns for quarterly and semi-annual data, respectively.[11] Newey-West *t*-statistics are used to test for the possible presence of autocorrelation and heteroskedasticity.

Table 8(a): Quarterly
Full sample regressions of long-horizon cumulative returns

Horizon *k*:		1	2	3	4	5	6
Panel A: Stock return univariate regressions							
py	coef.	-0.08272	-0.15451	-0.24317	-0.34735	-0.43908	-0.48479
	t-stat.	(-1.73)	(-1.75)	(-2.16)*	(-2.56)**	(-3.48)**	(-4.49)**
	R^2	**0.0588**	**0.1126**	**0.1981**	**0.3016**	**0.4293**	**0.5082**
pd		-0.01460	-0.03187	-0.03623	0.01447	-0.05005	-0.07901
		(-1.00)	(-1.40)	(-1.58)	(-0.67)	(-2.50)**	(-3.10)**
		0.0205	**0.0539**	**0.0510**	**0.0063**	**0.0655**	**0.1554**
Panel B: Excess return univariate regressions							
py		-0.07906	-0.14828	-0.23499	-0.33686	-0.42399	-0.46383
		(-1.63)	(-1.64)	(-2.02)*	(-2.41)**	(-3.24)**	(-4.07)**
		0.0524	**0.0991**	**0.1751**	**0.2696**	**0.3864**	**0.4569**
pd		-0.01392	-0.03027	-0.03345	-0.01082	-0.04586	-0.07444
		(-0.94)	(-1.27)	(-1.38)	(-0.48)	(-2.12)*	(-2.79)**
		0.0181	**0.0464**	**0.0412**	**0.0033**	**0.0531**	**0.1355**
Panel C: Excess return univariate regressions*							
py		-0.07809	-0.14687	-0.23383	-0.33711	-0.42635	-0.46743
		(-1.61)	(-1.63)	(-2.02)*	(-2.41)**	(-3.24)**	(-4.08)**
		0.0513	**0.0979**	**0.1754**	**0.2734**	**0.3929**	**0.4624**
pd		-0.01369	-0.03048	-0.03397	-0.01124	-0.46260	-0.07483
		(-0.93)	(-1.31)	(-1.42)	(-0.55)	(-2.18)*	(-2.84)**
		0.0176	**0.0474**	**0.0430**	**0.0036**	**0.0543**	**0.1364**
Panel D: Stock return multivariate regressions							
py		-0.07513	-0.13319	-0.22875	-0.37757	-0.43166	-0.44520
		(-1.43)	(-1.63)	(-1.95)	(-2.52)**	(-3.07)**	(-4.07)**
pd		-0.00581	-0.01705	-0.01149	0.02451	-0.00622	-0.03406
		(-0.37)	(-0.87)	(-0.53)	(1.04)	(-0.35)	(-2.06)
		0.0615	**0.1259**	**0.2025**	**0.3172**	**0.4302**	**0.5337**

Notes: This table shows parameter estimates with *t*-statistics based on Newey-West standard errors, indicated below in parentheses, and R^2s indicated in bold. Panel A gives results from univariate regressions of quarterly and cumulative stock returns on the price-GDP ratio (*py*), and the price-dividend ratio (*pd*). Panels B and C give results from univariate regressions of quarterly and cumulative excess returns on the price-output ratio (*py*), and the price-dividend ratio (*pd*). Panel D gives results from multivariate regressions of returns on both ratios. Significant statistics at the 1% level are indicated by ** and at the 5% level by *.

[11] For the multivariate regressions, only the most significant of the three return series is presented in each case, given that the focus of this paper is on the predictive power of each ratio individually.

Table 8(b): Semi-Annual
Full sample regressions of long-horizon cumulative returns

Horizon k:		1	2	3	4	5	6
Panel A: Stock return univariate regressions							
py	coef.	-0.02048	-0.04670	-0.06606	-0.08626	-0.09440	-0.09532
	t-stat.	(-1.75)	(-2.20)*	(-4.35)**	(-9.31)**	(-11.90)**	(-9.95)**
	R^2	**0.1171**	**0.3243**	**0.5469**	**0.7432**	**0.7451**	**0.7837**
pd		0.00188	0.00564	-0.00444	-0.00820	-0.01002	-0.01064
		(0.36)	(1.12)	(-1.09)	(-1.31)	(-1.04)	(-1.35)
		0.0055	**0.0271**	**0.0124**	**0.0348**	**0.0433**	**0.0512**
Panel B: Excess return univariate regressions							
py		-0.01602	-0.03603	-0.04478	-0.05316	-0.04411	-0.02160
		(-1.07)	(-1.40)	(-1.65)	(-1.84)	(-1.42)	(-0.63)
		0.0478	**0.1041**	**0.1275**	**0.1414**	**0.0799**	**0.0197**
pd		0.00533	0.00769	-0.00534	-0.01135	-0.01649	-0.01772
		(0.84)	(1.11)	(-0.92)	(-1.53)	(-1.82)	(-2.10)*
		0.0295	**0.0272**	**0.0091**	**0.0335**	**0.0575**	**0.0695**
Panel C: Excess return univariate regressions*							
py		-0.01335	-0.03857	-0.05234	-0.06479	-0.06359	-0.04830
		(-0.84)	(-1.34)	(-1.92)	(-2.39)**	(-2.20)*	(-1.40)
		0.0297	**0.1145**	**0.1592**	**0.1858**	**0.1441**	**0.0819**
pd		0.00526	0.01135	-0.00271	-0.00754	-0.01483	-0.01634
		(0.78)	(1.65)	(-0.48)	(-1.04)	(-1.83)	(-1.84)
		0.0256	**0.0569**	**0.0021**	**0.0131**	**0.0404**	**0.0492**
Panel D: Stock return multivariate regressions							
py		-0.02535	-0.05666	-0.06929	-0.05522	-0.09507	-0.09558
		(-2.03)*	(-3.20)**	(-5.58)**	(-9.72)**	(-11.65)**	(-9.07)**
pd		0.00574	0.01313	0.00482	0.00337	0.00111	0.00043
		(1.08)	(2.34)**	(0.81)	(1.05)	(0.33)	(0.12)
		0.1617	**0.4567**	**0.5602**	**0.7486**	**0.7456**	**0.7838**

Notes: This table reports parameter estimates with t-statistics based on Newey-West standard errors, indicated below in parentheses, and R^2s indicated in bold. Panel A gives results from univariate regressions of semi-annual and cumulative stock returns on the price-GDP ratio (*py*), and the price-dividend ratio (*pd*). Panels B and C give results from univariate regressions of semi-annual and cumulative excess returns on the price-output ratio (*py*), and the price-dividend ratio (*pd*). Panel D gives results from multivariate regressions of returns on both ratios. Significant statistics at the 1% level are indicated by ** and at the 5% level by *.

4.7.1. Quarterly Returns

In Table 8(a), the estimates from the regressions that use simple quarterly returns (where k = 1) indicate that the price-output ratio captures approximately 5.88% of the variation in quarterly New Zealand share returns, 5.24% and 5.13% of the variation of traditional excess returns, and 5.24% and 5.13% of the variation of traditional excess returns and excess returns using lagged interest rates, respectively.[12] This paper is interested in the comparison between the predictive powers of the *py*-ratio and that of the *pd*-ratio. For the New Zealand results, the *py*-ratio captures significantly more of the variation in each return series (share returns and both measures of excess return) than the *pd*-ratio.[13]

[12] These results from quarterly data are below the predictive power in of the *py*-ratio found in Rangvid (2006), which employed annual data.
[13] This is a result that reiterates those in Rangvid (2006).

According to the theoretical model in Equation (4), positive deviations from py_t should decrease returns, and thus the coefficient on the *py*-ratio should be negative. In the New Zealand case, the coefficient on the *py*-ratio is in fact negative for each return series and thus coincides with the theory.

In the multivariate regression of quarterly (k = 1) share returns on the *py*- and *pd*-ratios, the multivariate regression captures more of the variation of excess returns than any of the univariate regressions; however, the coefficients are not statistically significant.

4.7.2. Semi-annual Returns

In Table 8(b), for the regressions that use simple semi-annual returns (where k = 1), the price-output ratio captures approximately 11.71% of the variation in semi-annual New Zealand share returns and 4.78% and 2.97% of the variation of traditional excess returns and excess returns using lagged interest rates, respectively.[14] Again, the *py*-ratio captures significantly more of the variation of share returns than the *pd*-ratio for each return series. Just as for quarterly returns, the coefficients on the *py*-ratio for share returns and excess returns are all negative.

In the multivariate regression of quarterly (k = 1) share returns on the *py*- and *pd*-ratios, the multivariate regression captures more of the variation of excess returns than any of the univariate regressions; however, the coefficients are not statistically significant.

4.7.3. Long-Horizon Returns

For the longer-horizon regressions (where k = 2, 3,…,6), in both Tables 8(a) and 8(b), the *py*-ratio captures more and more variation in cumulative returns as the horizon increases, while, at the same time, the *t*-statistics also increase as the horizon increases, for each return series and for both quarterly and semi-annual data. For quarterly data, the *py*-ratio captures 30% of the variation in fourth-quarterly (k = 4) cumulative share returns and increases to 50% for sixth-quarterly (1.5 years) cumulative share returns. For semi-annual data, the *py*-ratio captures 54% of the variation in the third-semi-annual (k = 3) cumulative share returns and increases to 78% for the sixth semi-annual (three years) cumulative share returns. The *t*-statistics for the third- through the sixth-semi-annual cumulative regression are significant at the 1% level.

In comparing the *py*-ratio and the *pd*-ratio, over long horizons for both quarterly and semi-annual data, the *py*-ratio captures more of the variation in each return series than the *pd*-ratio. The r-squares of the long-horizon excess returns indicate that the *py*-ratio captures movements in share returns better than it captures movements in excess returns for both quarterly and semi-annual data.[15] Overall for the New Zealand data, the *py*-ratio captures movements in share returns well; the ratio captures more of the variation in returns than the *pd*-ratio.[16]

A point that arises from the New Zealand results is that the non-stationary *py*-ratio often captures more of the variation of returns than the stationary *pd*-ratio, a result that is contrary to the implications of the theoretical basis behind Rangvid's (2006) paper. A possible explanation of the significant differences of predictive power of the *py*-ratio when using Australian data compared to New Zealand data is the large difference in volatility of GDP. Although some of these results suggest that the theoretical background behind using the *py*-ratio in predicting returns may be questioned, an important implication that arises from Equation (4) is that the variation over time of the price-output ratio should capture the variation over time in returns, if output is not too volatile. The volatility of the New Zealand GDP series, both quarterly and semi-annual, of approximately 16% is lower as compared to that of the Australian GDP series' of approximately 26%.

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[14] The magnitude of these results are in line with those in Rangvid (2006), which suggests that with annual New Zealand data our results could be much closer to those in Rangvid (2006). However, given the lack of data points, it was not possible to compare results using annual data.

[15] These New Zealand results are consistent with Rangvid (2006) who also finds that the *py*-ratio is a better predictor of share returns than excess returns.

[16] These results are similar to the findings of Rangvid (2006) in that the *py*-ratio can capture a considerable amount of share returns, specifically over and above that of the *pd*-ratio.

4.8. New Zealand Evidence: Additional Analysis

4.8.1. Py-ratio and Interest Rate Prediction for New Zealand

It is documented in this study that the *py*-ratio generally captures more of the variation of share returns than excess returns, at both the single period and over longer horizons of sample period. To compare how the predictive power of the *py*-ratio differs for excess returns and share returns for New Zealand data, it is again interesting to examine the relationship between the *py*-ratio and interest rates, as was done for the Australian data.

Table 9 shows that the *py*-ratio has a relationship with future cumulative interest rates, but relative to previous results, this relationship is not particularly significant. As reported earlier, the New Zealand results show that the *py*-ratio should predict future share returns but not excess returns, given that the *py*-ratio seems to be a better predictor of share returns than excess returns, while this is more evident in the Australian result. The coefficients on the *py* variables are negative for the New Zealand regressions on interest rates, which is again in line with Rangvid's (2006) theory on predicting excess returns.

Table 9: NZ Quarterly
Regressions of cumulative interest rates (90-day bank bills) on *py, pe*, and *pd*

Horizon k:		1	2	3	4	5	6
Q3, 1991 - Q4, 2003							
py	coef.	-0.00366	-0.06230	-0.00819	-0.01048	-0.01509	-0.02096
	t-stat	(-1.38)	(-1.13)	(-0.99)	(-0.99)	(-1.14)	(-1.28)
	R^2	**0.0379**	**0.0290**	**0.0236**	**0.0231**	**0.0335**	**0.0487**
pd		-0.00068	-0.00159	-0.00278	-0.00365	-0.00419	-0.00457
		(-0.85)	(-1.10)	(-1.32)	(-1.36)	(-1.25)	(-1.18)
		0.0147	**0.0213**	**0.0316**	**0.0335**	**0.0303**	**0.0267**

Notes: This table presents results from the regressions of future cumulative short interest rates (90-day bank bills) on the price-GDP ratio (*py*), and the price-dividend ratio (*pd*) for the full sample period Q3 1991–Q4 2003. The table shows parameter estimates with t-statistics based on Newey-West standard errors, indicated below in parentheses, and R^2s indicated in bold. Significant statistics at the 1% level are indicated by ** and at the 5% level by *.

In terms of the *pd*-ratio, these interest rate results also show evidence for the theoretical explanations in Rangvid (2006) with all the coefficients on *pd* being negative. In comparing the *py*-ratio and the *pd*-ratio, given their low levels of r-squares, there is no significant difference in their abilities to predict interest rates.

5. Additional Considerations

5.1. Data Release Dates

In regards to both Australian and New Zealand GDP data, the lag between the end of the reporting period and the date at which the data is made publicly available is three months. Statistics New Zealand have stated that the lag is simply three months, while according to the Australian Bureau of Statistics, their GDP data is released on the first Wednesday of the third month after the end of reference quarter. Given the way *py*-ratio is defined, a potential problem with the release dates of GDP data becomes obvious. The price-to-GDP ratio is calculated as $py_t = p_t - y_{t-1}$, where t is in quarters/half years, p_t is the log of the price for period t of the stock index, and y_{t-1} is the log of the GDP for the period t-1.[17] This lag between the end of the period and the release of the GDP figure gives rise to a potential 'look-ahead bias' in the analysis.

In order to examine the degree of this possible look-ahead bias, Tables 10(a) and 10(b) present full sample quarterly and semi-annual results of a py_{lag}-ratio to compare with those of the py-ratio, for both Australian and New Zealand data. The py_{lag}-ratio is calculated as $py_{lag} = p_t - y_{t-2}$, where t is in quarters/half years, p_t is the log of the price for period t of the stock index, and y_{t-2} is the log of the GDP for the period t-2.[18] In looking at both the Australian and New Zealand results for quarterly and semi-annual data, it is clear that there is no significant difference between py and py_{lag} in any of the coefficients, t-statistics, or R's, for both stock returns and excess returns.

Table 10(a): Quarterly
Full sample regressions of long-horizon cumulative returns

Horizon k:		1	2	3	4	5	6
Australian Results: Q4, 1982 - Q2, 2006							
Panel A: Stock return univariate regressions							
py	coef.	-0.02987	-0.05692	-0.07854	-0.09553	-0.10790	-0.12453
	t-stat.	(-1.90)	(-2.14)*	(-2.16)*	(-2.30)*	(-2.33)**	(-2.40)**
	R^2	**0.0374**	**0.0760**	**0.0981**	**0.1125**	**0.1243**	**0.1470**
py_{lag}		-0.02999	-0.05749	-0.07929	-0.09620	-0.10864	-0.12457
		(-1.91)	(-2.17)*	(-2.19)*	(-2.32)*	(-2.36)**	(-2.42)**
		0.0378	**0.0777**	**0.1002**	**0.1144**	**0.1264**	**0.1475**
Panel B: Excess return univariate regressions							
py		-0.01523	-0.02740	-0.03363	-0.03468	-0.03027	-0.03026
		(-0.96)	(-1.03)	(-0.93)	(-0.85)	(-0.69)	(-0.62)
		0.0098	**0.0180**	**0.0185**	**0.0152**	**0.0100**	**0.0088**
py_{lag}		-0.01536	-0.02802	-0.03449	-0.03554	-0.03130	-0.03067
		(-0.97)	(-1.05)	(-0.95)	(-0.88)	(-0.72)	(-0.63)
		0.0100	**0.0189**	**0.0195**	**0.0161**	**0.0107**	**0.0091**
New Zealand Results: Q3,1991 - Q4,2003							
Panel C: Stock return univariate regressions							
py	coef.	-0.08272	-0.15451	-0.24317	-0.34735	-0.43908	-0.48479
	t-stat.	(-1.73)	(-1.75)	(-2.16)*	(-2.56)**	(-3.48)**	(-4.49)**
	R^2	**0.0588**	**0.1126**	**0.1981**	**0.3016**	**0.4293**	**0.5082**
py_{lag}		-0.08393	-0.15079	-0.25757	-0.34723	-0.43388	-0.48429
		(-1.78)	(-1.74)	(-2.26)*	(-2.60)**	(-3.57)**	(-4.76)**
		0.0618	**0.1076**	**0.2215**	**0.3028**	**0.4238**	**0.5084**
Panel D: Excess return univariate regressions							
py		-0.07906	-0.14828	-0.23499	-0.33686	-0.42399	-0.46383
		(-1.63)	(-1.64)	(-2.02)*	(-2.41)**	(-3.24)**	(-4.07)**
		0.0524	**0.0991**	**0.1751**	**0.2696**	**0.3864**	**0.4569**
py_{lag}		-0.08030	-0.14488	-0.24975	-0.33704	-0.41901	-0.46470
		(-1.67)	(-1.63)	(-2.13)*	(-2.45)**	(-3.32)**	(-4.29)**
		0.0552	**0.0949**	**0.1972**	**0.2711**	**0.3815**	**0.4597**

Notes: This table shows parameter estimates with t-statistics based on Newey-West standard errors, indicated below in parentheses, and R^2s indicated in bold. Panel A gives Australian results from univariate regressions of quarterly and cumulative stock returns on the original price-GDP ratio (py), and the price-GDP ratio using lagged GDP values (py_{lag}). Panel B gives Australian results from univariate regressions of quarterly and cumulative excess returns on the original price-output ratio (py), and the price-GDP ratio using lagged GDP values (py_{lag}). Panel C gives New Zealand results from univariate regressions of quarterly and cumulative stock returns on the original price-GDP ratio (py), and the price-GDP ratio using lagged GDP values (py_{lag}). Panel D gives New Zealand results from univariate regressions of quarterly and cumulative excess returns on the original price-output ratio (py), and the price-GDP ratio using lagged GDP values (py_{lag}).Significant statistics at the 1% level are indicated by ** and at the 5% level by *.

[17] The problem is best illustrated with an example. Using quarterly data, if we take p_t as at the 30th of June, then the corresponding y_{t-1} used in constructing py_t will be the log of GDP from the previous quarter; however, this data will not be available for another three months.

[18] Referring to the example in the previous footnote, taking p_t as the 30th of June, the corresponding y_{t-2} used in constructing py_{lag} will be the log of GDP from two quarters back, which will be the March quarter (data which will be available at the 30th of June).

Table 10(b): Semi-Annual
Full sample regressions of long-horizon cumulative returns

Horizon k:		1	2	3	4	5	6
Australian Results: 1983 - 2006							
Panel A: Stock return univariate regressions							
py	coef.	-0.06178	-0.09497	-0.13027	-0.17876	-0.23724	-0.28603
	t-stat.	(-1.91)	(-1.96)*	(-1.97)*	(-2.13)*	(-2.48)**	(-2.84)**
	R^2	**0.0750**	**0.0969**	**0.1338**	**0.1942**	**0.2500**	**0.2919**
py_{lag}		-0.06278	-0.09651	-0.12956	-0.17708	-0.23644	-0.28570
		(-1.95)	(-2.00)*	(-1.97)*	(-2.14)*	(-2.49)**	(-2.87)**
		0.0779	**0.1007**	**0.1333**	**0.1922**	**0.2507**	**0.2937**
Panel B: Excess return univariate regressions							
py		-0.02893	-0.02566	-0.02394	-0.03353	-0.05352	-0.06494
		(-0.88)	(-0.56)	(-0.39)	(-0.41)	(-0.55)	(-0.61)
		0.0167	**0.0072**	**0.0045**	**0.0067**	**0.0125**	**0.0147**
py_{lag}		-0.03012	-0.02780	-0.02434	-0.03351	-0.05491	-0.06696
		(-0.91)	(-0.61)	(-0.40)	(-0.42)	(-0.57)	(-0.64)
		0.0182	**0.0085**	**0.0047**	**0.0068**	**0.0133**	**0.0157**
New Zealand Results: 1991 - 2003							
Panel C: Stock return univariate regressions							
py	coef.	-0.02048	-0.04670	-0.06606	-0.08626	-0.09440	-0.09532
	t-stat.	(-1.75)	(-2.20)*	(-4.35)**	(-9.31)**	(-11.90)**	(-9.95)**
	R^2	**0.1171**	**0.3243**	**0.5469**	**0.7432**	**0.7451**	**0.7837**
py_{lag}		-0.02067	-0.04255	-0.06479	-0.08078	-0.09275	-0.09011
		(-1.82)	(-2.07)*	(-3.91)**	(-8.15)**	(-11.09)**	(-9.23)**
		0.1260	**0.2924**	**0.5653**	**0.7091**	**0.7688**	**0.7548**
Panel D: Excess return univariate regressions							
py		-0.01602	-0.03603	-0.04478	-0.05316	-0.04411	-0.02160
		(-1.07)	(-1.40)	(-1.65)	(-1.84)	(-1.42)	(-0.63)
		0.0478	**0.1041**	**0.1275**	**0.1414**	**0.0799**	**0.0197**
py_{lag}		-0.01628	-0.03371	-0.04688	-0.05276	-0.04964	-0.02523
		(-1.13)	(-1.37)	(-1.84)	(-1.99)*	(-1.80)	(-0.80)
		0.0522	**0.0989**	**0.1502**	**0.1516**	**0.1082**	**0.0290**

Notes: This table displays parameter estimates with t-statistics based on Newey-West standard errors, indicated below in parentheses, and R^2s indicated in bold. Panel A gives Australian results from univariate regressions of semi-annual and cumulative stock returns on the original price-GDP ratio (*py*), and the price-GDP ratio using lagged GDP values (py_{lag}). Panel B gives Australian results from univariate regressions of semi-annual and cumulative excess returns on the original price-output ratio (*py*), and the price-GDP ratio using lagged GDP values (py_{lag}). Panel C gives New Zealand results from univariate regressions of semi-annual and cumulative stock returns on the original price-GDP ratio (*py*), and the price-GDP ratio using lagged GDP values (py_{lag}). Panel D gives New Zealand results from univariate regressions of semi-annual and cumulative excess returns on the original price-output ratio (*py*), and the price-GDP ratio using lagged GDP values (py_{lag}).Significant statistics at the 1% level are indicated by ** and at the 5% level by *.

5.2. Using GDP Forecasts

Given the potential bias that the delay in the release of data can cause (although this is not evident in any samples examined here), it is interesting to examine how effective the use of forecast data can be in replacing the actual values. Several government agencies make quarterly forecasts of the economic outlook and of economic data, and, for the purposes of this analysis, GDP forecasts used are those provided by the New Zealand Institute of Economic Research (NZIER). In order to compare results using forecasts and those using actual data, Table 11 presents results for quarterly and semi-annual data for the full available sample of the *py*-ratio using the actual GDP values, *py*, and the forecasted GDP values, py_{fore}. For quarterly data, the *py*-ratio tends to be a slightly better predictor than the py_{fore}-ratio at short horizons, but then slightly worse at longer horizons. For semi-annual data, the *py*-ratio tends to be a slightly worse predictor than the py_{fore}-ratio at short horizons, but then slightly better at longer horizons. However, for both quarterly and semi-annual data, these differences are very small, and the py_{fore}-ratio still captures a highly significant amount of returns. This shows that GDP forecasts are a suitable replacement for actual GDP data, and, given the potential bias that could arise with the actual data (as discussed in Section 5.1), perhaps GDP forecasts would be the best variable for constructing the *py*-ratio.

Table 11: Full sample regressions of long-horizon cumulative returns

Horizon *k*:		1	2	3	4	5	6
Quarterly							
Panel A: Stock return univariate regressions							
py	coef.	-0.08272	-0.15451	-0.24317	-0.34735	-0.43908	-0.48479
	t-stat.	(-1.73)	(-1.75)	(-2.16)*	(-2.56)**	(-3.48)**	(-4.49)**
	R^2	**0.0588**	**0.1126**	**0.1981**	**0.3016**	**0.4293**	**0.5082**
py_{fore}		-0.06810	-0.12316	-0.20826	-0.29346	-0.36869	-0.41332
		(-1.65)	(-1.74)	(-2.23)*	(-2.62)**	(-3.57)**	(-4.77)**
		0.0540	**0.0981**	**0.2021**	**0.3049**	**0.4311**	**0.5273**
Panel B: Excess return univariate regressions							
py		-0.07906	-0.14828	-0.23499	-0.33686	-0.42399	-0.46383
		(-1.63)	(-1.64)	(-2.02)*	(-2.41)**	(-3.24)**	(-4.07)**
		0.0524	**0.0991**	**0.1751**	**0.2696**	**0.3864**	**0.4569**
py_{fore}		-0.06501	-0.11755	-0.20038	-0.28274	-0.35328	-0.39232
		(-1.56)	(-1.62)	(-2.08)*	(-2.44)**	(-3.28)**	(-4.25)**
		0.0480	**0.0854**	**0.1772**	**0.2690**	**0.3820**	**0.4666**
Semi-Annual							
Panel C: Stock return univariate regressions							
py	coef.	-0.02048	-0.04670	-0.06606	-0.08626	-0.09440	-0.09532
	t-stat.	(-1.75)	(-2.20)*	(-4.35)**	(-9.31)**	(-11.90)**	(-9.95)**
	R^2	**0.1171**	**0.3243**	**0.5469**	**0.7432**	**0.7451**	**0.7837**
py_{fore}		-0.01794	-0.03989	-0.05777	-0.07470	-0.07837	-0.07755
		(-1.79)	(-2.32)*	(-4.93)**	(-11.72)**	(-15.66)**	(-9.64)**
		0.1218	**0.4332**	**0.5898**	**0.7990**	**0.7506**	**0.7666**
Panel D: Excess return univariate regressions							
py		-0.01602	-0.03603	-0.04478	-0.05316	-0.04411	-0.02160
		(-1.07)	(-1.40)	(-1.65)	(-1.84)	(-1.42)	(-0.63)
		0.0478	**0.1041**	**0.1275**	**0.1414**	**0.0799**	**0.0197**
py_{fore}		-0.01327	-0.02849	-0.03563	-0.03964	-0.02644	-0.00466
		(-1.03)	(-1.31)	(-1.51)	(-1.53)	(-0.92)	(-0.14)
		0.0445	**0.0911**	**0.1139**	**0.1127**	**0.0420**	**0.0014**

Notes: This table reports parameter estimates with *t*-statistics based on Newey-West standard errors, indicated below in parentheses, and R^2s indicated in bold. Panel A gives results from univariate regressions of quarterly and cumulative stock returns on the original price-GDP ratio (*py*), and the price-GDP ratio using forecast GDP values (py_{fore}). Panel B gives results from univariate regressions of quarterly and cumulative excess returns on the original price-output ratio (*py*), and the price-GDP ratio using forecast GDP values (py_{fore}). Panel C gives results from univariate regressions of semi-annual and cumulative stock returns on the original price-GDP ratio (*py*), and the price-GDP ratio using forecast GDP values (py_{fore}). Panel D gives results from univariate regressions of semi-annual and cumulative excess returns on the original price-output ratio (*py*), and the price-GDP ratio using forecast GDP values (py_{fore}).Significant statistics at the 1% level are indicated by ** and at the 5% level by *.

6. Concluding Remarks

Financial variables, such as price-dividend ratio, price-earnings ratio, and dividend yield, have generally been found to be good predictors of long-horizon returns, rather than over the short term. However, during the 1990s, the documented predictive power of these ratios was not so strong.

Recently, several papers have suggested that ratios using macroeconomic variables may capture information about future returns over and above that which has been captured by the traditional financial ratios. In particular, using the sample data for the US and G-7 countries, Rangvid (2006) finds that the ratio of share price-to-GDP can capture a substantial proportion of the variation in future returns, over and above that which is captured by the price-dividend and price-earnings ratios.

Based on the analysis of Rangvid (2006), this paper examines whether the price-to-GDP ratio captures a significant proportion of variations in future returns on the aggregate stock markets of Australia and New Zealand. It is found that, using quarterly and semi-annual Australian returns data, the price-to-GDP ratio captures a significant fraction of the variation of returns at long horizons for the entire sample period (1982–2006). However, results are not as strong for sub-samples; for the sub-sample period 1995–2006, the price-to-GDP ratio fails to capture a significant portion of returns, even at long horizons. In terms of the ability of the price-to-GDP ratio to predict returns over and above that of the price-earnings and the price-dividend ratios, both the price-earnings and price-dividend ratios capture a greater fraction of share returns for the sample years 1995–2006 and 1990–1999. For the Australian data, the price-to-GDP ratio is a better predictor of share returns than excess returns.

Using quarterly and semi-annual New Zealand returns data, the price-to-GDP ratio captures a significant fraction of the variation of returns at both short and long horizons for the entire sample period (1991–2003). For this sample set, the price-to-GDP ratio captures more in the variation in returns than the price-dividend ratio. It is also found that the price-to-GDP ratio captures a greater proportion of the variation in share returns than in excess returns, a result that is consistent with the theory and results presented in Rangvid (2006).

Overall, the New Zealand results provide particularly strong evidence that the price-to-GDP ratio captures a high proportion of future returns on the aggregate share market. However, given that Australian results vary depending on the period used, this paper suggests that the price-to-GDP ratio's prediction of annual share returns may not be generalised to all countries, at least not Australia, for all time periods.

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Appendix A. Residual Analysis—Australian Data

Table A1: Quarterly
Residual Analysis of Full Sample

Panel A: Serial Correlation			
DW	2.2890		
Panel B: Correlation with independent variables			
	ε_t	P_t	y_{t-1}
ε_t	1.0000		
P_t	0.0238**	1.0000	
y_{t-1}	0.0812**	0.9793	1.0000

Table A2: Semi-Annual
Residual Analysis of Full Sample

Panel A: Serial Correlation			
DW	2.1031		
Panel B: Correlation with independent variables			
	ε_t	P_t	y_{t-1}
ε_t	1.0000		
P_t	0.0365**	1.0000	
y_{t-1}	0.1221**	0.9776	1.0000

Notes to Tables A1 and A2: These tables give the results from the analysis of the OLS residuals for the full sample periods. Panel A gives the results for the Durbin Watson test statistics for each sample. These indicate that there is no autocorrelation between the residuals of either sample. Panel B gives the correlations between the residuals and the independent regression variables for each sample. These indicate that the residuals are not correlated with these variables, as the correlation is insignificant from zero for each series. Significant statistics at the 1% level are indicated by ** and at the 5% level by *.

Appendix B. Residual Analysis—New Zealand Data

Table B1: Quarterly
Residual Analysis of Full Sample

Panel A: Serial Correlation			
DW	2.2112		
Panel B: Correlation with independent variables			
	ε_t	P_t	y_{t-1}
ε_t	1.0000		
P_t	0.0393**	1.0000	
y_{t-1}	0.1011**	0.9374	1.0000

Table B2: Semi-Annual
Residual Analysis of Full Sample

Panel A: Serial Correlation			
DW	2.2032		
Panel B: Correlation with independent variables			
	ε_t	P_t	y_{t-1}
ε_t	1.0000		
P_t	0.0492**	1.0000	
y_{t-1}	0.1308**	0.9413	1.0000

Notes to Tables B1 and B2: These tables give the results from the analysis of the OLS residuals for the full sample periods. Panel A gives the results for the Durbin Watson test statistics for each sample. These indicate that there is no autocorrelation between the residuals of either sample. Panel B gives the correlations between the residuals and the independent regression variables for each sample. These indicate that the residuals are not correlated with these variables, as the correlation is insignificant from zero for each series. Significant statistics at the 1% level are indicated by ** and at the 5% level by *.