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Author: David G. McMillan

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Stock Return Predictability:Using the Cyclical Component of the Price Ratio

David G McMillan

Division of Accounting and Finance, University of Stirling

Address for Correspondence: Professor David McMillan, Accounting and Finance Division, University of Stirling, FK9 4LA, Scotland, UK
Phone: +44(0)1786-467309; Fax: +44(0)1786-467308
e-mail: david.mcmillan@stir.ac.uk

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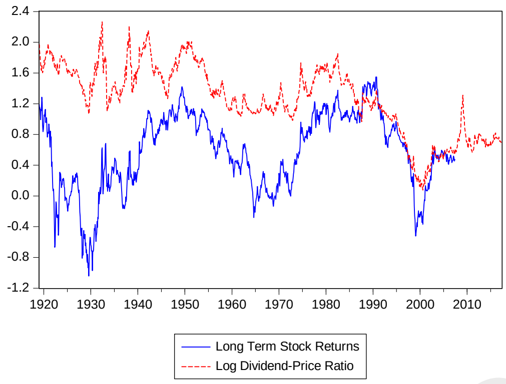
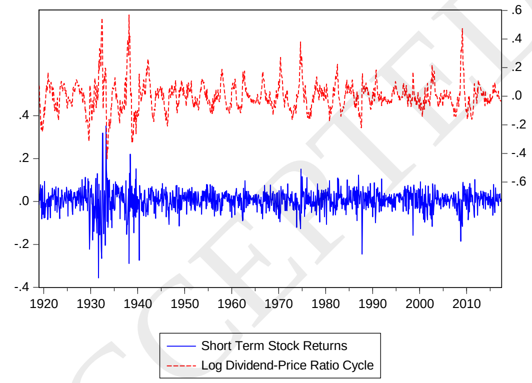
Graphical Abstract





Abstract
We examine whether the cyclical component of the log dividend-price and price-earnings ratios contain forecast power for stock returns. While the levels of these series contain slow moving information for predicting long horizon returns, they typically provide poor short horizon forecasts. Using three approaches to extract the ratios cyclical component, we conduct several in- and out-of-sample tests. In-sample estimation using the cyclical component leads to economically sensible values, as well as an improved fit compared to the ratio level results. Out-of-sample evidence reveals forecast improvement over a historical

mean model, although this varies according to the metric used. The historical mean model is preferred using mean absolute and squared error measures, but the predictive models perform better using Mincer-Zarnowitz and encompassing regressions. Using economic based forecast evaluation, the predictive models are clearly preferred, with a stronger ability to predict the future direction of return movements and with higher trading returns. A further examination of the results reveal that this greater performance largely arises from a superior ability to predict future negative returns.

Keywords: Stock Returns, Predictability, Dividend-Price Ratio, Price-Earnings Ratio, Forecasting, Cycles
JEL: C22, G12

1. Introduction.

This paper examines market-level stock return predictability but, in contrast, to the existing literature, considers the cyclical behaviour of financial ratios as opposed to their levels. The current literature argues, for example, that the log of the dividend-price ratio can act as a predictor for subsequent stock returns. The underlying idea, based on the dividend discount present value model, is that the log dividend-price ratio acts as a proxy for expected returns. This view is based on the work of Fama and French (1988) and Campbell and Shiller (1988), for which the rationale is that stock prices and dividends form a cointegrating set with a cointegrating vector of (1,-1). Given this, the log dividend-price ratio essentially acts as an error-correction term, measuring the deviation from this equilibrium position. Subsequently, a large body of work considers the dynamics of the log dividend-price ratio, and other similar ratios (notably, the price-earnings ratio), in predicting stock returns.[1] This literature is defined by a lack of consensus regarding the presence of predictability.

We argue that the log dividend-price (*ldp*) ratio does act as an attractor for stock returns but that it essentially contains both a slow-moving time-varying trend and a cyclical component and it is the cyclical component that drives predictability in the short run. The *ldp* represents the stock price level relative to fundamentals, which in turn are based on

[1] Examples of this, now extensive literature include, Goyal and Welsh (2003), Ang and Bekaert (2007), Campbell and Thompson (2008), Cochrane (2008, 2011), Welsh and Goyal (2008), Kellard et al. (2010), Park (2010), McMillan and Wohar (2010, 2013) and McMillan (2014, 2015).

considerations of risk and cash flow. According to the line of thought that began with Fama and French (1988) and Campbell and Shiller (1988), an increase in risk leads to a fall in current prices and a rise in *ldp* which predicts higher future returns as compensation. Alternatively, a rise in current dividends leads to a higher *ldp* and signals higher future returns. While these relations can reasonably be expected to hold over a longer horizon, in the short term, investors are concerned not with the position of prices relative to dividends but with the speed of change in the position between prices and dividends, for example, whether prices are accelerating faster than dividends. It is this component within *ldp* that we believe has predictive power for short term stock returns and is the focus here.

Our view builds upon recent research that equally argues that the *ldp* ratio itself may not provide predictive power, or at best only weak predictive power for stock returns. Several researchers argue this may be due to the presence of breaks (see, for example, Paye and Timmermann, 2006; Lettau and van Nieuwerburgh, 2008) or that periods of predictability are only short-lived (Timmermann, 2008). However, our view is more aligned with the recent work of Algaba and Boudt (2017) and Lawrenz and Zorn (2017) who argue, in different ways, that adjustments are required to the *ldp* ratio to reveal the short horizon predictive power. Extending the view that *ldp* by itself is not the best variable to predict future stock returns, we argue that the presence of a cyclical component within the ratio will provide improved forecast power. This cyclical component captures the current direction of the market relative to fundamentals. This provides a dynamic measure of the relative movement between prices and dividends (or earnings). Specifically, whether prices are accelerating away from fundamentals, in either direction, as investors become more optimistic or pessimistic or whether changes in prices are smaller than fundamentals suggesting uncertainty or consolidation by investors.

In predicting stock returns, we therefore extract the cyclical component from *ldp*. The extraction of cyclical components in explaining stock return movement is considered for other predictor variables. Cooper and Priestley (2009, 2013) use measures of detrending to identify the cyclical component of industrial production and the capital-to-output ratio respectively. Mazzoni (2010) considers a range of filtering methods for stock returns. We utilise the Hodrick and Prescott (1997) filter, including its one-sided version, as it represents a common approach to trend and cycle decomposition. We also consider the recent approach of Hamilton (2017), which is critical of the Hodrick-Prescott approach.

Using monthly US stock market index return data over a near 100-year period, we examine whether the cyclical component of the *ldp* has predictive power for returns. In addition to the *ldp* series, we also examine the log of the price-earnings ratio (*lpe*) to add robustness and because this ratio is less impacted by strategic management decisions (such as dividend smoothing, e.g., Chen et al, 2012). While, the cyclical component of *ldp* (or *lpe*) is our variable of primary interest, in predicting future stock returns we also consider three further variables that we believe have merit in containing forecast power. Following Cooper and Priestley (2009), we use a measure of the output gap, while we consider two variables that link movements between the stock and bond markets. The FED model, which links the ratio of equity and bond yields, is found to exhibit predictive power for stock returns by, for example, Bekaert and Engstrom (2010) and Maio (2013). Further, we use the trailing correlation between stock and bond returns. This measure acts as a proxy for risk and thus can predict future movements in expected returns. Notably, while stock and bond returns typically exhibit a positive correlation, during periods of market stress, flight-to-quality behaviour can drive the correlation negative (see for example, Gulko, 2002). Thus, a negative returns correlation is synonymous with heightened market risk as investors seek out safe assets and eschew riskier ones.

We examine the in-sample fit between the model that uses the price-to-fundamental (dividends or earnings) ratio and those using the cyclical component. Of note, we are interested in whether the coefficient signs make economic sense as well as their statistical significance. In addition, we examine the out-of-sample forecast performance of all our models, in comparison to each other as well as a historical mean model that acts as a base in previous work (e.g., Campbell and Thompson, 2008). Our results show that, in-sample, the cycle components achieve a better statistical fit and economically more sensible coefficient values. Out-of-sample, the forecast results using the mean squared and absolute error favour the historical mean, but forecasts based on the Mincer-Zarnowitz regression and encompassing tests as well as economic, trading, based measures support our predictive model. Moreover, this forecast gain appears largely in the model's ability for forecast negative returns. These results will be of interest not only to academics engaged in modelling market behaviour but also to investors who can use the information here to aid in market timing strategies.

2. Review of the Stock Return Predictability Literature.

Fama and French (1988) and Campbell and Shiller (1988) argue that a ratio using the current stock price and a measure of fundamental (dividend or earnings) value has predictive power for subsequent stock returns. Moreover, that the strength of predictability increases with the subsequent time horizon for stock returns. Following this, a range of work has provided further supportive evidence for this view. This includes, for example, the work of Campbell and Thompson (2008), Cochrane (2008, 2011), Kellard et al. (2010), McMillan and Wohar (2010, 2013) and McMillan (2014, 2015).

However, set against this, several researchers argue that evidence of such predictability is in short supply. Nelson and Kim (1993) argue that the relatively short samples used in this line of research can lead to inconsistent results, while Ang and Bekaert (2007), Goyal and Welch (2003), Welch and Goyal (2008), Hjalmarsson (2010) and Park (2010) all provide evidence against predictability. Notable within these two competing lineages of research is that evidence for short horizon (e.g., monthly) predictability is less common that for longer horizons. Cochrane (2008, 2011), for example, argues strongly in favour of long horizon predictability at the expense of short horizon, while Campbell and Thompson (2008) report stronger supportive annual results compare to monthly.

An emerging line of research argues that the mixed nature of the results arises due to the presence of breaks (or time-variation more generally) either in the predictive coefficient (Paye and Timmermann, 2006) or within the predictive variable (Lettau and van Nieuwerburgh, 2008). Moreover, Timmermann (2008) argues that while predictive models for stock returns generally perform poorly, there exists short-lived pockets of predictability. McMillan (2014, 2015) seeks to explicitly model time-variation within the predictive relation using interaction effects and a state-space model, linking movement with a selection of economic variables. Chen (2009) and McMillan and Wohar (2013) both argue that returns predictability may switch over different periods of time with dividend growth predictability. Further, both Campbell and Thompson (2008) and Park (2010) argue that evidence in favour of predictability declines over time. Henkel et al (2011) argue that predictability only arises during economic downturns. More recently, Hammerschmid and Lohre (2018) argue that predictability depends upon economic regimes, while Baltas and Karyampas (2018) highlight that forecast success is instead dependent upon identifying market regimes.

Alternatively, others have argued that the *ldp* ratio should be adjusted prior to consideration in the predictive regression. Algaba and Boudt (2017) introduce, what they term, the generalised price-dividend ratio, which is based on the cointegrating relation between stocks and dividends and argue that this measure contains predictive power for stock returns. As with some of the above cited work, this generalised ratio is based on the view that the relation between prices and dividends is time-varying, which they introduce through rolling and recursive regressions. Lawrenz and Zorn (2017) use a conditional price ratio to predict stock returns. Here, the price ratio (the paper uses the price relative to dividends, earnings and cash flow), is conditioned on both the series historical average as well as the global average. Thus, there is an expanding view that greater evidence of predictability is uncovered only when looking deeper into the behaviour of the *ldp* or *lpe* series.

Beyond the use of ratios involving the stock price and a measure of fundamentals, alternative predictor variables are considered. For example, Welch and Goyal (2008) consider a kitchen sink approach with over fifteen variables, while Hjalmarsson (2010) and Hammerschmid and Lohre (2018) also consider multiple variables. With specific reference to this paper, following Cooper and Priestley (2009), we consider the output gap, although we utilise the same filters as for the *ldp*/*lpe* series, whereas Cooper and Priestley use both a linear and quadratic trend. We also use two variables that link movements between the stock and bond markets. First, we use the FED model variable that is constructed as a ratio of the earnings yield to the 10-year Government bond yield. Despite some controversy in its use,[2] this variable is found to have significant predictive power (support for the FED variable, and a related measure, is reported by Clare et al, 1994; Levin and Wright, 1998; Harris, 2000; Brooks and Persand, 2001; McMillan, 2009a, 2012; Bekaert and Engstrom, 2010; Maio, 2013). Second, we use the trailing correlation between stock and bond returns. We argue this measure is a proxy for risk and thus predicts future movements in expected returns. In general, stock and bond returns exhibit a positive correlation (see, for example, Shiller and Beltratti, 1992; Campbell and Ammer, 1993). Notably, both markets respond in a similar

[2] For example, Asness (2003) points out that on a theoretical basis while long term bond yields are a claim on a nominal income stream, equity is a claim on real assets. Thus, there is no reason to expect these variables to exhibit a relation.

fashion to macroeconomic conditions. For example, a rise in interest rates will be associated with a decline in both stock and bond prices. However, in periods of market stress, the link between stock and bond prices will weaken and the correlation can become negative (see for example, Gulko, 2002).[3] Under such conditions, we observe flight-to-safety behaviour in which investors seek out safe assets, thus raising their value, and sell riskier ones, reducing their value. Thus, a negative correlation between stock and bond returns is synonymous with heightened market risk.

This paper therefore builds upon the line of research that argues the *ldp* (or *lpe*) ratio in its original form does not provide predictive power for short horizon stock returns. While a lively debate exists around the presence of predictability, using the ratios themselves for monthly returns typically results in limited supportive evidence. Current research thus looks more closely at the behaviour of the ratios, such as the existence of breaks or other adjustments. Continuing this theme, we consider the presence of cycles within the ratio and ask whether cyclical behaviour can capture short horizon monthly predictability. We consider three measures of trend and cycle extraction for US market-level returns, while recognising that other trend/cycle methods exists and that a subsequent study to consider a wider selection of methods and markets would further strengthen the nature of the results here.

3. Methodology and Background.

Theoretical motivation for the stock return predictive regression is based on the dividend discount present value model of Campbell and Shiller (1988). Log stock returns (r_t) are given by:

(1) $$r_t \equiv \log(P_t + D_t) - \log(P_{t-1})$$

[3] Gregoriou et al (2009) note that during the financial crisis period, stocks responded to interest rate changes in the wrong way with interest rate cuts leading to stock price falls.

where P_t and D_t represent prices and dividends. As the time-varying log return is a non-linear function of log prices and dividends, Campbell and Shiller provide the well-known approximation around a first-order Taylor expansion of the mean price-dividend ratio:

(2) $$r_t \approx k + \rho p_t + (1 - \rho d_t) - p_{t-1}$$

where k and ρ are linearisation parameters. Solving equation (2) forward, taking expectations and imposing the transversality condition, which rules out explosive behaviour, we can re-write (2) in terms of the log price-dividend (p_t-d_t) ratio:[4]

(3) $$p_t - d_t = (k / 1 - \rho) + E_t \sum_{i=0}^{\infty} \rho^i (\Delta d_{t+i+1} - r_{t+i+1})$$

Equation (3) states that the price-dividend ratio will be high if dividend growth is expected to be high or future returns low. Hence, movement in the price-dividend ratio arises from changes in expected returns (discount rates) or dividend growth. This then motivates the predictive regression, whereby the dividend-price ratio is used to forecast returns

(4) $$r_{t+1} = \alpha + \beta\, ldp_t + \varepsilon_{t+1}$$

where r_{t+1} is next periods stock return, ldp_t the log dividend-price ratio, for which we expect β to take a positive value and ε_{t+1} a random error term.[5]

As noted in the Introduction, several papers argue that the log dividend-price ratio can act as a predictor for stock returns (e.g., Kellard et al., 2010; McMillan and Wohar, 2010), however, a further body of work argues that no such predictability occurs (e.g., Ang and Bekaert, 2007; Welsh and Goyal, 2008). Cochrane (2011) argues that the log dividend-price ratio acts as a proxy for expected returns, which evolves slowly. Figure 1 presents an illustration of this, where we plot the log dividend-price ratio (*ldp*) against the forward 10-

[4] The transversality condition, which rules out bubbles, is a theoretical construct to ensure the existence of a unique stock price. This is not to deny the potential presence of bubbles, which then becomes an empirical matter. A bubble component can be added to the stock price equation and this does not affect the analysis below. An interesting and relevant discussion in provided by Gurkaynak (2005).

[5] A debate also exists about the ability of the *ldp* to predict future dividend growth (see, for example, Cochrane, 2008, 2011; Ang, 2011; Rangvid et al, 2014).

year holding-period S&P Composite index returns. Evident from this figure is the positive association between the two sets of variables. This leads to the view that *ldp* acts as a predictor for long horizon returns.

In analysing the predictive power of the dividend-price ratio, as discussed above, a recurring line of research considers whether the *ldp* series in this form is the most applicable for predicting short horizon returns. While much of this research focusses on the potential for time-variation in the predictive relation, a recent theme considers the dynamics of the *ldp* ratio. Notably, Algaba and Boudt (2017) introduce the generalised price-dividend ratio and Lawrenz and Zorn (2017) use a conditional price ratio to predict stock returns. We argue that the *ldp* ratio contains a slowly evolving (trend) component that can explain the long run movement of stock returns, for which Figure 1 provides indicative evidence. However, as indicated by the mixed empirical evidence discussed above, it is not able to consistently predict short horizon (monthly) stock return. Instead, we believe that there exists a shorter term, cyclical, component that drives short horizon return movements. This short term component measures how prices change relative to fundamentals rather than the position of prices relative to fundamentals and will carry information useful to investors in predicting short horizon movements in stocks. To extract the cyclical component,[6] we first consider the Hodrick-Prescott (Hodrick and Prescott, 1997) filter, the trend component of which is given by:

$$(5) \qquad \frac{min}{\{g\}_{t=-1}^{T}} \left(\sum_{t=1}^{T}(y_t - g_t)^2 + \lambda \sum_{t=2}^{T-1}[(g_{t+1} - g_t) + (g_t - g_{t-1})^2]\right)$$

Where λ determines the smoothness of the trend component, g, for the time-series, y. As noted above, this filter is a two-sided measure and uses information that would not be available to an investor in real time. Therefore, we also consider the one-sided Hodrick-

[6] In addition to the three methods discussed to extract the cyclical component, we also consider deviations from a moving average of five and twenty-five years. The results are qualitatively similar to those reported and are available upon request.

Prescott filter introduced by Stock and Watson (1999). The one-sided HP trend component is constructed as the Kalman filter estimate of g_t in the following:

(6) $$y_t = g_t + u_t$$

(7) $$(1-L)^2 g_t = \eta_t$$

Where L represents the lag operator and the two error terms, u_t and η_t are white noise terms, uncorrelated with the trend term and themselves, with relative variance given by $q=var(u_t) / var(\eta_t)$. The choice of λ (14,400) is based on the frequency power rule of Ravn and Uhlig (2002).[7]

Hamilton (2017) argues that the Hodrick-Prescott filter can induce spurious behaviour within the series. Hamilton instead suggests a simple regression approach as:

(8) $$y_{t+h} = \mu + \Sigma_{i=1}^{p} \gamma_i y_{t-i} + w_{t+h}.$$

Following Hamilton (2017), we use a lag length value of p=4, while we use a h-step ahead value of three, which represents a period of one-quarter. The cyclical component is then given by w.

The standard approach to stock return predictability utilises equation (4) where the *ldp* series is used to predict subsequent values of stock returns. Our belief is that for short horizon predictability (e.g., one-month) it is the cyclical component of the *ldp* series that carries greater predictability. Therefore, using the filtering approaches in equations (5)-(8), we extract the cyclical component, which replaces the original *ldp* series in equation (4).

4. Data and In-Sample Predictability.

[7] We also considered the preferred value of 129,600 of Ravn and Uhlig, but the qualitative nature of the results is unchanged.

We utilise monthly US data over the time-period from 1919:1 to 2017:6.[8] In addition to the market level stock price, earnings and dividends data, we also utilise data on output through industrial production as well as data on both long term (10-year) and short term (3 month) government debt. For the long term bond, we obtain data on both the bond index and its yield, for the short term bill, we only use data on the yield. The predictor variables we use are thus, the cyclical component of *ldp* and alternatively of the *lpe*, the cyclical component of (log) industrial production, the FED model variable (earnings-to-price ratio divided by the 10-year bond yield) and the historical five-year rolling correlation between the returns on stocks and bonds.

For these latter two variables (the FED model and the correlation between stock and bond returns), we are seeking to capture the interaction between these two investment classes. The FED model captures the relative valuation of stock and bonds. The rationale is that the respective yields should not drift too far apart and a FED value above one indicates undervalued stock relative to bonds and a value below one indicates expensive stock. Investors are thus expected to switch between the two assets accordingly thus ensuring that the yields cannot drift apart. The FED model thus represents relative valuation. As noted above, while the FED model has proved controversial, evidence, nonetheless, supports its predictive power. We also utilise a rolling correlation between stock and bond returns. We argue this captures risk in the economy. The FED model indicates that there should exist a positive relation in the movements of stock and bond prices, for example, a rise in interest rates would lead to a fall in both stock and bond prices. For the latter, higher rates reduce the bond price given the nature of fixed coupon payments. For the former, the higher rates increase the discount rate on future earnings and dividends and so reducing the current value.

[8] Data is collected from the website of Robert Shiller (http://www.econ.yale.edu/~shiller/data.htm) as well as Datastream and the Federal Reserve. The start of the sample period is determined by the availability of industrial production data.

However, in times of extreme market stress, stock and bond prices can move apart. For an economy experiencing a severe recession, a fall in interest rates still leads to a higher bond price, however, the falling rates signal to the market that the macroeconomic outlook remains bleak and so stock prices continue to fall. Thus, a falling stock and bond return correlation could signal higher macroeconomic risk.

Table 1 presents summary statistics for our data to illustrate the nature of the data, while Figure 2 graphs each of the series. The characteristics reported here are consistent with those reported in the literature. Table 1 also presents the key correlations for the explanatory variables.[9] As with any multivariate regression model, there is the potential for multicollinearity to affect the nature of the estimated results. Of interest, we can see that the correlations using the original values of the *ldp* and *lpe* series with the FED and stock and bond return correlation series are higher than for the cyclical components of the *ldp* and *lpe* series. As they both capture cyclical behaviour, the correlation between the cyclical components of the *ldp* and *lpe* series with industrial production are higher than for the original *ldp* and *lpe* series but are not unduly worrying, and certainly less so than the value of 0.5 between the FED model and the original *ldp* and *lpe* series.[10]

In-Sample Empirical Results

In the subsequent analysis, we consider eight main forecast models. Each model includes a measure of the dividend-price and price-earnings ratio together with the output (industrial production) cycle, the FED model and the stock and bond return correlation. For ease of clarity, we label and refer to these models, in which Model 1 and 5 include the original *ldp* and *lpe* variables, Models 2 and 6 include the Hodrick-Prescott Filtered cyclical components,

[9] The correlations between the industrial production cycle, the FED model and the stock and bond correlation are not tabulated but are all less than 0.06.

[10] The coefficient variance inflation factors of the below regressions were examined as an indicator of multicollinearity and were all around one in value.

Models 3 and 7 include the one-sided Hodrick-Prescott filtered cycle and Models 4 and 8 include the Hamilton cycle.

Initially, we estimate the predictive regression of equation (4) using just the *ldp* and *lpe* variables as the sole explanatory variable, in common with much of the literature, with the result in Table 2.[11] The coefficient result for *ldp*, consistent with the view expressed above, is statistically insignificant, while the coefficient for the *lpe* is significant at the 5% level. However, in both cases the coefficient value is small, indicating a very weak relation between these series and subsequent stock returns. The associated values of the adjusted R-squared are equally very small and confirm the view of a limited explanatory relation from the levels of these ratios to monthly stock returns.

Table 2 further reports the results of the regression expanded to include the three additional variables, which represent Model 1 with the *ldp* series and Model 5 with the *lpe* series. For Model 1, we can again see that the *ldp* variable is not statistically significant and is now of the wrong sign.[12] The output variable (cyclical component of industrial production) is significant at the 1% level with a negative coefficient.[13] This is consistent with the view that in an expanding economy, current stock prices rise and expected future returns fall. The FED variable is positive and 5% significant. This coefficient sign is consistent with the view expressed above in which a higher FED value indicates undervalued stock such that investors will subsequently move into stocks raising its future value. The time-varying stock and bond return correlation is also positive and statistically significant at the 5% level. This suggests that as the correlation rises, the economy is not in a period of market stress and stocks and bonds move together as expected. This normal state of affairs leads to higher future stock

[11] We do not assign a model number to these regressions as they are not used in the forecast exercise.
[12] The change in coefficient sign maybe as a result of multicollinearity between the *ldp* and FED series, although in both sets of results in Table 2, the coefficient is insignificant and thus statistically zero.
[13] Here, the cycle is extracted using the Hodrick-Prescott filter. In the analysis below, the filter used for industrial production matches with the filter used for the *ldp* series.

values. Conversely, a falling correlation indicates a movement towards a period of market stress and thus falling stock prices.

Model 5 presents the same expanded regression for the log price-earnings ratio (*lpe*). Here, we can see that *lpe* continues to be statistically significant at the 5% level and carries the correct sign, indicating that a higher price relative to earnings leads to lower future stock returns. Following the approach of Campbell and Shiller (1988) this arises as the higher relative price indicates a lower discount rate (risk premium) and lower expected returns. Again, we can see a negative and 1% significant relation between the output cycle and stock returns. Now, however, both the FED variable and the rolling stock and bond return correlation are statistically insignificant, while the FED variable also has the incorrect sign.

Table 3 presents the same stock return predictive regressions but now we replace the *ldp* and *lpe* series with their cyclical components. First, we consider the results where the cyclical component is obtained using the Hodrick-Prescott filter. As before, we initially just examine a regression that includes only the *ldp* and *lpe* terms. Here, we can see that both cyclical components are statistically significant at the 5% level or higher and of the expected sign. In comparison with the results for the levels, we note that the parameters are now substantially larger, indicating that the strength of the relation is stronger. Equally, the adjusted R-squared values are larger with the cyclical components. Thus, these results suggest that the cyclical components have predictive power for stock returns that is not present in the level of the ratios. As the results in this table present our main in-sample estimates, we also present the standardised coefficients in square brackets. These provide an alternative way of interpreting the results as the scaling of the explanatory variables differs and thus this allows greater comparability. Here, we can interpret these values as the effect on returns of a one standard deviation change in the predictor variable. Thus, we can see a substantial change in returns following a one standard deviation change in the cyclical component of the *ldp* or *lpe* series of approximately 10-20%.

Examining the results based on the *ldp* cyclical series that include all predictive variables (Model 2), we can see that the *ldp* series continues to exhibit a positive and 1% statistically significant predictive effect on stock returns consistent with the dividend discount model. Thus, rising dividends relative to prices indicates higher future returns. For the remaining predictor variables, the inference remains broadly similar as for Table 2. The coefficient signs are consistent with expectation (as discussed above), although the FED variable is no longer statistically significant. For the *lpe* cyclical variable (Model 6), this is both statistically significant, at the 5% level, and of the correct sign. The same is true for the other predictor variables, with the output cycle variable coefficient negative and 1% statistically significant and the rolling stock/bond correlation variable significant at the 5% level, again, the FED model variable is not significant.

In comparing the two sets of extended regressions, i.e., using the original and cyclical *ldp* and *lpe* ratios with the three additional predictor variables, we can make several observations. For the original *ldp* and *lpe* series (Models 1 and 5 respectively), in both regressions, at least one predictor variable has the incorrect coefficient sign compared to our theoretically based expectations (the *ldp* series in its own regression and the FED model in the *lpe* based regression). Conversely, in the cyclically adjusted version, for both the *ldp* and *lpe* regressions (Models 2 and 6 respectively), all the coefficients have the correct signs. We can also compare the two models in terms of the adjusted R-squared values and the information criteria. Here, we can observe that the adjusted R-squared is higher (in both cases it is approximately double, and indeed more so for the *ldp* regressions) and the information criteria (Akaike and Schwarz) lower, for the cyclically adjusted versions. These results support the cyclical *ldp* and *lpe* as providing improved predictive power over the original *ldp* and *lpe* values.

As noted a potential drawback in the use of the HP filter, particularly when we wish to consider out-of-sample forecast power, is its two-sided nature. The above HP filter uses information that in principle would not be available to an investor in real time. Therefore, we consider the one-sided HP filter (Model 3 for the *ldp* and Model 7 for the *lpe*). These results are also reported in Table 3 and are broadly consistent with those reported above for the HP filter, although they are slightly weaker in terms of coefficient magnitude, statistical significance and overall model fit. Nonetheless, we still observe predictive power for both the dividend and earnings series that is greater than for the levels of the series and the additional predictor variables continue to exhibit the correct coefficient sign and significance.

In applying the approach of Hamilton (2017) to extract the cyclical component, we use a value of three for *h* and follow the advice of Hamilton in choosing four for *p*. The use of three equates to a quarter of a year within our monthly data, experimentation with an annual lead does not affect the qualitative nature of the results.[14] Table 3 again presents the results of equation (4) using the Hamilton obtained cyclical *ldp* (Model 4) and *lpe* (Model 8). The results are again consistent with those previously reported. The cyclical components of the ratios are, at least, 5% statistically significant and of the appropriate sign. Equally, the coefficients of the additional predictor variables have the expected signs and are largely statistically significant (although the FED model variable is insignificant in the *lpe* regression, while both the FED variable and the stock/bond correlation exhibit more marginal significance in the *ldp* regression).

[14] Again, to avoid using information that would not be available to an investor in real time, we additionally lag the cyclical price ratio by three.

Overall, the results obtained using the cyclical components of the *ldp* and *lpe* appear stronger in terms of both coefficient sign and statistical significance than those obtained using the levels of the two price-to-fundamental ratios. This supports the view that these ratios can be used to predict monthly stock returns but that the predictive content is only clearly seen when extracting the cyclical component from the overall ratio series.

Explaining the Cyclical Component

The previous section demonstrates that the cyclical component of the *ldp* and *lpe* ratios exhibit predictive power for subsequent returns in contrast to the level of the series, which may capture longer run behaviour (discussed below). We argue that this difference arises as the information content of these different components for investors differs. Over a long horizon, the relative level of prices and dividends (earnings) will provide information in how prices will move over the succeeding years. However, it will not convey information regarding the movement of prices in the following month. Here, investors are more concerned with the relative movements in prices and fundamentals (dividends or earnings). Specifically, if prices are accelerating away from fundamentals this suggests that investors are confident about the direction of the market, while if price movements are smaller than fundamentals then investors may be uncertain about the direction of the market.

We seek to consider this issue by examining the predictive relation under the two regimes outlined above, i.e., whether the change in prices is greater or less than the change in fundamentals. Thus, we run the following regression:

(9) $$r_{t+1} = \alpha + \beta_1\, ldp_t I_t + \beta_1\, ldp_t\,(1\text{-}I_t) + \varepsilon_{t+1}$$

Where I_t represents a dummy variable that equals one if the absolute value of the return is greater than the absolute value of the change in dividends (or earnings) and zero in the converse case. When the dummy is equal to one, this indicates a direction to the market and information for investors. When the dummy is equal to zero, this suggests uncertainty about the market direction.[15] For the *ldp* (and *lpe*) series, we use the Hodrick-Prescott filter with the results for the alternative filtering methods available upon request.

The results of this exercise are reported in Table 4 and demonstrate support for the above rationale. When the change in the absolute value of the return is greater than the change in the absolute value of the fundamental then we see evidence of significant predictability. This implies that prices are moving quicker than fundamentals and that investors are confident in the direction of the market. Thus, under this circumstance, the *ldp* and *lpe* cyclical components convey information to investors. In contrast, when the absolute change in prices is less than the absolute change in fundamentals, this implies uncertainty or consolidation with no obvious market direction. As such, here we observe no predictive power from the cyclical component of the two ratios.

Long-Horizon Regressions

We argue that the cyclical component of the *ldp* and *lpe* series provides information to investors regarding the short term movement of the market. The cyclical component informs the market of the relative momentum in the movement of prices relative to fundamentals (dividends or earnings). As such, we would expect, over longer stock return horizons, the relative predictive power of this cyclical component to wane in comparison to the original *ldp* and *lpe* series. Therefore, we conduct a series of long-horizon regression:

$$r_{t+h} = \alpha + \beta_1 \, ldp_t + \beta_2 \, ldp^c_t + \varepsilon_{t+h} \quad (10)$$

where r_{t+h} refers to the h period stock return and ldp^c_t refers to the cyclical component of *ldp*. Our view is that this cyclical component will have greater predictive power for shorter

[15] Across both the *ldp* and *lpe* series, the dummy variable is equal to one for approximately 80% of the sample.

horizon returns, while the *ldp* series itself will have greater predictive power for longer horizon returns.

The results of this exercise are presented in Table 5. We present results for both dividend and earnings and over horizons ranging from one-month to fifteen-years. We only present the HP filter obtained results, but those for the one-sided HP filer and the Hamilton approach are similar in nature. Within these results we can observe the general pattern where the coefficient on the original *ldp* and *lpe* series are either insignificant or of the wrong sign or both, at the short horizon end of the spectrum of results, while the cyclical versions are of the correct sign and statistically significant. As we move to the longer horizon end of the spectrum of results we see the original series first having the correct coefficient sign and then becoming statistically significant, while the cyclical components lose their significance and then exhibit the incorrect sign. Hence, we see a switch in the sign and significance of the cyclical and long-term components as we move from short to long horizon returns.

Notwithstanding this, these results do present an interesting distinction between the dividend and earnings based regressions. For the dividend regressions, the switch from the significance of the cyclical component to the levels component does not occur until the fifteen-year horizon. Prior to this holding period, the cyclical component retains its predictive power across all stock return horizons, while the original *ldp* series in not significant and of the correct sign at any horizon. For the earnings regression, we observe more of an expected pattern of results. Below the two-year horizon, the cyclical component dominates in terms of the correct coefficient sign and statistical significance. At the two-year horizon both the cyclical component and the level are statistically insignificant. At holding periods longer than two years, the original *lpe* now exhibits both the correct sign and statistical significance and this remains the case for the remaining (longer) horizons.

4. Forecasting.

To examine whether the cyclical *ldp* and *lpe* components (as well as our other predictor variables) contain useful information for investors we examine the forecasting power of the regression models (Models 1-8) for stock returns. We do this using a rolling forecast exercise.[16] Specifically, we estimate the in-sample predictive 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.[17] In examining the forecasts, we are interested in whether the predictive regressions examined above contain forecast power over and above that obtained from a historical mean forecast.[18] Whether stock return predictive regressions can outperform a historical mean forecast remains a source of debate within the literature (see, for example, Campbell and Thompson, 2008; Welch and Goyal, 2008). Thus, we can consider whether the use of the cyclical components of *ldp* and *lpe* can outperform not only the historical mean but also the original *ldp* and *lpe*.

We subject our forecasts to a range of metrics designed to capture different aspects of forecast accuracy. We consider forecast measures 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 mean absolute error (MAE) and root mean squared error (RMSE) metrics as such:

(11) $$MAE_i = \frac{1}{\tau}\sum_{t=1}^{\tau}\left|r_t - r_t^f\right|$$

[16] To extract the cyclical component of the *ldp* and *lpe* series we also re-estimate the trend/cycle decomposition. However, we do this on a recursive basis, this including all the available history when estimating the trend.
[17] 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.
[18] We also conduct the historical mean forecasts in a rolling manner, thus, allowing the constant parameter to vary over time.

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

where r_t is the actual return, $r_t^{f_i}$ is the forecast return based on the historical mean and the alternative prediction models, and τ is the forecast period. Both the MAE and RMSE measure the magnitude of the forecast error but while the MAE weights each forecast error equally, the RMSE over weights larger forecast errors. Further, we also utilise the Mincer-Zarnowitz (MZ) regression R-squared approach. Here, we run a regression of the realised returns on the forecast returns over the out-of-sample period and examine the R-squared value. The R-squared measures the proportion of the realised returns that is explained by the forecast returns and thus, the forecast model that produces the highest R-squared is preferred.

We also consider two measures that provide a direct comparison between alternate forecast models. Thus, allowing us to consider the incremental forecast power in our predictor variables. 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:

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

again, τ is the forecast sample size, r_t is the actual return and $r_t^{f_i}$ represents the forecasts. Here, we compare two forecasts, so *i=1,2*, where forecast one represents the baseline forecasts and two, the alternative forecasts. Where the R_{oos}^2 value is positive then the alternative predictive model has greater forecasting power than the baseline forecast model. To add statistical robustness to this measure, we use the test of Clark and West (2007), which considers whether the mean squared error of two competing forecasts are statistically different. Clark and West propose a simple adjustment to the difference in the MSE to account for additional parameter estimation error in the larger model. When applied to a pair of rolling sample forecasts under a random walk null model, the adjusted test statistic has (asymptotically) a standard normal distribution. Clark and West thus suggest generating the following time-series:

(14) $$CW = FE_1 - FE_2 + FE_3$$

Where FE_1 represents the forecast error for the historical mean series, FE_2 for the predictive model and FE_3 is the difference between the historical mean and predictive model forecasts. The generated CW series is then regressed on a constant, with associated the *t*-statistic providing the measure of significance.

The forecast encompassing test regression is given as such:

(15) $$r_t = \alpha + \beta_1 r_t^{f_1} + \beta_2 r_t^{f_2} + \varepsilon_t$$

again r_t is the actual return, $r_t^{f_2}$ is the forecast value obtained from the predictive regression model and $r_t^{f_1}$ is the baseline 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:

(16) $$SR = \sum_{t=1}^{\tau} s_t \text{ where } s_t = I(r_t r_t^{f_i} > 0) = 1\text{; 0 otherwise.}$$

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 model 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:

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

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

We provide an additional trading based forecast measure (although the SR and MT tests do provide some trading information with respect to buy and sell signals). The use of trading based forecast measures provides further economic content to the forecasts. Such an approach is initially considered in the work of Pesaran and Timmermann (1995, 2000) and Marquering and Verbeek (2004) and has become more prominent in recent work, for example, in the work of Campbell and Thompson (2008), Maio (2016), Baltas and Karyampas (2018) and Hammerschmid and Lohre (2018). To examine this, we consider a simple trading rule in which if the forecast of next periods return is positive then buy the stock, while if the forecast for the next periods return is negative, then (short) sell the stock. This allows us to obtain a time series for trading returns, which we denote, π. To provide information relevant to market participants, we can then use this time series to generate the Sharpe ratio as such:

(18) $$SHARPE_i = \frac{\bar{\pi} - r_f}{\sigma}$$

Where the Sharpe ratio is calculated as the ratio of the mean excess trading return ($\bar{\pi}$, the trading return minus a short-term Treasury bill as the risk-free rate) and the standard deviation (σ) of the excess trading return. 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 would be willing to pay to invest in the active trading strategy as opposed a strategy based on following the market. Portfolio returns are generated as discussed above, while, following Maio (2016), the change in CEV is calculated as:

(19) $$CEV = E(R_t^{f_2}) - E(R_t^{f_1}) + \frac{\gamma}{2}[Var(R_t^{f_1}) - Var(R_t^{f_2})]$$

Where $R_t^{f_2}$ is the portfolio return obtained from the predictive forecast model, $R_t^{f_1}$ is the portfolio return from the baseline historical mean model and γ is the coefficient of relative risk aversion, set to three.

Forecast Results

We use 60-month (five year) rolling regressions to obtain our forecasts of both the predictive and historical mean models. Table 6 presents the forecast results based upon metrics designed to capture aspects of the magnitude of the forecast error, the MAE, RMSE and MZ R-squared. In common with much of the literature, we can observe that the historical mean forecasts perform adequately on the basis of the MAE and RMSE and thus appear to outperform the forecast models based upon explicit predictive variables. The Hodrick-Prescott obtained cyclical component of the *ldp* and *lpe* (Models 2 and 6) perform reasonably well in comparison only being marginally larger, with performance deteriorating for the remaining models. The MZ R-squared provides a different answer, however, and suggests that these latter model types are better able to explain movements in realised returns. Indeed, the R-squared values are all greater than that obtained for the historical mean, with Models 2 and 6 (the Hodrick-Prescott obtained cyclical component of the *ldp* and *lpe*) performing the best.

A similar mixed picture is given by the different sets of measures that are designed to provide a more direct comparison in the forecast performance of the models, i.e., the out-of-sample R-squared and the forecast encompassing tests. Notably, the former suggests preference for the historical mean approach and the latter for the predictive models. This is perhaps not surprising as the former is based on the squared error metric and the latter an extension of the MZ regression approach. Moreover, both sets of results are statistically significant at the 5% level, with a single exception for both tests (the one-sided HP filter for the *ldp* series, Model 3, which is nonetheless significant at the 10% level).

The above measures essentially capture the size of the forecast error and are statistical in nature. However, it is equally important to consider the directional aspect of forecasting and the economic content. In this vein, we now consider the success ratio, its related market timing test and the trading rule based measures. These results are reported in Table 7 and suggest a more consistent pattern in favour of the predictive models. The economic based forecast measures indicate that the predictive models achieve a superior performance across the success ratio, trading Sharpe ratio and CEV measure. More specifically, we can see that the success ratio for all the predictive models is larger than that achieved by the historical mean model. Moreover, these values are largest for regression models that include the

Hodrick-Prescott *ldp* and *lpe* cyclical components (Models 2 and 6), while the values for the Hamilton filter (Models 4 and 8) are only marginally lower. Further, the success ratio is statistically significant at the 5% level for Models 2 and 6 and at the 10% level for Models 4 and 8 on the basis of the market timing test. Moreover, this test is notably insignificant for the historical mean model. Considering the Sharpe ratio, again, this is higher for all the predictive models in comparison to the historical mean model. Of interest, the Hodrick-Prescott filter *lpe* (Model 6) based regression achieves the highest Sharpe ratio, with the equivalent filtered series for the *ldp* series (Model 2) second preferred. The Hamilton filtered (Models 4 and 8) and original ratio series (Models 1 and 5) also perform well. Examining further trading based performance, all the predictive models exhibit a positive CEV, which indicates that investors are willing to pay a fee in order to follow the predictive model trading strategies. As a final point, we can observe that the price-earnings ratio based models perform better than the dividend-price ratio based ones. This may arise as earnings represents a better proxy for fundamentals as dividends can be more affected by managerial influence through smoothing or signalling behaviour and thus represent a less accurate picture of fundamentals.

Further Analysis

The above results suggest that the predictive models contain information relevant to investors, notably that they provide directional forecasts that allow trading signals to be generated. It is therefore of interest to further consider the nature of these results, which in turn may allow us to understand where the difference in the predictive ability arises. We thus reconsider forecast performance when separating returns between positive and negative values. This separation appears particularly pertinent given the relative success of the predictive models in the trading (sign) based evaluation over the statistical measures and is considered by McMillan (2009b) who demonstrates that the success of a non-linear model over a linear model arises from the formers ability to forecast negative returns compared to the latter.

Table 8 thus reports the success ratio and average trading returns of the alternative forecast models, when realised returns are positive and negative. The trading returns are reported as the average return in each regime, the average return when the sign is correctly forecast and when the sign is incorrectly forecast. Examining the results associated with positive returns, we can observe that the historical mean model achieves the highest success ratio at 78%, while the predictive models achieve approximately a two-thirds success ratio. Despite this, however, the historical mean model achieves the lowest average trading return when forecasting positive returns. Notably, the return achieved when the model forecasts the correct sign is similar to the predictive models, however, the negative return when this model incorrectly forecasts the return sign is larger than those reported for the predictive models.

Turning to the negative return forecasts, here we can see that the predictive models achieve a substantially greater sign forecast success ratio than the historical mean model, approximately, twice as large. We can also observe that the average trading return for the historical mean model is negative, as indeed, it is for the original *ldp* and *lpe* predictive models (Models 1 and 5). In contrast, for the cyclical component models, the average trading return is positive. Comparing the returns across when the forecast sign is correct and incorrect we can see this difference arises from a small improvement across both situations. That is, the average trading return is slightly improved, more positive with correct forecasts and less negative with incorrect forecasts, for the cyclical component predictive models.

This section seeks to consider where the difference in the trading performance between the historical mean and the predictive models arises. The results reveal that while the historical mean model may forecast more positive return values correctly it misses large negative returns such that the return associated with those positive forecasts is lower than for models that forecast the number of positive returns less accurately. We can also observe that the historical mean performs poorly in forecasting negative returns. In sum, the difference arises therefore, as the historical mean model over-forecasts positive return values such that the superior performance of the predictive models arises from their ability to forecast negative returns.

5. Summary and Conclusion.

This paper seeks to examine the ability of the cyclical component of the log dividend-price ratio and log price-earnings ratio, together with a small set of additional variables, to forecast US stock returns. A large literature considers the original values of the above log ratio series, with mixed results especially for short horizon returns. We argue that a cyclical component within these ratios reveals the relative movement between prices and fundamentals and can provide such short horizon predictability. Investors care more about whether, for example, prices are accelerating away from fundamentals and this influences trading decisions and thus contains relevant information that has value in forecasting. We view this paper as building upon recent work that questions whether the original ratio series contain forecast power for future short term price movements. While some work considers breaks or regime shifts within the predictive relation and further work considers adjustments to the ratio series, we believe a cyclical component captures the change in prices relative to fundamentals that contains useful information for investors.

Using monthly data over the time period from 1919:1 to 2017:6, the in-sample regressions using the original log level of the price ratios reveals borderline 5% significance for the price-earnings ratio and insignificance (and the incorrect sign) for the dividend-price ratio in predicting one-month ahead stock returns. Furthermore, within these regressions we note that the industrial production cycle has a negative and significant relation, while the

FED model variable and the trailing stock/bond return correlation is only significant in the dividend-price model. These results largely confirm those in the literature that note only weak evidence of predictive power arising from these ratios.

We argue that this arises as movement in the ratios evolves slowly, such that they have better predictive power for longer horizon returns. However, for short horizon return predictability, it is the relative movements between prices and fundamentals (dividends or earnings) and whether prices are accelerating away or consolidating towards fundamentals that contains predictive power. Using the one- and two-sided Hodrick-Prescott filter and the recent filter of Hamilton, we extract the cyclical component and re-estimate the predictive regressions. The in-sample results now exhibit significance of the cyclical ratio components and of the correct sign, while the model fit, as determined by the adjusted R-squared and two information criteria, indicate a noticeable improvement. In regard of the other variables considered in the predictive model, the industrial production cycle continues to exhibit a negative and significant relation, indicating that higher output is consistent with lower macroeconomic risk and thus lower expected returns (higher stock prices). The FED model variable is positive throughout, although at best is borderline significance. The trailing stock/bond correlation is positive and statistically significant, with a higher correlation indicating normal economic conditions and a positive outlook for future economic conditions and higher future stock returns.

To provide more robust evidence as to whether these variables exhibit predictive power, we undertake an out-of-sample forecast exercise using rolling regressions to allow for time-variation within the nature of the relations. Using the historical mean model as the baseline, our results indicate that based on statistical forecast metrics, the conclusion is mixed. The historical mean model is preferred using the mean absolute and mean squared error measures, while the forecast models are preferred using the Mincer-Zarnowitz R-squared and encompassing tests. However, using economic measures based on forecasting the correct sign as well as using two trading rule measures, the predictive models outperform the historical mean approach. Of further note, the price-earnings models tend to be preferred to the dividend-price models and this may reflect that fact that company management can adjust dividend series to reflect other (e.g., signalling) considerations. Moreover, the enhanced forecast power of the predictive models, and those that include the cyclical ratio components, lie in their ability to predict negative returns.

In sum, our results indicate that the cyclical component of the price ratios provide both improved in-sample performance over the original log values and out-of-sample performance over the historical mean model. These results imply that for short horizon forecasting of stock returns, the information content within price ratios arises not from their levels but from the relative movement between prices and fundamentals. That is, whether prices are accelerating away from dividends. From an economic perspective, the results presented here enhance our understanding of the nature of the links between stock prices and fundamentals, such that it is not just the level of valuation ratios that matters but shorter run components within that ratio are also important. The results contain both economic value to investors as well as information relevant to those engaged in understanding and modelling movements in stock prices. It remains to be seen whether the results here apply equally to other trend and cycle filters and markets

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Table 1. Summary Statistics

	Returns	LDP	LPE	ΔLIP	FED	Cor. B/S
Mean	0.486	1.267	2.709	0.257	0.019	0.102
Std Dev	5.334	0.449	0.427	1.914	0.015	0.257
Skew	-0.538	-0.441	0.715	0.285	1.775	-0.545
Kurt	10.927	2.548	5.427	14.161	6.274	2.59
	Explanatory Variable Correlations					
	Ind. Prod. Cyc.		FED		Cor. B/S	
LDP	-0.095		0.527		0.323	
LDP Cyc HP	-0.327		0.074		-0.002	
LDP Cyc HP1	-0.327		0.010		-0.033	
LDP Cyc Ham	-0.291		0.057		-0.044	
LPE	-0.152		-0.549		-0.306	
LPE Cyc HP	-0.274		-0.164		0.006	
LPE Cyc HP1	-0.272		-0.122		0.008	
LPE Cyc Ham	-0.205		-0.158		0.010	

Notes: The above values represent the mean, standard deviation, skewness and kurtosis of the stock return, log dividend-price ratio, log price-earnings ratio, change in industrial production, FED variable (earnings-to-price ratio divided by the 10-year bond yield) and the trailing five-year correlation between stock and bond return series. The explanatory variable correlations are reported in the lower portion of the table. The industrial production cycle is extracted in the same way as for the *ldp* and *lpe* series, i.e., using the Hodrick-Prescott (HP), one-sided Hodrick-Prescott (HP1) and Hamilton (Ham) filters. For the correlation with the original *ldp* and *lpe* series, we use the Hodrick-Prescott filter for industrial production.

Table 2. Predictive Regression Results

	DP / PE	Ind Prod Cyc	FED	Cor Bd/St	Adj. R-sq	AIC/ BIC
LDP Only	0.003 (0.81)	-	-	-	-0.001	-3.0241 / -3.0155
LDP Model 1	-0.007 (-1.17)	-0.161*** (-4.03)	0.294** (2.05)	0.017** (2.28)	0.027	-3.0487 / -3.0272
LPE Only	-0.009** (-2.05)	-	-	-	0.004	-3.0285 / -3.0199
LPE Model 5	-0.010** (-1.98)	-0.164*** (-4.02)	-0.025 (-0.22)	0.008 (1.28)	0.029	-3.0504 / -3.0290

Notes: Entries are the regression results (with Newey-West *t*-values) from equation (4). This regression includes the original log level of the dividend-price (DP) and price-earnings (PE) ratios. The other variables are the Hodrick-Prescott filter for log industrial production, the FED model variable and the trailing correlation between stock and bond returns. The asterisks denote statistical significance at the 1% (***), 5% (**) and 10% (*) level.

Table 3. DP and PE Cycles Predictive Regression Results

	Model #	DP / PE	Ind Prod Cyc	FED	Cor Bd/St	Adj R-sq.	AIC/ BIC
Dividend-Price Ratio Results							
DP Cyc HP	-	0.096*** (3.53) [0.188]	-	-	-	0.034	-3.0593 / -3.0507
DP Cyc HP	2	0.078*** (2.89) [0.152]	-0.102*** (-2.74) [-0.100]	0.137 (1.36) [0.039]	0.013** (2.11) [0.063]	0.049	-3.0680 / -3.0465
DP Cyc HP1	3	0.004* (1.88) [0.009]	-0.153*** (-3.63) [-0.150]	0.182* (1.95) [0.052]	0.013** (2.27) [0.063]	0.029	-3.0466 / -3.0255
DP Cyc Ham	4	0.039** (2.51) [0.592]	-0.378*** (-6.10) [0.350]	0.184* (1.85) [0.077]	0.011* (1.89) [0.058]	0.094	-3.1129 / -3.0914
Price-Earnings Ratio Results							
PE Cyc HP	-	-0.029** (-2.22) [-0.095]	-	-	-	0.008	-3.0324 / -3.0238
PE Cyc HP	6	-0.044** (-2.45) [-0.142]	-0.193*** (-4.65) [-0.189]	0.104 (1.07) [0.029]	0.013** (2.30) [0.064]	0.047	-3.0655 / -3.0440
PE Cyc HP1	7	-0.015** (-2.01) [-0.058]	-0.162*** (-3.87) [-0.158]	0.189* (1.95) [0.034]	0.013** (2.16) [0.064]	0.031	-3.0492 / -3.0277
PE Cyc Ham	8	-0.058*** (-4.11) [-0.880]	-0.009*** (-5.84) [-0.008]	0.081 (0.83) [0.008]	0.012** (2.12) [0.058]	0.048	-3.0658 / -3.0577

Notes: Entries are the regression results (with Newey-West *t*-values) from equation (4). These regressions include the Hodrick-Prescott (HP), one-sided Hodrick-Prescott (HP1) and Hamilton (Ham) filtered dividend-price (DP) and price-earnings (PE) ratios. The other variables are the filtered log industrial production, the FED model variable and the trailing correlation between stock and bond returns series. Industrial production is filtered using the same approach as noted for the DP or PE series in the equivalent regression. The asterisks denote statistical significance at the 1% (***), 5% (**) and 10% (*) level.

Table 4. DP and PE Cycles Predictive Regression by Regime Results

	$I_t = 1$	$I_t = 0$	Adj R-sq.	AIC/ BIC
Dividend-Price Ratio				
DP Cyc HP	0.118*** (3.74)	0.016 (0.58)	0.039	-3.0610 / -3.0481
Price-Earnings Ratio				
PE Cyc HP	-0.044** (-2.56)	0.008 (0.49)	0.013	-3.0348 / -3.0219

Notes: Entries are the regression results (with Newey-West *t*-values) from equation (9). The regressions include the Hodrick-Prescott (HP) filtered dividend-price (DP) and price-earnings (PE) ratios. Where $I_t = 1$ this indicates that the absolute return is greater than the absolute change in dividends or earnings, with $I_t = 0$ indicating the converse. The asterisks denote statistical significance at the 1% (***), 5% (**) and 10% (*) level.

Table 5. Long Horizon Predictive Regressions

	1 Month	1 Year	2 Years	5 Years	7 Years	10 Years	15 Years
	Dividend-Price Ratio Results						
DP	-0.014** (-2.31)	-0.110** (-2.34)	-0.112 (-1.61)	0.065 (0.82)	0.193** (2.64)	0.155 (1.31)	0.446*** (3.28)
DP Cyc HP	0.092*** (3.62)	0.852*** (7.87)	1.276*** (7.62)	0.967*** (3.76)	0.628*** (2.76)	0.602* (1.89)	0.411 (1.21)
	Price-Earnings Ratio Results						
PE	0.003 (0.52)	-0.010 (-0.51)	-0.067 (-1.00)	-0.161* (-1.73)	-0.250*** (-2.59)	-0.657*** (-7.00)	-0.741*** (-5.23)
PE Cyc HP	-0.047*** (-4.25)	-0.270** (-2.29)	-0.179 (-1.08)	-0.062 (-0.28)	0.137 (0.62)	0.234 (1.29)	0.588*** (2.91)

Notes: Entries are the regression results (with Newey-West *t*-values) from equation (10). The results here are only presented for the Hodrick-Prescott (HP) filtered DP and PE series. The asterisks denote statistical significance at the 1% (***), 5% (**) and 10% (*) level.

Table 6. Statistical Forecast Results

	Model #	MAE	RMSE	MZ R-sq	OOS R-sq	Enc
HM		0.037†	0.055†	0.003	-	-
DP	1	0.040	0.058	0.014	-0.117** (2.34)	0.226** (2.06)
DP Cyc HP	2	0.039	0.057	0.019	-0.085*** (2.60)	0.270** (2.30)
DP Cyc HP1	3	0.041	0.059	0.010	-0.146* (1.93)	0.188* (1.86)
DP Cyc Ham	4	0.043	0.063	0.012	-0.137** (2.29)	0.293** (2.39)
PE	5	0.040	0.058	0.012	-0.114*** (2.67)	0.277** (2.42)
PE Cyc HP	6	0.039	0.057	0.020†	-0.085*** (2.77)	0.286*** (2.84)
PE Cyc HP1	7	0.041	0.060	0.011	-0.140* (2.04)	0.201** (1.98)
PE Cyc Ham	8	0.042	0.061	0.014	-0.129** (2.57)	0.322*** (2.69)

Notes: Entries are the values of the mean absolute error (MAE, equation 11)), root mean squared error (RMSE, equation (12)) and Mincer-Zarnowitz R-squared. Entries under the column OOS R-sq are from equation (13) with the test of Clark and West, equation (14), in parenthesis below. Entries under the Enc column are the β_2 coefficient and *t*-value from equation (15). HM stands for the historical mean model. The † indicates the preferred forecast model based on the MAE, RMSE and MZ R-sq approaches. The asterisks denote statistical significance at the 1% (***), 5% (**) and 10% (*) level.

Table 7. Economic Based Forecast Results

	Model #	Success Ratio	Market Timing	Sharpe Ratio	CEV
HM		0.52	-0.49	0.016	-
DP	1	0.54	1.65*	0.090	0.398
DP Cyc HP	2	0.56	2.68***	0.119	0.556
DP Cyc HP1	3	0.53	1.54	0.094	0.421
DP Cyc Ham	4	0.55	1.87*	0.104	0.498
PE	5	0.55	1.78*	0.115	0.531
PE Cyc HP	6	0.57†	3.31***	0.128†	0.606†
PE Cyc HP1	7	0.54	1.66*	0.098	0.524
PE Cyc Ham	8	0.55	1.88*	0.116	0.587

Notes: Entries are the success ratio (equation 16), the market timing test (equation 17), the Sharpe ratio (equation 18) and the certainty equivalence value (CEV, equation 19). The † indicates the preferred forecast model for the Success Ratio, Sharpe Ratio and CEV. The asterisks denote statistical significance at the 1% (***), 5% (**) and 10% (*) level.

Table 8. Return According to Forecast Sign

		Positive				Negative			
	Model #	SR	Return	Return if Correct	Return if Incorrect	SR	Return	Return if Correct	Return if Incorrect
HM		0.78†	0.004	0.034	-0.044	0.21	-0.008	0.049	-0.038
DP	1	0.66	0.007	0.036	-0.036	0.39	-0.001	0.045	-0.037
DP Cyc HP	2	0.64	0.010†	0.037†	-0.034†	0.45†	0.003	0.048	-0.035
DP Cyc HP1	3	0.64	0.008	0.036	-0.035	0.36	0.001	0.052†	-0.034
DP Cyc Ham	4	0.64	0.009	0.036	-0.035	0.44	0.002	0.051	-0.035
PE	5	0.68	0.006	0.035	-0.039	0.37	-0.003	0.043	-0.039
PE Cyc HP	6	0.67	0.010†	0.036	-0.036	0.43	0.004†	0.050	-0.033†
PE Cyc HP1	7	0.65	0.008	0.035	-0.035	0.38	0.002	0.049	-0.034
PE Cyc Ham	8	0.66	0.009	0.035	-0.034†	0.41	0.002	0.050	-0.033†

Notes: Entries are the success ratio (SR) and the returns according to whether returns are positive or negative and whether the forecast sign is correct or not. The † indicates the preferred forecast model.

Figure 1. Forward 10-Year Holding-Period Returns and the Log Dividend-Price Ratio

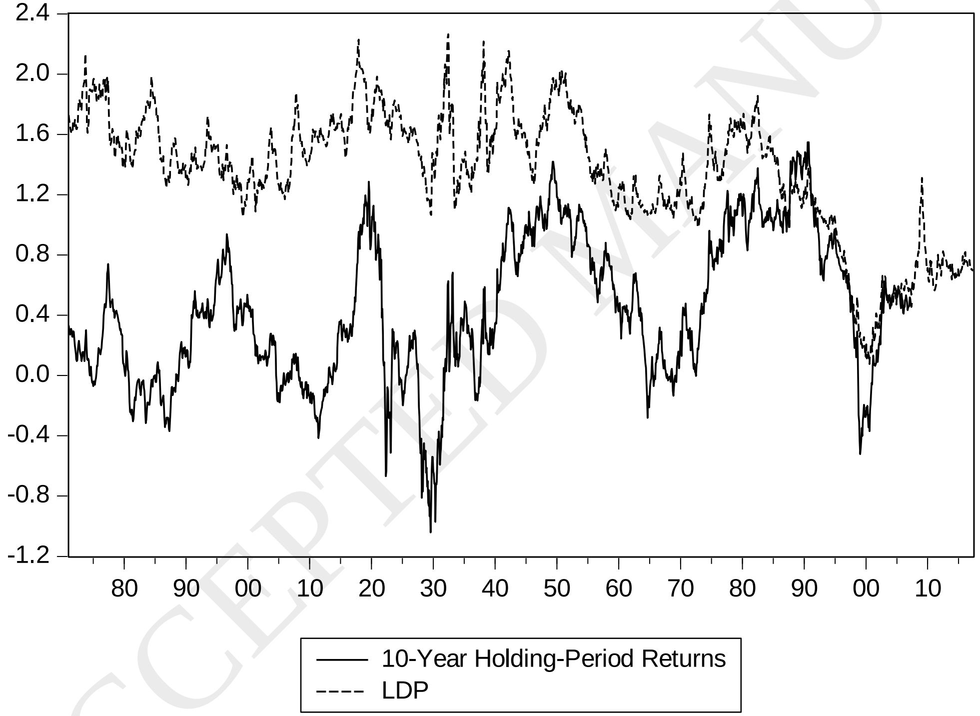

Figure 2. Data Plots