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The dividend-price ratio does predict dividend growth: International evidence

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The dividend-price ratio does predict dividend growth: International evidence*

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Abstract

Unpredictable dividend growth by the dividend-price ratio is considered a 'stylized fact' in post war US data. Using long-term data, covering more than 80 years from the US and three European countries, we revisit this stylized fact, and we also report results on return predictability. We find large cross-country differences regarding return and dividend growth predictability. For the US, we confirm Chen's (2008) finding of a 'tale of two periods' but with the important difference that short- and long-horizon *real* returns are significantly predictable in both sub-periods (1871-1949 and 1950-2008), while long-horizon *real* dividend growth is unpredictable in the early period and significantly predictable in the 'wrong' direction in the post war period. These results are directly opposite to those reported by Chen using *nominal* returns and dividend growth. For the UK, the results are more or less similar to those for the US. For Sweden and Denmark we find no evidence of return predictability, but strong evidence of predictable dividend growth in the 'right' direction on both short and long horizons and over both the full sample periods and the post war period. We also document that implied long-horizon coefficients from VAR's often differ substantially from direct estimates in multi-year regressions. Throughout, we report both standard asymptotic tests and simulated small-sample tests and, following Cochrane (2008), we investigate the *joint* distribution of dividend-price ratio coefficients in return and dividend growth regressions.

JEL Classification: G12, E44
Keywords: Dividend-price ratio, equity return and dividend growth, short- and long horizon predictability, VAR model, asymptotic and small-sample tests.

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1 Introduction

It has become an almost stylized fact for the US that stock returns are predictable by the dividend-price ratio while dividend growth is not. This predictability pattern is especially pronounced when returns and dividend growth are measured over long (multi-year) horizons, and it has been interpreted as implying that almost all variation in dividend yields is due to changing expectations of future long-term returns with changing expectations of future long-term dividend growth playing essentially no role, see e.g. Cochrane (2001, 2008).[1] Recently, this 'stylized fact' has been challenged by Chen (2008) who shows that for the period up to the end of the Second World War, the opposite predictability pattern characterizes the US stock market: Long-horizon returns are unpredictable while long-horizon dividend growth is predictable by the dividend-price ratio. However, for the post war period, Chen obtains results consistent with the 'stylized fact' view, namely predictable stock returns and unpredictable dividend growth.

The finding that changing expectations of future dividend growth have no role to play in explaining movements in the dividend-price ratio is discomforting and runs counter to standard textbook models for stock price determination in which changes in expected future cashflows are an important source for movements in prices. One possible explanation for the lack of dividend growth predictability by the dividend-price ratio in the post war US data is provided by Lettau and Ludvigson (2005). They argue that movements in expected dividend growth are positively correlated with movements in expected returns and this comovement has offsetting effects on the dividend-price ratio which make it unable to uncover the time-varying nature of expected dividend growth. Lettau and Ludvigson find that the cointegrating residual from consumption, dividend, and labor income, by contrast, has significant predictive power for future dividend growth. Menzly, Santos and Veronesi (2004) provide a general equilibrium habit persistence explanation for a common component in expected returns and expected dividend growth, and they show that changes in risk preferences eliminate the dividend-price ratios ability to predict future dividend growth. From Menzly et al.'s model what should predict dividend growth is the dividend-price ratio scaled by a particular price-consumption ratio, and this implication is borne out in the post war US data. Chiang (2008) argues that because of smoothing, manipulation, and censoring of dividends, and because of structural shifts in firms corporate financial policy, measured dividends may be a poor measure of true value-relevant cashflows and this may explain the lack of dividend growth predictability by the dividend-price ratio. Instead, Chiang uses a subset of US stocks, namely real estate investment trust (REIT) stocks whose dividends are a better measure of value-relevant cashflows, and he finds that indeed with these data dividend growth is strongly predictable by the dividend-price ratio.

As noted by e.g. Paye and Timmermann (2006), the literature on return predictability

[1] Campbell and Shiller (1988) documented that the dividend-price ratio does significantly predict one-year dividend growth with the 'correct' negative sign in annual US data up to 1986. Ang (2002) confirmed that result on data up to 2000, but he also found that on horizons beyond one year there is no significant dividend growth predictability by the dividend-price ratio.

is weighted towards US data with relatively few studies examining predictability in global returns. This bias towards the US is even more pronounced when it comes to analyzing dividend predictability. Campbell (2003) conducts a comprehensive international study of asset price determination within a consumption-based framework. In parts of his analysis he finds some evidence of dividend growth predictability by the dividend-price ratio in several countries (but not in the US). However, in most of the cases the significant predictability is confined to dividend growth over relatively short horizons, and Campbell concludes from this that there is no convincing evidence in the international data that long-run forecasts of dividend growth change over time.[2] In another international study, Ang and Bekaert (2007) also conclude that there is only weak evidence of linear dividend growth predictability by the dividend-price ratio.

In this paper we further analyze the dividend-price ratios ability to predict future stock returns and dividend growth. We pay special attention to dividend growth predictability over long horizons, and in addition to using the long-term annual US data that many previous authors have used, we analyze long annual time series for aggregate stock prices and dividends in the three European countries Denmark, Sweden and the UK. For these three countries we have annual data covering more than 80 years in the case of Denmark and Sweden and more than 100 years for the UK. Surprisingly, for these European countries we find predictability patterns that in some ways - and especially for the two Scandinavian countries - are very different from what characterize the US.

For the US we find results basically identical to those reported by Cochrane (2008) and Chen (2008), except at four important points. First, for the early period (up to 1949), we find statistically significant return predictability at both short and long horizons in the 'right' direction, i.e. an increase (decrease) in the dividend-price ratio predicts a subsequent increase (decrease) in returns. Second, for this early period, although we find that the dividend-price ratio significantly predicts short-horizon dividend growth in the 'right' direction, i.e. an increase (decrease) in the ratio predicts a subsequent fall (rise) in dividend growth, we do not find any significant predictability in long-horizon real dividend growth. These results are in contrast to Chen (2008) who finds no predictability of returns but significant predictability - with the 'correct' sign - of long-horizon dividend growth for this sub-period. The reason for these discrepancies turns out to be that Chen uses *nominal* variables whereas we use *real* variables. Thus, for the US Chen's finding of insignificant long-horizon return predictability and significant long-horizon dividend predictability is crucially dependent on his use of nominal instead of real returns and dividends. The earlier literature has mostly focused on real dividends and real (or excess)

[2]Most of Campbell's (2003) analysis is based on quarterly data from the 1970s to the late 1990s. However, he also reports results with long-term annual data from US, UK and Sweden; these annual data are essentially identical to the data we use from these three countries, except that our sample periods are longer. In addition we include data from Denmark. Dimson et al. (2002) contains stock returns over a 100 year period for 16 countries. However, their publicly available database does not contain individual series for dividends or dividend yields, and requests to the authors for supplying these series have not been successful. Except for the US, UK, Swedish, and Danish data we analyze, we are not aware of similar data from other countries that contain long-term series for both prices and dividends.

returns, so Chen's use of nominal variables is unusual in this respect.[3] Third, for the post war period (1950-2008) we find statistically significant long-horizon dividend growth predictability in the 'wrong' direction. This is also in contrast to Chen, but again the reason is that we use real dividends whereas Chen uses nominal dividends. Thus, we find a 'tale of two periods' for the US, just as Chen documents, but with the important difference being that long-horizon real dividend growth is unpredictable in the early sub-period and predictable in the 'wrong' direction in the post war period. This is in sharp contrast to Chen's findings for *nominal* dividend growth. Finally, we find that in some cases the implied long-run coefficients on the dividend-price ratio from first-order VAR models differ substantially from direct long-run estimates in time-overlapping multi-year regressions. This is in contrast to Cochrane (2008) and Chen (2008) who both find that implied long-run estimates from VAR's are qualitatively similar to direct long-run estimates. Our results indicate that one should be careful in deriving long-run implications from low-order VAR models.

Turning to the European countries, for the UK over the full sample period 1900-2008, we find that the dividend-price ratio significantly predicts one-year dividend growth in the 'right' direction. However, for horizons beyond one year the dividend-price ratio loses its predictive ability for dividends. As with some of the US results this again implies that the long-run dividend predictability implied from a first-order VAR differs quantitatively as well as qualitatively from direct long-horizon regressions. For returns, the dividend-price ratio has clear predictive ability at both short and long horizons, and in the 'right' direction. These results are, however, not robust to sub-sample analyses. In particular, long-horizon returns are unpredictable in the first sub-period 1900-1949 and predictable in the second sub-period 1950-2008, while long-horizon dividend growth is (marginally) predictable in both sub-periods but with a change in the direction of predictability: in the first sub-period the dividend-price ratio predicts dividend growth in the 'right' direction, while in the post war period the ratio significantly predicts dividend growth in the 'wrong' direction. Thus, the results for the UK are a 'tale of two periods' just as it is the case for the US.

For the two Scandinavian countries Denmark and Sweden the results are very clear, and in contrast to the US and UK there is now no 'tale of two periods'. Short-horizon and long-horizon real dividend growth are strongly predictable in the 'right' direction - statistically as well as economically - from the dividend-price ratio, whereas stock returns show almost no signs of predictability, neither at short nor long horizons. These results hold both over the full sample periods (Denmark: 1922-2008; Sweden: 1919-2008) and for the post war period (1950-2008). Thus, in Scandinavia there is strong evidence that most if not all variation in dividend-price ratios reflects changing expectations of future long-term cashflows discounted by a constant expected return, in perfect accordance with standard textbook models for stock price determination.

[3] In addition to nominal returns, Chen (2008) also analyzes excess returns, but with respect to dividend growth he only considers nominal dividends and does not investigate predictability in real dividend growth. Ang and Bekaert (2007) is another recent study examining predictability in nominal dividend growth.

Throughout we report tests based on both asymptotic distributional theory and on simulated small-sample distributions. This is especially important when looking at multi-year time-overlapping data. And since Cochrane (2008) finds that when considering long-horizon predictability it is important to go beyond just 5 or 10 year horizons, we investigate predictability at horizons up to 20 years. In addition to analyzing the standard regressions where return predictability and dividend growth predictability are analyzed in isolation, we also investigate the joint distribution of the dividend-price ratio coefficients in the two regressions; this gives more powerful tests of predictability since, as Cochrane (2008) forcefully argues, a null hypothesis of no return (dividend growth) predictability must mean dividend growth (return) predictability, if there are no bubbles. We simulate p-values for two joint hypotheses, either no return predictability together with dividend growth predictability, or no dividend growth predictability together with return predictability. It turns out that for most of our analyses where there is only marginal evidence of predictability using the standard hypothesis tests, the joint tests result in highly significant evidence of predictability.

The rest of the paper is organized as follows. Section 2 describes the long-term data used in the empirical analysis. Section 3 reports the empirical results on both short and long horizons, and using both asymptotic tests and small-sample tests in a joint hypothesis setup. The section also contains results from a sub-sample analysis and a number of further robustness analyses, before providing a possible explanation for the differences found between the countries examined in the empirical analyses. Finally, section 4 contains some concluding remarks.

2 The long-term US and European data

We analyze dividend growth and return predictability for the US and three European countries: Denmark, Sweden, and the UK. For each of these countries we have long-term annual time series for aggregate stock prices and dividends. Using long-term annual data enables us to analyze direct long-run predictability, while at the same time avoiding the well-known problems with seasonality in monthly or quarterly dividends.

The source for the UK data is Barclays Capital (2009), which contains annual data on UK stock prices and dividends in the period 1900-2008. The "Barclays Equity Index" is measured at December each year and the "Income Index" relates to the dividend income received in the 12 months prior to that date. Nominal values are converted to real values by dividing by the "Cost of Living Index". The Swedish data covers the period 1919-2008, and is up to 2007 an updated version of the data from Frennberg and Hansson (1992). We have used Morgan Stanley Capital International (MSCI) data for the last year in the Swedish dataset. Prices are measured at the end of the year, while dividend is the dividend income payable throughout that year. Nominal series are deflated by the implicit consumption deflator.[4] The Danish data are from Lund and Engsted (1996), Engsted and Tanggaard (2001), and MSCI, and covers the period 1922-2008. Up to

[4]The UK and Swedish data correspond to those used by Campbell (2003), with the exception of

1996 the stock index is a value-weighted portfolio of stocks from the Copenhagen Stock Exchange. The index at the end of year t is defined as the February value of year $t+1$. Dividends for year t are defined as dividends paid out between February of year t and February of year $t+1$, see the appendix in Lund and Engsted (1996) for details. Nominal values are deflated by the consumption deflator. For the period after 1996 these data are spliced together with Danish data from MSCI. Finally, we use two US datasets. The first is from Center for Research in Security Prices (CRSP) and covers the period 1926-2008, while the second is the S&P data from the website of Robert Shiller and covers the period 1871-2008. These US data are identical to the data used by Chen (2008), except that Chen's sample period stops at 2005 and that he uses nominal and excess returns and nominal dividends, whereas we use real returns and real dividends throughout.

Table 1 shows descriptive statistics for each country over the full sample period and over two sub-samples with the first ranging from the start of the samples to 1949, and the second from 1950 to 2008. The table reveals a number of interesting differences between the four countries. Looking at the full sample period, we see that the mean annual dividend growth is much higher in Sweden (3.7%) and somewhat lower in the UK and Denmark (1.1% and 0.8%, respectively), than in the US (2.0%). Furthermore, the dividend-price ratio is much less persistent in the UK than in the other three countries. The mean and standard deviation of returns are quite similar across countries, mean returns ranging from 6.7% in Denmark to 8.4% in Sweden, and standard deviations ranging from 17.9% in the US (S&P) to 21.9% in Sweden. Turning to the sub-sample periods, we see that while the mean return on stocks and the mean dividend growth remain virtually unchanged over the two sub-periods for the US, they change a lot for the three European countries. The mean return on stocks increases from 4.4% to 8.8% in the UK, from 4.8% to 10.4% in Sweden, and from 3.6% to 8.1% in Denmark. We also see an increase in the mean dividend growth for these countries. In the UK it increases from 0.5% to 1.6%, in Sweden from -0.4% to 5.9%, and in Denmark from -1.4% to 1.8%. Another interesting difference between the US and the three European countries is that while the standard deviation of returns decreases across the two sub-sample periods for the US, it increases for the three other countries. With respect to the variability of dividend growth, standard deviations fall dramatically in the post war period in the UK and US, while they increase in Sweden and Denmark. In the former two countries the standard deviations are between 4.9% and 13.2% in the 1950-2008 period, but 20% in the Scandinavian countries. This points to an interesting difference between the US and UK on the one hand and the two Scandinavian countries on the other hand, regarding firms' dividend policy. We return to this issue in section 3.5 below. A common feature in the data from the four countries is that the persistence of the dividend-price ratio increases across the two sub-periods, as seen from the $\phi(1)$ coefficients in Table 1. Figure 1 shows time-series plots of the dividend-price ratio.

In the following, we initially analyze dividend growth and return predictability using the full samples, and then in Section 3.3 we perform a sub-sample analysis using the

having been updated to include the latest years and, in the case of the UK, to include data prior to 1920.

sample periods mentioned above.

3 Empirical results

Using a linearization of the definition of the one-period log return, Campbell and Shiller (1988) derive the approximate identity

$$r_{t+1} = \Delta d_{t+1} + (d_t - p_t) - \rho\,(d_{t+1} - p_{t+1}) + c, \tag{1}$$

where r_{t+1}, d_{t+1}, and p_{t+1} denote log stock return, log dividend, and log stock price, respectively, $\rho = 1/\left(1 + e^{E[d-p]}\right)$, and c is a linearization constant. Iterating (1) forward, imposing a no-bubble transversality condition $\lim_{j\to\infty} \rho^j E_t\,(d_{t+j} - p_{t+j}) = 0$, and taking conditional expectations, we get the following important identity

$$d_t - p_t = E_t \sum_{j=0}^{\infty} \rho^j\,(r_{t+1+j} - \Delta d_{t+1+j}) - \frac{c}{1-\rho}. \tag{2}$$

According to (2) the dividend-price ratio will be a good predictor of future long-term returns and/or future long-term dividend growth. Thus, given no bubbles and given forward-looking expectations, there is a sound theoretical argument as to why the dividend-price ratio should predict future returns and/or changes in dividends, and existing predictability studies using US data usually refer to (2) as the underlying theoretical framework.

3.1 Short-horizon predictability

Initially, we consider Cochrane's (2008) first-order VAR representation of r_{t+1}, Δd_{t+1}, and $d_{t+1} - p_{t+1}$, restricted to have only the log dividend-price ratio as regressor

$$r_{t+1} = a_r + b_r\,(d_t - p_t) + \varepsilon^r_{t+1}, \tag{3}$$
$$\Delta d_{t+1} = a_d + b_d\,(d_t - p_t) + \varepsilon^d_{t+1}, \tag{4}$$
$$d_{t+1} - p_{t+1} = a_{dp} + \phi\,(d_t - p_t) + \varepsilon^{dp}_{t+1}. \tag{5}$$

The system is estimated using simple OLS and standard errors are Newey and West (1987) adjusted to account for heteroscedasticity.[5]

Table 2 shows the results for each country over the full sample period. With the exception of $\widehat{b}_r$ in Sweden and $\widehat{b}_d$ in the US (CRSP), all estimated coefficients have the

[5] Tests for residual autocorrelation (not reported) do not reveal misspecification with respect to the dynamics in (3)-(5), except in a few cases for the post war period where the residuals in the Δd_{t+1} equations for the UK and US (S&P) display some autocorrelation.

’correct’ sign, cf. (2). Regarding return predictability, we find strong evidence in favour of the dividend-price ratio being able to predict future stock returns in the UK. In the US there is also evidence of return predictability using CRSP data, while b_r is only marginally significant in the S&P data. In Sweden and Denmark we find no evidence of return predictability. Turning to dividends, Table 2 shows that the dividend-price ratio does significantly predict dividend growth in the UK, Sweden, and the US (S&P), with the evidence being especially strong in Sweden. In Denmark there is only marginal evidence of dividend growth predictability, while using CRSP data we find no evidence of dividend growth predictability in the US.

The discrepancy between the results for the US using S&P data and CRSP data, respectively, can be assigned to the way data is constructed. As Chen (2008) shows, the assumptions made regarding reinvestment of dividends have great importance when it comes to determining whether or not dividend growth is predictable. CRSP annual returns are constructed assuming that monthly dividends are reinvested in the stock market, and hence when dividend growth is backed out from annual returns with and without dividends, as they are in the CRSP data, the dividend growth series will behave as return does. Since the dividend-price ratio predicts future stock returns and dividend growth in opposite directions, this property will reduce dividend growth predictability. The S&P data does not suffer from this property and, hence, these data are preferable when examining dividend growth predictability, as argued by Chen (2008). The difference between the CRSP and the S&P data is also apparent when looking at the cross-correlation of the residuals in Table 2. The correlation between the innovations to returns and dividend growth is 0.13 in the S&P data but 0.68 in the CRSP data, and the correlation between the innovations to dividend growth and the dividend-price ratio is 0.46 in S&P data but only 0.04 in CRSP.

Dividends in the three European datasets are not backed out from other series but are measured directly, as in the S&P data for the US. Hence, our European dividend growth series are not ’contaminated’ by returns as is the case with the CRSP dividend growth series.

3.1.1 Joint hypothesis testing

As argued by Cochrane (2008), we can obtain stronger tests for predictability than the marginal tests shown in Table 2. The approximate identity (1) links the regression coefficients of the VAR, (3)-(5), and hence by projecting on the dividend-price ratio, we get the following approximate identity between the regression coefficients

$$b_r = 1 - \rho\phi + b_d. \tag{6}$$

Furthermore, the errors in (3)-(5) are also linked by the approximate identity

$$\varepsilon^r_{t+1} = \varepsilon^d_{t+1} - \rho\varepsilon^{dp}_{t+1}. \tag{7}$$

This implies that we can infer the data, coefficients, and errors of any one equation from those of the other two. It also means that when we want to test, say, $b_r = 0$, we have to change the dividend growth coefficient b_d or the dividend-price ratio autocorrelation coefficient ϕ accordingly. The intuition here is - assuming no bubbles - that if the dividend-price ratio does not predict future stock returns, then it must predict future dividend growth, cf. (2), or stated otherwise, we can not have a null hypothesis in which we both have unpredictable returns and unpredictable dividend growth.

In testing these joint hypotheses we follow Cochrane (2008) and simulate data under the respective nulls, and thereby test the hypotheses using simulated small-sample distributions. We test a null of no return predictability ($b_r = 0$) and a null of no dividend growth predictability ($b_d = 0$). In both cases we use the estimated dividend-price ratio autocorrelation coefficient $\widehat{\phi}$ and calculate the dividend growth coefficient b_d and return coefficient b_r, respectively, using (6). Table 3 shows the coefficients under the two null hypotheses along with the estimated ρ for each country.

When simulating data under the respective nulls we have to choose two variables to simulate and let the third follow from the approximate identity (1). We simulate the dividend-price ratio and the variable which is predictable under the null, i.e. under the null of no return predictability we simulate dividend growth, and under the null of no dividend growth predictability we simulate returns. We draw ε_t^{dp} and ε_t^{d} or ε_t^{r}, depending on the null hypothesis, as random normals using the estimated covariance matrix. The first observation $d_0 - p_0$ is drawn from the unconditional density $d_0 - p_0 \sim \mathcal{N}\left[0, \sigma^2\left(\varepsilon^{dp}\right)/\left(1-\phi^2\right)\right]$ and then the VAR system is simulated forward.[6] We simulate the system 10,000 times, and for each simulation we estimate the VAR system (3)-(5) and collect the coefficients.

For the null hypothesis of no return predictability, we calculate the simulated probability that the coefficients are *larger* than their sample values, while for the null hypothesis of no dividend growth predictability, we calculate the simulated probability that the coefficients are *smaller* than their sample values. Hence, we get simulated p-values that can be interpreted in the usual way, where a p-value smaller than a chosen significance level implies that we reject the null hypothesis.

Table 4 shows the simulated p-values. In Panel A, we find clear evidence in favour of return predictability in the UK, and against return predictability in Sweden and Denmark. For the US, the results are not so clear-cut. Evaluating only $P(b_r > \widehat{b}_r)$, we find p-values of 11% and 18% depending on the data source, which in itself does not lead to a rejection of the null hypothesis. However, under the null hypothesis of no return predictability, we must have dividend growth predictability of sufficient magnitude, c.f. Table 3. Depending on the data source the simulated dividend growth forecasting coefficients are only larger than their estimated values 0.03% and 1.16% of the time, respectively. Hence, even in the S&P data where $\widehat{b}_d = -0.084$ is statistically significant

[6] Using the framework of Ang and Liu (2007), Chen (2008) simulates from a slightly different system, where the relation between expected dividend growth/returns and the dividend-price ratio is nonlinear, and a function of the level of the dividend-price ratio.

(c.f. Table 2), the estimate is not sufficiently negative to make $b_r = 0$ plausible. Figure 2 displays these results graphically.

Table 4, Panel B, shows the simulated p-values under the null hypothesis of no dividend growth predictability. In the UK, Sweden, and the US (S&P), we find strong evidence in favour of dividend growth predictability, while the opposite is the case for the US using CRSP data. Evaluating only the marginal distribution $P(b_d < \widehat{b}_d)$ there is a probability of 6.34% of observing a dividend growth forecasting coefficient smaller than the estimated value when it comes to Denmark. This implies that we cannot reject the null hypothesis based on the marginal distribution at the conventional 5% significance level. However, in the joint test we also have to take $P(b_r < \widehat{b}_r)$ into account, and since we only observe a return forecasting coefficient smaller than the estimated value 0.09% of the time, we reject the null hypothesis based on the joint test. Figure 3 displays these results graphically.

Summing up the short-horizon results, we have confirmed Cochrane's (2008) finding of return predictability but no dividend growth predictability in the US (CRSP) data, and Chen's (2008) finding of both return and dividend growth predictability in the US (S&P) data. In addition, we have documented strong dividend growth predictability with the 'correct' sign in Denmark and Sweden, while returns are unpredictable in these two countries. The results for the UK are basically similar to the US (S&P) results: both returns and dividend growth are significantly predictable by the dividend-price ratio, and in the 'right' directions.

3.2 Long-horizon predictability

The literature on return and dividend growth predictability basically contains two approaches to examine long-horizon predictability. First, we can use 'direct' time-overlapping multi-year regressions with suitable adjustments to the standard errors to account for the moving average structure imposed on the error term from using overlapping data. Second, we can use first-order VAR models to infer long-run implications. These two approaches are not guaranteed to yield the same result, and hence we will report results using both approaches. Moreover, the vast majority of studies in this string of the literature use *unweighted* returns and dividend growth when examining predictability even though according to (2) r_{t+1+j} and Δd_{t+1+j} should be *weighted* by ρ^j. Following Cochrane (2008) we report results using both weighted and unweighted returns and dividend growth.

The 'direct' approach simply amounts to running the following regressions for different values of k

$$
\begin{aligned}
r_{t,t+k} &= a_{r,k} + b_{r,k} (d_t - p_t) + \varepsilon^r_{t+k}, \\
\Delta d_{t,t+k} &= a_{d,k} + b_{d,k} (d_t - p_t) + \varepsilon^d_{t+k},
\end{aligned}
$$

where $r_{t,t+k}$ and $\Delta d_{t,t+k}$ denote either the unweighted or weighted sum of one-period returns and dividend growth, respectively, from period t to $t + k$. The use of overlapping data implies that the errors have a moving average structure of order $k-1$ by construction. A standard way to deal with this is to use Newey-West adjusted standard errors with $k-1$ lags. However, as shown by Ang and Bekaert (2007), Newey-West standard errors lead to severe over-rejections of the null hypothesis of no return predictability at long horizons. Instead, Ang and Bekaert find that the standard errors developed by Hodrick (1992) retain the correct size in small samples, and with this in mind, we report both Newey-West standard errors with $k-1$ lags and Hodrick standard errors.

Depending on the use of weighted or unweighted returns and dividend growth, the implied long-run coefficients from the first-order VAR system (3)-(5) are calculated as

$$b_{i,k} = \sum_{j=1}^{k} \rho^{j-1}\phi^{j-1}b_i = \frac{1-\rho^k\phi^k}{1-\rho\phi}b_i,$$
$$b_{i,k} = \sum_{j=1}^{k} \phi^{j-1}b_i = \frac{1-\phi^k}{1-\phi}b_i,$$

where $i = r, d$. Letting k approach infinity, the long-run coefficients can be calculated as $b_{i,k} = b_i/\left(1-\rho\phi\right)$ and $b_{i,k} = b_i/\left(1-\phi\right)$.

Table 5 shows the results when using the 'direct' aproach on returns for $k = 5, 10, 15,$ and 20 years. For completeness the table also contains the results for $k = 1$ year, which are simply reproductions from Table 2. Furthermore, Table 5 contains results using both unweighted and weighted returns, but initially we will only focus on the unweighted case, and then return to the weighted case in section 3.4.

For the UK we find clear evidence of long-horizon return predictability. R^2 values are high, and the t-statistics are for all values of k above the critical value associated with any reasonable choice of significance level, irrespective of the choice of standard errors. However, as expected, the evidence is less strong when applying Hodrick standard errors compared to Newey-West standard errors. For Sweden the 'wrong' negative sign we found in the one-period forecasting regression reappears in the multiperiod case for all the chosen horizons. The coefficients are, however, not significant and the R^2 is never above 5%. For Denmark the coefficient has the 'correct' positive sign in the one-period regression, but for $k > 1$ it turns negative. But, similar to the case of Sweden, R^2 values are low, the coefficients are not statictically different from zero and, hence, we find no evidence of return predictability on short or long horizons for neither Sweden nor Denmark. For the US the conclusions are more or less insensitive to the choice of data. Using Newey-West standard errors the evidence is very clear and in favour of long-horizon return predictability, but with Hodrick standard errors the coefficients turn insignificant at the 5% level for $k = 5$ and 10; hence, the results only provide strong support for return predictability in the US at very long horizons (15 and 20 years).

Table 6 shows the results for the multiperiod regressions for dividend growth. For the UK we found short-horizon dividend growth predictability in Tables 2 and 4, but as Table 6 shows this is not accompanied by long-horizon predictability. Hence, short-horizon predictability does not necessarily translate into long-horizon predictability. We also find that for $k = 5, 10$, and 15 years, the $b_{d,k}$ coefficient has the 'wrong' positive sign. For both Sweden and Denmark there is strong evidence of dividend growth predictability on both short and long horizons when Newey-West standard errors are used, but from Table 6 it is also evident that the long-horizon predictability can be questioned when applying Hodrick standard errors. However, the R^2 values point to very strong predictability. Regarding the US we find results similar to those in the UK in the sense that the short horizon dividend growth predictability found using the S&P data does not translate into long-horizon predictability. However, based on CRSP data there is actually partial evidence of long-horizon dividend growth predictability, but with the 'wrong' positive sign. For $k = 15$ and 20 years the t-statistic is 2.4 and 2.6 when using Newey-West standard errors, but only 0.9 and 1.0 when Hodrick standard errors are applied.

The overall conclusion from Table 6 is that we do find statistically significant long-run dividend growth predictability with the 'correct' sign in both Sweden and Denmark when using the usual Newey-West standard errors, but this evidence becomes statistically insignificant when Hodrick standard errors are used. And with the findings of Ang and Bekaert (2007) regarding the better size properties of the Hodrick standard errors in mind, the results seem to support the general perception that long-run dividend growth is virtually unpredictable. These conclusions are, however, based on asymptotic theory and marginal tests. In the following section we will present the results from simulated joint tests constructed in the same way as in the one-period case, and as will become evident, the conclusions derived from Table 6 do not carry over to the joint hypothesis setup.

Before turning to the joint tests, we compare the coefficient estimates obtained from the 'direct' approach using multiperiod regressions with the coefficient estimates obtained from the implied approach based on the first-order VAR model. The implied long-run coefficients are shown in Table 7, which also reproduces the one-period coefficients for completeness. Cochrane (2008) and Chen (2008) both find that implied long-run estimates are qualitatively similar to direct long-run estimates, but by comparing Table 7 with Tables 5 and 6, it is clear that this conclusion does not apply in general. For example, in most cases the direct long-run return coefficients are much larger in absolute value than the implied long-run coefficients, and for Denmark they have different signs. For dividend growth there are significant differences in terms of either sign or size between the direct and implied coefficients for the UK and the US (S&P). The conclusion from this comparison is that we should be careful when deriving long-run implications from low-order VAR models. This will also become clear in the following section.[7]

[7] Cochrane (2008) prefers the implied long-run estimates due to the higher power against the null of no return predictability associated with these estimates compared to the direct estimates in his application. He does note, however, that implied and direct estimates need not coincide.

3.2.1 Joint hypothesis testing

Similar to the case with short-horizon predictability, we can obtain stronger tests for predictability if we use joint tests instead of marginal tests. Using the simulated data from section 3.1.1, we calculate small-sample p-values, and Table 8 shows the results for the implied and the direct regression coefficients under the null hypothesis of no return predictability when using unweighted returns.

Starting with the UK we find that the qualitative conclusions based on joint tests and simulated small-sample p-values are consistent with those obtained using marginal and asymptotic tests, cf. Table 5. In both cases there is clear evidence in favour of long-horizon return predictability. However, it is worth mentioning that while the p-values associated with the direct regression coefficients show decreasing significance for increasing values of k, which is consistent with the results in Table 5, the p-values associated with the implied coefficients are equal to zero for all values of k. For both Sweden and Denmark there is no evidence of long-horizon return predictability. Again this is consistent with the findings in Table 5. For the US (S&P), direct regression coefficients, and $k = 5$ and 10 years, we find only weak evidence of return predictability when looking at the marginal p-values. The probability of observing a simulated regression coefficient larger than the estimated coefficient is 8.2% and 6.5 %, respectively, which implies that we maintain the null hypothesis of no return predictability at the conventional 5% significance level. If we compare this to Table 5, we see that this result is consistent with the result obtained using Hodrick standard errors. However, if we instead evaluate the joint test of observing *both* a simulated return coefficient larger than its estimated value *and* a simulated dividend growth coefficient larger than its estimated value, we find much stronger evidence against the null hypothesis of no return predictability. For larger values of k we arrive at the same conclusion using both marginal and joint tests. For the US using CRSP data we find inconsistency between the conclusions based on simulated small-sample p-values using direct regression coefficients on the one side, and simulated small-sample p-values using implied coefficients as well as asymptotic distributions on the other side. According to Table 8 there is only weak evidence in favour of long-horizon return predictability when using the direct regression coefficients, and at the conventional 5% significance level we are in fact not able to reject the null hypothesis, irrespective of the use of marginal or joint tests. This is in contrast to the results using implied coefficients according to which we have long-horizon return predictability for all values of k, and also to the results in Table 5, where we found evidence in favour of return predictability for $k = 15$ and 20 years when using Hodrick standard errors. These results again illustrate that we should be careful in deriving long-run implications from low-order VAR models.

Table 9 shows the results for the null hypothesis of no dividend growth predictability. Similar to the case with returns the table contains the simulated p-values for the regression coefficients and the implied coefficients using unweighted dividend growth. In Table 6 we found no evidence of long-horizon dividend growth predictability in the UK. We obtain results consistent with this when evaluating the small-sample p-values for the direct regression coefficients in both marginal and joint tests, cf. Table 9. However, according to the p-values for the implied long-run coefficients there is strong evidence in favour of dividend growth predictability. So, again, the direct and implied results differ. Turning to Sweden and Denmark we find strong evidence in favour of long-horizon dividend growth predictability. The asymptotic tests in Table 6 gave mixed results regarding long-horizon dividend growth predictability in these countries, but as Table 9 shows, the conclusion is very clear when relying on small-sample distributions: The dividend-price ratio does predict long-horizon dividend growth in Sweden and Denmark. For the US (S&P), our conclusion for $k = 5$ and 10 years depends on whether we use a marginal or a joint test. Based on the marginal test there is a probability of 19.0% and 57.2%, respectively, of observing a simulated dividend growth coefficient smaller than the estimated value, which clearly implies that we maintain the null hypothesis. However, no dividend growth predictability must imply that returns are predictable in a joint hypothesis setup, and since there is only 0.2% and 3.0% probability, respectively, of observing a simulated return coefficient smaller than the estimated value, we reject the null hypothesis and conclude that dividend growth is predictable in the US (S&P) on 5 and 10 year horizons. For larger values of k there is no evidence of dividend growth predictability, and similar to the results for the UK, we find that the implied long-run coefficients do not give a good description of the actual long-run behavior. Finally, for the US with CRSP data we find no evidence of dividend growth predictability at any horizon.

Summing up the long-horizon results for the full sample periods, in the UK multi-year returns are strongly predictable by the dividend-price ratio while multi-year dividend growth is unpredictable. For Denmark and Sweden the exact opposite is the case. For the US the results are somewhat sensitive to the choice of data, but based on the S&P data the results are very similar to the UK results: strongly predictable multi-year returns and unpredictable 15 and 20 year dividend growth.

3.3 Sub-sample analysis

Using nominal US data over the period 1872-2005, Chen (2008) finds evidence of reversal of both return and dividend growth predictability. He shows that dividend growth is strongly predictable and stock returns are largely unpredictable in the period prior to the second world war, while the opposite is the case using post war data. With these findings in mind we examine if the conclusions drawn in the previous sections are robust across two sample periods. We examine the period from the start of the samples up to 1949, and the period 1950-2008. For Sweden, Denmark, and the US using CRSP data we have only a few observations in the first sub-period. This makes long-horizon regression estimates unreliable and, hence, for this early period we only report results for $k = 1$ year for these countries. To conserve space we only report results using unweighted returns and dividend growth, respectively, and only direct regression estimates.

Table 10 shows the regression results for returns, and Table 12 shows the corresponding simulated small-sample p-values. For the UK we found evidence of both short- and long-horizon return predictability when using the full sample, but from Tables 10 and 12 it is clear that in the first sub-sample returns are only significantly predictable by the dividend-price ratio for $k = 1$ and 5 years. However, using post war data we find strong evidence of return predictability on horizons up to 15 years, while for the 20 year horizon the result is only marginally significant. For both Sweden and Denmark we found no evidence of return predictability in the full sample, and this conclusion carries over to the two sub-periods.

Chen (2008) argues (using nominal data) that long-horizon US returns are not predictable in any period. Our results for the US using the S&P data suggest that this conclusion depends crucially on the use of nominal data. We use real returns and find evidence of both short- and long-horizon return predictability in both sub-periods.[8] Table 10 shows that this result for some horizons is only marginally significant based on marginal and asymptotic tests, but according to Table 12 real returns are significantly predictable at the conventional 5% level when using the joint hypothesis setup. Turning to CRSP data we find the same inconsistency between the results based on asymptotic and small-sample tests as we found when analyzing the full sample period. According to Table 10 there is evidence of return predictability on both short and long horizons, but the simulated p-values in Table 12 suggest only short-horizon (1 year) return predictability.

Regarding dividend growth predictability, Tables 11 and 13 show the results. For the UK we find strong evidence of a 'tale of two periods' in the sense that in the first sub-period long-horizon dividend growth is (marginally) predictable with the 'correct' negative sign, while it is predictable with the 'wrong' positive sign in the second sub-period. According to Table 11, $\widehat{b}_{d,k}$ is positive for $k > 1$. The very *high* p-values in Table 13 then basically implies that there is a very *low* probability of observing a $b_{d,k}$ coefficient as *high* as the estimated coefficients under the null of no dividend growth predictability. For example, for $k = 15$ years there is a probability of 99.5% of observing a dividend growth coefficient *lower* than the estimated coefficient ($\widehat{b}_{d,15} = 0.639$), or stated otherwise, there is a probability of 0.5% of observing a dividend growth coefficient *higher* than the estimated one under the null. Thus, the reported p-value of 99.5% means strongly statistically significant dividend growth predictability in the 'wrong' direction.

The dividend growth predictability found in Sweden and Denmark on both short and long horizons in the full sample is also present in the post war data. Although the marginal tests based on Hodrick standard errors in Table 11 only reveal maginal significance, the evidence is very clear and in favour of predictability when looking at the joint tests in Table 13. Hence, in the two Scandinavian countries the dividend-price ratio does predict both short- and long-horizon dividend growth, also after the second world war. In the first sub-sample 1-year dividend growth is strongly predictable in both countries.

Similar to the case of returns, Chen (2008) argues that there is a 'tale of two periods' when it comes to dividend growth predictability in the US. He finds that the predictability is present prior to the second world war, but disappears in the post war years. Using S&P

[8] Using *excess* returns, Chen (2008) also finds significant long-horizon predictability in the post war period, but still no significant predictability in the pre war period.

data we find that this is only the case for horizons up to 5 years. Again, the difference between the data used by Chen (2008) and ours is that we use real instead of nominal variables, and as is evident from the results in Tables 11 and 13, this has a significant impact on the conclusions for long horizons. Using real data we actually also find that dividend growth becomes predictable in the US in the post war sub-sample on 15 and 20 year horizons, but with the 'wrong' sign, like in the UK. Finally, consistent with the full sample period, dividend growth is not predictable in the US using CRSP data. This holds for both sub-periods and on both short and long horizons and can, as mentioned previously and pointed out by Chen (2008), be assigned to the way the CRSP dividends are constructed.

Summing up the sub-sample results, in the UK the results regarding both return and especially dividend growth predictability are very different across the two sample periods, with dividend growth being predictable in both sub-periods but with different signs. For Denmark and Sweden the results found in the full sample period are also found in the post war sample, i.e. no return predictability, but dividend growth predictability. For the US using S&P data returns are predictable on both short and long horizons in both sub-samples, while dividend growth is predictable on short horizons with the 'correct' negative sign in the first sub-period and on long horizons with the 'wrong' positive sign in the second sub-period.

3.4 Further robustness analysis

The results presented in the previous sections are very robust and do not in any significant way depend on the assumptions/choices made in the empirical analysis. In this section we comment on these assumptions/choices. First, throughout the simulations we report p-values for the coefficients. We have also calculated p-values for the t-statistics using both Newey-West and Hodrick standard errors and find that these result in the same qualitative conclusions. This holds on both short and long horizons.[9] Second, when simulating data for the joint hypothesis testing we draw the errors in the restricted VAR system (3)-(5) as random normals using the estimated covariance matrix, cf. section 3.1.1. We have also tried to bootstrap the errors from the empirical distribution, but this does not change the results in any noticable way. Third, in the sub-sample analysis we examine the period from the start of the samples up to 1949, and the period 1950-2008. These sub-periods are slightly different than those examined by Chen (2008); he uses the end of the second world war as break date. However, the results in our sub-sample analysis are not sensitive to the exact choice of cut-off point between the two sample periods. We get similar results when using e.g. the year 1945 as the break date.

Fourth, throughout the empirical analysis we have not accounted for the fact that the dividend-price ratio autocorrelation coefficient ϕ is estimated with a bias. When performing the small-sample tests based on simulated data we automatically account for any

[9] Cochrane (2008) reports p-values for both coefficients and t-statistics, and also finds that these give the same qualitative conclusions.

possible bias in the estimated forecasting coefficients, b_r and b_d, but the simulated data is based on a downward biased autocorrelation coefficient $\widehat{\phi}$ for the dividend-price ratio. However, adjusting $\widehat{\phi}$ for the bias quantified in the simulations, which is approximately equal to the Kendall (1954) bias for a first-order autocorrelation coefficient, leaves the qualitative conclusions more or less unchanged. The only exception is for the US using CRSP data, where the evidence of return predictability is weakened when accouting for bias in $\widehat{\phi}$. This is in line with Cochrane (2008), who also uses CRSP data and shows that the evidence of return predictability is weakened when the autocorrelation coefficient increases.

Finally, in Tables 5, 6, and 7 we also report results based on *weighted* returns and dividend growth as dictated by (2). Unweighted returns are used in the majority of papers analyzing return predictability, and as Table 5 shows the results are in most cases insensitive to the choice between unweighted and weighted returns, although for the US using S&P data and Hodrick standard errors, the statistical significance of long-horizon return predictability is somewhat weakened when returns are weighted. According to Table 6 the effect of using weighted dividend growth is also only of minor importance. These conclusions regarding the minor effect of using weighted returns and dividend growth also hold in the joint hypothesis tests and the sub-sample analysis. The overall conclusions are the same, and hence for the sake of brevity we do not report the results here.

3.5 Explaining the cross-country differences

We have documented large cross-country differences in the dividend-price ratios ability to predict future returns and dividend growth. On the one hand, the UK is in some ways similar to the US in that it is a 'tale of two periods' with quite different behavior in the post war period compared to the earlier period. On the other hand, the two Scandinavian countries, Denmark and Sweden, stand out as having very different predictability patterns compared to the US and UK: in Scandinavia returns are largely unpredictable while dividend growth is strongly predictable by the dividend-price ratio, and this holds for both the full sample periods and the shorter post war period.

It is obviously of interest to examine in more detail the possible reasons for these cross-country differences. Taken at face value the results imply that in Scandinavian stock markets dividend-price ratio variation reflects changing forecasts of future long-term cashflows discounted by a constant discount rate, i.e. expected returns are constant, while in post war US and UK expected returns vary over time and movements in the dividend-price ratio reflects this variation with changing forecasts of future cashflows playing a minor role.

Why is dividend growth so much more predictable in Denmark and Sweden compared to the US and the UK? There is some evidence that the dividend policy of European companies differs from the dividend policy of US companies. First, in the US the fraction of industrial firms paying cash dividends has dropped from over 80% in the 1950s to 21% in 1999, c.f. Fama and French (2001). In Europe this drop is not nearly as dramatic; in most countries the fraction of dividend paying firms was 60% or higher in 2005. Interestingly, the UK stands out as an exception: 92% of listed companies in the UK payed cash dividends in 1989, and this fraction dropped to 42% in 2005, c.f. von Eije and Megginson (2008). Second, in the US share repurchases have been an important part of payout policy since 1982, while this behavior first played an important role in European firms in the mid or late 1990s, c.f. von Eije and Megginson (2008). According to Hedensted and Raaballe (2009) and de Ridder (2006), there were essentially no share repurchases in Denmark and Sweden until 1999 and 2000, respectively.

Chen et al. (2008) show that adding repurchases to dividends does not lead to predictability of 1-year nominal dividend growth in the post war US period. Thus, we should not expect the difference in repurchases to explain the differences in dividend growth predictability between the US and the Scandinavian countries. Chen et al. argue that dividend smoothing by US firms is the main responsible for the lack of short-horizon dividend growth predictability in the post war period. Under dividend smoothing, firms gradually adjust dividends to long-term earnings. Chen et al. use a number of simple models to document increased smoothing behavior when moving from the pre war period to the post war period. These models build on the seminal study of Lintner (1956) and make use of both dividends and earnings. Unfortunately, we do not have access to publicly available earnings data many years back for our three European countries, so we are not able to carry out Chen et al.'s analysis on our data. However, Chen et al. argue that a major characteristic of increased dividend smoothing is reduced variability of dividend growth. The argument is essentially identical to the argument put forward by Mankiw and Miron (1986) in a different context, namely interest rate smoothing by the monetary authorities; such smoothing will lead to changes in interest rates having low variability and being unpredictable. We should expect the same to happen to dividends when firms are smoothing dividends. From Table 1 we see that in the US (S&P) and UK the standard deviation of 1-year dividend growth decreased dramatically from the early period to the post war period; in the latter period the standard deviations are around 5-6%. By contrast, in Denmark and Sweden the variability of dividend growth remains high in the post war periods; in fact, the standard deviations increase over time to 20% in both countries in the post war period.

These results lend support to the dividend smoothing hypothesis put forward by Chen et al. (2008) and imply that Scandinavian firms have not been engaged in dividend smoothing to nearly the same extent as in the US and the UK, and that this is the explanation for the cross-country differences regarding short-horizon dividend growth predictability.[10]

[10] That European firms' dividend policy differs from that of US firms is further supported by Andres et al. (2009) who show that in contrast to the US, German firms have more flexible dividend policies as they are willing to cut dividends when profitability is *temporarily* down. In Europe, UK is the exception, and Renneboog and Trojanowski (2007) have shown that UK companies smooth dividends to long-term earnings in much the same way as US companies. Thus, it seems that Denmark and Sweden in this respect are more similar to the rest of Europe - except UK -, while the UK is more like the US.

4 Concluding remarks

In this paper, we have explored the dividend-price ratios ability to predict short- and long-horizon stock returns and dividend growth. For the US it has been considered a 'stylized fact' that stock returns are predictable by the dividend-price ratio while dividend growth is not, c.f. e.g. Cochrane (2008). However, Chen (2008) notes that the results for returns are sensitive depending on whether one uses nominal, real, or excess returns, and he challenges the 'stylized fact' by showing that nominal stock returns are largely unpredictable at all times and at all horizons (except at the 1-year horizon in the post war period), excess returns are unpredictable at short horizons at all times but predictable at long horizons in the post World War II period, and nominal dividend growth is significantly predictable at both short and long horizons in the 'right' direction in the period up to 1945 but completely unpredictable in the period thereafter.

In the present paper we have confirmed that predictability results for returns are sensitive to the use of nominal, real, or excess returns, and we have shown that Chen's results for dividend growth predictability are also crucially dependent on his use of nominal dividends. We document that *real* US stock returns are significantly predictable not only in the post war period but also in the pre war period, and that long-horizon *real* dividend growth in the US is unpredictable in the pre war period but significantly predictable in the 'wrong' direction in the post war period. These results are directly opposite to those reported by Chen using nominal variables.

We have also investigated return and dividend growth predictability on long-term data from three European countries: UK, Sweden, and Denmark. For the UK the results are more or less identical to those for the US. For the two Scandinavian countries real stock returns are unpredictable from the dividend-price ratio while real dividend growth is strongly predictable in the 'right' direction. This holds for both short and long horizons and across sub-periods. Thus, there are large cross-country differences in the dividend-price ratios ability to predict future returns and dividend growth.

The statistically significant predictability patterns we have discovered are also *economically* significant. In those cases where we find statistically significant long-horizon predictability, the R^2 values are very high (often close to 50%) and the dividend-price ratio coefficients are numerically large. This also holds for the unusual cases where we find statistically significant dividend growth predictability in the 'wrong' direction. For example, in the post war US (S&P) data the dividend-price ratio coefficient in the regression for 15-year dividend growth is 0.455 and the R^2 is 34%, see Table 11.

Regarding the large cross-country differences in dividend growth predictability, the reason for these differences is not clear, but evidence from other studies examining payout policy suggests that the most plausible explanation is that firms in the respective countries have very different payout policies, c.f. section 3.5. In the US and the UK firms to a large extent follow a dividend smoothing policy which, *ceteris paribus*, reduces dividend growth predictability. In the Scandinavian countries the variability of 1-year dividend growth is very high indicating much less dividend smoothing. A puzzle remains, however: Why does an increase (decrease) in the dividend-price ratio predict an increase (decrease) in long-horizon real dividend growth in the US and the UK in the post war period? It is not clear how to interpret this in light of the dividend smoothing hypothesis, and in any case it runs counter to the implications of standard asset pricing theory. Recent studies (e.g. Menzly et al., 2004; Ang and Liu, 2007; and Ang and Bekaert, 2007) construct theoretical models that can imply a positive dividend-price ratio coefficient in linear dividend growth regressions. However, it is not clear how these models can account for our finding that only long-horizon - and not short-horizon - dividend growth is linearly predictable in the 'wrong' direction. We leave this as an interesting topic for future research.

5 References

Andres, C., Betzer, A., Goergen, M. and Renneboog, L. (2009). The dividend policy of German firms. A panel data analysis of partial adjustment models. Journal of Empirical Finance 16, 175-187.

Ang, A. (2002). Characterizing the ability of dividend yields to predict future dividends in log-linear present value models. Working paper, Columbia University.

Ang, A. and Bekaert, G. (2007). Stock return predictability: Is it there? Review of Financial Studies 20(3), 651-707.

Ang, A. and Liu, J. (2007). Risk, return, and dividends. Journal of Financial Economics 85(1), 1-38.

Barclays Capital (2009). The Equity Gilt Study 2009. Barclays Capital, London.

Campbell, J.Y. (2003). Consumption-based asset pricing. In: Constantinides, G., Stulz, R.M. and Harris, M. (eds.), Handbook of the Economics of Finance, North-Holland.

Campbell, J.Y. and Shiller, R.J. (1988). The dividend-price ratio and expectations of future dividends and discount factors. Review of Financial Studies 1, 195-228.

Chiang, K.C.H. (2008). High dividend yield does predict lower dividend growth: A natural experiment. Working paper, University of Vermont.

Chen, L. (2008). On the reversal of return and dividend growth predictability: A tale of two periods. Journal of Financial Economics (forthcoming)

Chen, L., Da, Z. and Priestley, R. (2008). Dividend smoothing and predictability. Unpublished working paper, Olin School of Business, Washington University in St. Louis.

Cochrane, J.H. (2001). Asset Pricing. Princeton University Press, Princeton.

Cochrane, J.H. (2008). The dog that did not bark. A defense of return predictability. Review of Financial Studies 21(4), 1533-1575.

de Ridder, A.D. (2006). Share repurchases and firm behavior. Unpublished working paper, The Royal Institute of Technology in Stockholm.

Dimson, E., Marsh, P. and Staunton, M. (2002). Triumph of the Optimists. 101 years of global investment returns. Princeton University Press, New Jersey.

Engsted, T. and Tanggard C. (2001). The Danish stock and bond markets: comovement, return predictability and variance decomposition. Journal of Empirical Finance 8, 243-271.

Fama, E.F. and French, K.R. (2001). Disappearing dividends: Changing firm characteristics or lower propensity to pay? Journal of Financial Economics 60, 3-43.

Frennberg, P. and Hansson, B. (1992). Computation of a monthly index for Swedish stock returns 1919-1989. Scandinavian Economic History Review 40, 3-27.

Hedensted, J.S. and Raaballe, J. (2009). Characteristics of dividend payers and generous dividend payers. Unpublished working paper, University of Aarhus.

Hodrick, R.J. (1992). Dividend yields and expected stock returns: Alternative procedures for inference and measurement. Review of Financial Studies 5, 357-386.

Kendall, M.G. (1954). Note on bias in the estimation of autocorrelation. Biometrica 41, 403-404.

Lettau, M. and Ludvigson, S.C. (2005). Expected returns and expected dividend growth. Journal of Financial Economics 76, 583-626.

Lintner, J. (1956). Distribution of incomes of corporations among dividends, retained earnings and taxes. American Economic Review 46, 97-113.

Lund, J. and Engsted, T. (1996). GMM and present value tests of the C-CAPM: evidence from the Danish, German, Swedish and UK stock markets. Journal of International Money and Finance 15(4), 497-521.

Mankiw, N.G. and Miron, J. (1986). The changing behavior of the term structure of interest rates. Quarterly Journal of Economics 51, 211-228.

Menzly, L., Santos, T., and Veronesi, P. (2004). Understanding predictability. Journal of Political Economy 112(1), 1-47.

Newey, W.K. and West, K.D. (1987). A simple positive semi-definite, heteroscedasticity and autocorrelation consistent coveraince matrix. Econometrica 55, 703-708.

Paye, B.S. and Timmermann, A. (2006). Instability of return prediction models. Journal of Empirical Finance 13, 274-315.

Renneboog, L. and Trojanowski, G. (2007). Control structures and payout policy. Managerial Finance 33, 43-64.

von Eije, H. and Megginson, W.L. (2008). Dividends and share repurchases in the European union. Journal of Financial Economics 89, 347-374.

6 Tables and figures

Variable	Start sample −2008			Start sample −1949			1950 − 2008		
	Mean	SD	$\phi(1)$	Mean	SD	$\phi(1)$	Mean	SD	$\phi(1)$
UK									
R	0.068	0.202	-0.047	0.044	0.150	0.143	0.088	0.237	-0.130
D/D_{-1}	0.011	0.156	-0.128	0.005	0.220	-0.189	0.016	0.065	0.438
D/P	0.045	0.012	0.471	0.045	0.009	0.305	0.045	0.015	0.525
Sweden									
R	0.084	0.219	0.115	0.048	0.168	0.390	0.104	0.240	0.024
D/D_{-1}	0.037	0.184	0.246	-0.004	0.142	0.166	0.059	0.200	0.241
D/P	0.040	0.013	0.829	0.051	0.008	0.610	0.034	0.010	0.751
Denmark									
R	0.067	0.215	-0.072	0.036	0.125	-0.031	0.081	0.247	-0.093
D/D_{-1}	0.008	0.187	-0.083	-0.014	0.167	0.280	0.018	0.196	-0.233
D/P	0.039	0.016	0.833	0.046	0.013	0.624	0.036	0.016	0.879
US (S&P)									
R	0.079	0.179	0.036	0.079	0.187	0.011	0.079	0.168	0.083
D/D_{-1}	0.020	0.117	0.128	0.022	0.149	0.089	0.019	0.049	0.469
D/P	0.045	0.016	0.781	0.053	0.014	0.521	0.034	0.013	0.859
US (CRSP)									
R	0.082	0.205	0.019	0.081	0.260	0.076	0.082	0.181	-0.032
D/D_{-1}	0.020	0.143	-0.127	0.021	0.171	0.012	0.020	0.132	-0.214
D/P	0.040	0.015	0.894	0.053	0.011	0.553	0.034	0.013	0.884

Notes: The sample periods are 1900-2008 for the UK, 1919-2008 for Sweden, 1922-2008 for Denmark, 1871-2008 for the US using S&P data, and 1926-2008 for the US using CRSP data. SD denotes the standard deviation and $\phi(1)$ denotes the first-order autocorrelation coefficient.

Table 1. Descriptive statistics.

	Dependent variable	$\widehat{b}_r,\widehat{b}_d,\widehat{\phi}$	t	R^2 (%)	Cross-corr. of residuals r	Δd	$d-p$
UK							
	r	0.305	4.19	17.22	0.179	0.195	-0.722
	Δd	-0.157	-2.21	7.42		0.148	0.539
	$d-p$	0.559	4.91	31.84			0.218
Sweden							
	r	-0.003	-0.05	0.00	0.207	0.416	-0.742
	Δd	-0.207	-4.20	21.36		0.146	0.301
	$d-p$	0.824	14.45	68.70			0.204
Denmark							
	r	0.031	0.57	0.56	0.195	0.380	-0.611
	Δd	-0.102	-1.73	6.81		0.179	0.500
	$d-p$	0.895	15.41	79.52			0.215
US (S&P)							
	r	0.070	1.95	2.79	0.171	0.131	-0.820
	Δd	-0.084	-2.90	8.95		0.111	0.459
	$d-p$	0.877	20.52	76.87			0.200
US (CRSP)							
	r	0.109	2.20	5.25	0.199	0.680	-0.704
	Δd	0.016	0.40	0.25		0.141	0.042
	$d-p$	0.937	22.11	87.53			0.151

Notes: For each country we estimate the forecasting regressions $r_{t+1} = a_r + b_r\,(d_t - p_t) + \varepsilon^r_{t+1}$, $\Delta d_{t+1} = a_d + b_d\,(d_t - p_t) + \varepsilon^d_{t+1}$, and $d_{t+1} - p_{t+1} = a_{dp} + \phi\,(d_t - p_t) + \varepsilon^{dp}_{t+1}$. The sample periods are 1900-2008 for the UK, 1919-2008 for Sweden, 1922-2008 for Denmark, 1871-2008 for the US using S&P data, and 1926-2008 for the US using CRSP data. The t statistics are calculated using Newey-West adjusted standard errors using zero lags. The numbers on the diagonal in the cross-correlation matrices of residuals are standard deviations of the residuals.

Table 2. Restricted VAR(1) estimates.

	ρ	$H_0 : b_r = 0$ b_r	b_d	ϕ	$H_0 : b_d = 0$ b_r	b_d	ϕ
UK	0.958	0.000	-0.464	0.559	0.464	0.000	0.559
Sweden	0.969	0.000	-0.206	0.824	0.206	0.000	0.824
Denmark	0.969	0.000	-0.136	0.895	0.136	0.000	0.895
US (S&P)	0.970	0.000	-0.158	0.877	0.158	0.000	0.877
US (CRSP)	0.969	0.000	-0.096	0.937	0.096	0.000	0.937

Notes: In both null hypothesis, ϕ is set equal to the estimated value, and b_r and b_d are calculated using the relation $b_r = 1 - \rho\phi + b_d$ assuming the other one is equal to zero. ρ is calculated as $1/\left(1 + e^{E[d-p]}\right)$.

Table 3. Null hypotheses in the joint tests.

Panel A. H_0 : No return predictability		
	$P\left(b_r > \widehat{b}_r\right)$	$P\left(b_d > \widehat{b}_d\right)$
UK	0.01	0.00
Sweden	66.60	44.99
Denmark	41.27	12.42
US (S&P)	11.40	0.03
US (CRSP)	18.27	1.16
Panel B. H_0 : No dividend growth predictability		
	$P\left(b_r < \widehat{b}_r\right)$	$P\left(b_d < \widehat{b}_d\right)$
UK	0.28	0.77
Sweden	0.00	0.05
Denmark	0.09	6.34
US (S&P)	0.00	0.54
US (CRSP)	34.69	65.35

Notes: Each column gives the simulated probability (%) based on 10,000 simulations that the coefficients are either greater or smaller than (depending on the null hypothesis) their sample values.

Table 4. Simulated p-values for joint tests on short-run predictability.

	k	Unweighted $\widehat{b}_{r,k}$	t_{NW}	t_H	R^2 (%)	Weighted $\widehat{b}_{r,k}$	t_{NW}	t_H	R^2 (%)
UK									
	1	0.305	4.19	2.66	17.22	0.305	4.19	2.66	17.22
	5	0.857	5.35	3.30	32.40	0.808	5.59	3.11	33.94
	10	1.015	3.58	2.58	21.66	0.951	4.14	2.42	27.22
	15	1.140	3.28	2.57	17.95	1.049	3.94	2.37	25.78
	20	0.996	2.26	2.10	14.77	0.981	3.14	2.07	26.06
Sweden									
	1	-0.003	-0.05	-0.05	0.00	-0.003	-0.05	-0.05	0.00
	5	-0.027	-0.14	-0.09	0.06	-0.022	-0.12	-0.07	0.04
	10	-0.277	-1.65	-0.50	4.44	-0.222	-1.54	-0.40	3.85
	15	-0.384	-1.47	-0.51	4.63	-0.277	-1.33	-0.37	3.80
	20	-0.423	-1.40	-0.47	3.44	-0.261	-1.03	-0.29	2.47
Denmark									
	1	0.031	0.57	0.56	0.56	0.031	0.57	0.56	0.55
	5	-0.067	-0.49	-0.29	0.75	-0.059	-0.46	-0.25	0.67
	10	-0.263	-1.21	-0.58	6.24	-0.214	-1.10	-0.47	5.60
	15	-0.440	-1.62	-0.70	7.92	-0.290	-1.18	-0.46	5.49
	20	-0.063	-0.16	-0.09	0.08	0.024	0.08	0.03	0.02
US (S&P)									
	1	0.070	1.95	1.85	2.79	0.070	1.95	1.85	2.79
	5	0.337	3.19	1.87	13.64	0.310	3.14	1.72	13.47
	10	0.598	2.74	1.79	17.43	0.504	2.65	1.51	17.44
	15	1.053	3.66	2.35	29.37	0.819	3.52	1.83	29.46
	20	1.167	4.46	2.27	32.35	0.934	5.11	1.82	39.05
US (CRSP)									
	1	0.109	2.20	2.00	5.25	0.109	2.20	2.00	5.25
	5	0.309	2.52	1.24	11.24	0.292	2.55	1.18	11.54
	10	0.775	2.58	1.72	27.28	0.660	2.44	1.46	26.29
	15	1.498	3.83	2.67	43.88	1.202	3.56	2.14	43.76
	20	1.674	7.62	2.86	45.10	1.398	7.42	2.39	54.43

Notes: For each country we estimate the forecasting regression $r_{t,t+k} = a_{r,k} + b_{r,k}\,(d_t - p_t) + \varepsilon^r_{t+k}$ for $k = 1, 5, 10, 15$, and 20. Unweighted and weighted returns are calculated as $r_{t,t+k} = \sum_{j=1}^{k} r_{t+j}$, and $r_{t,t+k} = \sum_{j=1}^{k} \rho^{j-1} r_{t+j}$, respectively. t_{NW} denotes the t-statistic calculated using Newey-West adjusted standard errors with $k-1$ lags, and t_H denotes the t-statistic calculated using Hodrick standard errors. The sample periods are 1900-2008 for the UK, 1919-2008 for Sweden, 1922-2008 for Denmark, 1871-2008 for the US using S&P data, and 1926-2008 for the US using CRSP data.

Table 5. Multiperiod regressions for returns.

	k	Unweighted $\widehat{b}_{d,k}$	t_{NW}	t_H	R^2 (%)	Weighted $\widehat{b}_{d,k}$	t_{NW}	t_H	R^2 (%)
UK									
	1	-0.157	-2.21	-1.93	7.42	-0.157	-2.21	-1.93	7.42
	5	0.010	0.08	0.07	0.01	-0.013	-0.11	-0.10	0.02
	10	0.060	0.22	0.31	0.13	0.028	0.12	0.15	0.04
	15	0.040	0.12	0.21	0.04	0.006	0.02	0.03	0.00
	20	-0.196	-0.64	-1.24	1.23	-0.108	-0.43	-0.68	0.57
Sweden									
	1	-0.207	-4.20	-3.24	21.36	-0.207	-4.20	-3.24	21.36
	5	-0.497	-2.80	-1.99	23.89	-0.475	-2.85	-1.90	25.25
	10	-0.911	-5.80	-1.70	49.38	-0.799	-5.79	-1.50	52.21
	15	-1.282	-5.71	-1.79	44.87	-1.018	-5.93	-1.42	47.36
	20	-1.484	-3.92	-1.80	36.60	-1.077	-4.07	-1.31	39.67
Denmark									
	1	-0.102	-1.73	-1.60	6.81	-0.102	-1.73	-1.60	6.81
	5	-0.528	-5.02	-1.82	38.09	-0.498	-5.05	-1.72	38.98
	10	-0.901	-5.66	-1.62	52.63	-0.786	-5.87	-1.42	54.53
	15	-1.256	-6.64	-1.72	54.72	-0.997	-7.26	-1.36	57.97
	20	-1.229	-4.17	-1.56	31.83	-0.951	-5.20	-1.21	39.11
US (S&P)									
	1	-0.084	-2.90	-2.83	8.95	-0.084	-2.90	-2.83	8.95
	5	-0.128	-1.69	-1.48	4.14	-0.126	-1.76	-1.46	4.72
	10	-0.017	-0.16	-0.12	0.04	-0.046	-0.52	-0.33	0.43
	15	-0.029	-0.18	-0.15	0.08	-0.065	-0.49	-0.34	0.61
	20	0.100	0.71	0.39	0.95	0.001	0.01	0.00	0.00
US (CRSP)									
	1	0.016	0.40	0.40	0.25	0.016	0.40	0.40	0.25
	5	-0.047	-0.46	-0.23	0.63	-0.043	-0.45	-0.21	0.60
	10	0.154	1.18	0.45	5.05	0.134	1.26	0.39	4.97
	15	0.383	2.41	0.95	16.52	0.307	2.51	0.76	15.44
	20	0.362	2.61	0.85	10.31	0.316	3.14	0.74	12.84

Notes: For each country we estimate the forecasting regression $\Delta d_{t,t+k} = a_{d,k} + b_{d,k}(d_t - p_t) + \varepsilon^d_{t+k}$ for $k = 1, 5, 10, 15$, and 20. Unweighted and weighted dividend growth are calculated as $\Delta d_{t,t+k} = \sum_{j=1}^{k} \Delta d_{t+j}$, and $\Delta d_{t,t+k} = \sum_{j=1}^{k} \rho^{j-1} \Delta d_{t+j}$, respectively. t_{NW} denotes the t-statistic calculated using Newey-West adjusted standard errors with $k-1$ lags, and t_H denotes the t-statistic calculated using Hodrick standard errors. The sample periods are 1900-2008 for the UK, 1919-2008 for Sweden, 1922-2008 for Denmark, 1871-2008 for the US using S&P data, and 1926-2008 for the US using CRSP data.

Table 6. Multiperiod regressions for dividend growth.

	k	Unweighted $\widehat{b}_{r,k}$	Unweighted $\widehat{b}_{d,k}$	Weighted $\widehat{b}_{r,k}$	Weighted $\widehat{b}_{d,k}$
UK					
	1	0.305	-0.157	0.305	-0.157
	5	0.655	-0.337	0.629	-0.324
	10	0.691	-0.356	0.657	-0.338
	15	0.693	-0.357	0.658	-0.339
	20	0.693	-0.357	0.658	-0.339
	∞	0.693	-0.357	0.658	-0.339
Sweden					
	1	-0.003	-0.207	-0.003	-0.207
	5	-0.011	-0.729	-0.010	-0.688
	10	-0.015	-1.006	-0.014	-0.905
	15	-0.017	-1.110	-0.015	-0.974
	20	-0.017	-1.150	-0.015	-0.995
	∞	-0.018	-1.174	-0.015	-1.005
Denmark					
	1	0.031	-0.102	0.031	-0.102
	5	0.125	-0.413	0.117	-0.388
	10	0.196	-0.649	0.174	-0.576
	15	0.237	-0.785	0.201	-0.666
	20	0.261	-0.863	0.215	-0.710
	∞	0.293	-0.968	0.227	-0.750
US (S&P)					
	1	0.070	-0.084	0.070	-0.084
	5	0.273	-0.328	0.255	-0.307
	10	0.414	-0.498	0.363	-0.436
	15	0.487	-0.586	0.408	-0.491
	20	0.525	-0.632	0.427	-0.514
	∞	0.566	-0.681	0.441	-0.531
US (CRSP)					
	1	0.109	0.016	0.109	0.016
	5	0.481	0.072	0.451	0.068
	10	0.829	0.125	0.723	0.109
	15	1.081	0.162	0.888	0.133
	20	1.262	0.190	0.987	0.148
	∞	1.736	0.261	1.139	0.171

Notes: The implied coefficients for unweighted and weighted returns and dividend growth are calculated as $\frac{1-\phi^k}{1-\phi}b_i$, and $\frac{1-\rho^k\phi^k}{1-\rho\phi}b_i$, respectively, for $i = r, d$. For k approaching infinity, the long-run coefficients are calculated as $\frac{1}{1-\phi}b_i$, and $\frac{1}{1-\rho\phi}b_i$, for unweighted and weighted returns and dividend growth, respectively.

Table 7. Implied long-run coefficients from the restricted VAR(1).

	k	Multiperiod regression coefficients $P\left(b_{r,k} > \widehat{b}_{r,k}\right)$	$P\left(b_{d,k} > \widehat{b}_{d,k}\right)$	Implied long-run coefficients $P\left(b_{r,k} > \widehat{b}_{r,k}\right)$	$P\left(b_{d,k} > \widehat{b}_{d,k}\right)$
UK					
	1	0.00	0.00	0.00	0.00
	5	0.02	0.00	0.00	0.00
	10	0.13	0.03	0.00	0.00
	15	0.33	0.38	0.00	0.00
	20	3.16	6.46	0.00	0.00
	∞	-	-	0.00	0.00
Sweden					
	1	66.60	44.99	66.60	44.99
	5	70.55	15.54	66.65	57.67
	10	87.04	54.96	66.67	64.67
	15	88.49	79.16	66.68	66.11
	20	89.16	86.10	66.68	66.72
	∞	-	-	66.70	66.67
Denmark					
	1	41.27	12.42	41.27	12.42
	5	77.35	39.37	39.12	15.48
	10	87.84	58.21	36.47	21.34
	15	91.24	76.93	34.52	27.79
	20	75.09	72.13	33.04	32.55
	∞	-	-	30.76	39.29
US (S&P)					
	1	11.40	0.03	11.40	0.03
	5	8.16	0.00	7.33	0.10
	10	6.49	0.00	3.49	0.35
	15	0.92	0.21	1.88	1.06
	20	1.46	0.33	1.23	1.86
	∞	-	-	0.65	3.29
US (CRSP)					
	1	18.27	1.16	18.27	1.16
	5	35.56	6.65	12.02	0.97
	10	23.39	5.24	5.75	0.81
	15	8.50	5.24	2.37	0.75
	20	10.14	10.41	0.99	0.73
	∞	-	-	0.24	0.58

Notes: Each column gives the simulated probability (%) based on 10,000 simulations that the coefficients are greater than their sample values. Unweighted returns are used.

Table 8. Simulated p-values for joint tests on long-horizon return predictability.

	k	Multiperiod regression coefficients $P\left(b_{r,k} < \widehat{b}_{r,k}\right)$	$P\left(b_{d,k} < \widehat{b}_{d,k}\right)$	Implied long-run coefficients $P\left(b_{r,k} < \widehat{b}_{r,k}\right)$	$P\left(b_{d,k} < \widehat{b}_{d,k}\right)$
UK					
	1	0.28	0.77	0.28	0.77
	5	22.49	60.15	0.04	0.11
	10	52.22	67.58	0.11	0.06
	15	69.41	66.80	0.11	0.06
	20	59.10	44.77	0.11	0.05
	∞	-	-	0.11	0.05
Sweden					
	1	0.00	0.05	0.00	0.05
	5	0.03	1.29	0.00	0.00
	10	0.03	0.75	0.00	0.00
	15	0.15	0.51	0.00	0.00
	20	0.37	0.73	0.00	0.00
	∞	-	-	0.00	0.00
Denmark					
	1	0.09	6.34	0.09	6.34
	5	0.04	2.82	0.08	2.50
	10	0.09	2.38	0.12	0.78
	15	0.18	1.40	0.17	0.33
	20	3.43	4.30	0.21	0.19
	∞	-	-	0.23	0.14
US (S&P)					
	1	0.00	0.54	0.00	0.54
	5	0.19	18.95	0.00	0.08
	10	2.96	57.17	0.00	0.00
	15	44.13	57.57	0.00	0.00
	20	55.82	74.19	0.00	0.00
	∞	-	-	0.00	0.00
US (CRSP)					
	1	34.69	65.35	34.69	65.35
	5	15.14	42.93	39.32	66.36
	10	36.28	67.73	47.85	67.77
	15	74.61	77.96	57.56	68.91
	20	74.25	72.56	65.08	70.09
	∞	-	-	79.01	73.00

Notes: Each column gives the simulated probability (%) based on 10,000 simulations that the coefficients are smaller than their sample values. Unweighted dividend growth is used.

Table 9. Simulated p-values for joint tests on long-horizon dividend growth predictability.

	k	Start sample −1949				1950 − 2008			
		$\widehat{b}_{r,k}$	t_{NW}	t_H	R^2 (%)	$\widehat{b}_{r,k}$	t_{NW}	t_H	R^2 (%)
UK									
	1	0.315	3.06	1.69	21.85	0.305	3.35	2.14	16.09
	5	0.879	2.86	2.86	28.20	0.828	4.97	2.38	36.96
	10	0.302	1.94	0.80	2.23	1.424	9.98	2.69	42.84
	15	0.258	0.73	0.67	1.11	1.728	6.93	2.87	39.93
	20	-0.282	-0.64	-1.02	1.68	1.672	8.19	2.66	38.26
Sweden									
	1	-0.028	-0.21	-0.21	0.07	0.039	0.47	0.46	0.33
	5	-	-	-	-	0.031	0.11	0.08	0.06
	10	-	-	-	-	-0.077	-0.27	-0.11	0.25
	15	-	-	-	-	-0.064	-0.26	-0.07	0.09
	20	-	-	-	-	0.180	0.39	0.16	0.44
Denmark									
	1	0.024	0.31	0.30	0.36	0.045	0.72	0.70	1.07
	5	-	-	-	-	-0.102	-0.70	-0.36	1.74
	10	-	-	-	-	-0.310	-1.50	-0.57	9.32
	15	-	-	-	-	-0.478	-2.07	-0.63	9.31
	20	-	-	-	-	0.172	0.34	0.19	0.46
US (S&P)									
	1	0.094	1.23	1.23	1.65	0.115	2.43	2.11	9.07
	5	0.643	3.94	2.50	20.59	0.452	4.69	1.69	25.82
	10	0.694	2.74	1.86	17.97	0.996	4.05	2.24	31.02
	15	1.023	4.70	1.95	32.95	1.923	5.12	3.63	57.00
	20	1.203	6.39	1.80	44.20	1.998	5.94	3.80	57.99
US (CRSP)									
	1	0.501	2.41	1.94	14.44	0.126	2.43	2.11	8.89
	5	-	-	-	-	0.410	3.98	1.46	22.46
	10	-	-	-	-	0.990	3.41	2.13	38.28
	15	-	-	-	-	1.813	4.74	3.31	55.96
	20	-	-	-	-	1.655	5.61	3.09	44.09

Notes: For each country we estimate the forecasting regression $r_{t,t+k} = a_{r,k} + b_{r,k}(d_t - p_t) + \varepsilon^r_{t+k}$ for $k = 1, 5, 10, 15$, and 20. Unweighted returns are used and calculated as $r_{t,t+k} = \sum_{j=1}^{k} r_{t+j}$. t_{NW} denotes the t-statistic calculated using Newey-West adjusted standard errors with $k-1$ lags, and t_H denotes the t-statistic calculated using Hodrick standard errors. The sample starts in 1900 for the UK, 1919 for Sweden, 1922 for Denmark, 1871 for the US using S&P data, and 1926 for the US using CRSP data.

Table 10. Multiperiod regressions for returns on sub-samples.

	k	Start sample −1949 $\widehat{b}_{d,k}$	t_{NW}	t_H	R^2 (%)	1950 − 2008 $\widehat{b}_{d,k}$	t_{NW}	t_H	R^2 (%)
UK									
	1	-0.476	-3.21	-1.76	22.94	-0.016	-0.51	-0.49	0.58
	5	-0.282	-1.23	-0.66	3.16	0.149	1.47	1.58	5.29
	10	-0.559	-2.26	-1.03	6.88	0.450	3.59	2.81	13.51
	15	-0.808	-2.46	-1.48	10.95	0.639	5.62	3.89	18.10
	20	-1.082	-3.35	-3.48	24.64	0.305	3.17	1.70	5.45
Sweden									
	1	-0.438	-3.62	-2.58	20.60	-0.241	-4.04	-3.18	23.41
	5	-	-	-	-	-0.540	-2.46	-2.07	25.61
	10	-	-	-	-	-0.873	-3.76	-1.49	38.30
	15	-	-	-	-	-1.179	-8.54	-1.46	33.26
	20	-	-	-	-	-1.147	-2.64	-1.28	18.22
Denmark									
	1	-0.281	-2.93	-2.26	21.03	-0.072	-1.12	-1.05	3.91
	5	-	-	-	-	-0.488	-4.86	-1.55	47.53
	10	-	-	-	-	-0.862	-4.65	-1.43	55.15
	15	-	-	-	-	-1.324	-7.01	-1.67	59.52
	20	-	-	-	-	-1.054	-2.28	-1.23	17.85
US (S&P)									
	1	-0.378	-5.68	-3.39	39.00	-0.009	-0.45	-0.46	0.66
	5	-0.397	-3.04	-1.73	11.02	-0.036	-0.53	-0.57	1.31
	10	-0.100	-0.47	-0.36	0.64	0.061	0.49	0.59	1.64
	15	-0.332	-1.62	-0.84	6.03	0.455	2.58	3.93	34.23
	20	0.047	0.23	0.10	0.16	0.395	2.92	3.61	28.71
US (CRSP)									
	1	0.018	0.10	0.10	0.04	0.024	0.50	0.50	0.65
	5	-	-	-	-	-0.049	-0.46	-0.21	1.01
	10	-	-	-	-	0.090	0.67	0.27	2.42
	15	-	-	-	-	0.389	2.28	0.97	22.93
	20	-	-	-	-	0.164	1.11	0.43	3.96

Notes: For each country we estimate the forecasting regression $\Delta d_{t,t+k} = a_{d,k} + b_{d,k}(d_t - p_t) + \varepsilon^d_{t+k}$ for $k = 1, 5, 10, 15$, and 20. Unweighted dividend growth is used and calculated as $\Delta d_{t,t+k} = \sum_{j=1}^{k} \Delta d_{t+j}$. t_{NW} denotes the t-statistic calculated using Newey-West adjusted standard errors with $k-1$ lags, and t_H denotes the t-statistic calculated using Hodrick standard errors. The sample starts in 1900 for the UK, 1919 for Sweden, 1922 for Denmark, 1871 for the US using S&P data, and 1926 for the US using CRSP data.

Table 11. Multiperiod regressions for dividend growth on sub-samples.

	k	Start sample −1949		1950 − 2008	
		$P\left(b_{r,k} > \widehat{b}_{r,k}\right)$	$P\left(b_{d,k} > \widehat{b}_{d,k}\right)$	$P\left(b_{r,k} > \widehat{b}_{r,k}\right)$	$P\left(b_{d,k} > \widehat{b}_{d,k}\right)$
UK					
	1	0.12	0.29	1.47	0.00
	5	0.02	0.18	3.08	0.00
	10	22.95	11.99	0.57	0.02
	15	33.93	41.50	0.73	0.36
	20	86.17	71.07	4.30	10.03
Sweden					
	1	66.26	52.32	47.54	20.29
	5	-	-	65.69	17.52
	10	-	-	76.98	57.14
	15	-	-	79.49	79.20
	20	-	-	72.49	81.73
Denmark					
	1	52.01	23.61	44.27	10.74
	5	-	-	83.15	45.99
	10	-	-	89.75	63.88
	15	-	-	92.05	84.39
	20	-	-	70.53	71.85
US (S&P)					
	1	20.34	2.74	23.73	0.00
	5	1.80	0.56	28.13	0.24
	10	8.87	0.94	13.41	1.36
	15	3.67	16.42	0.68	0.42
	20	3.96	6.68	2.67	4.64
US (CRSP)					
	1	8.50	0.94	23.21	3.00
	5	-	-	35.13	13.61
	10	-	-	22.96	14.00
	15	-	-	8.89	11.83
	20	-	-	17.68	25.03

Notes: Each column gives the simulated probability (%) based on 10,000 simulations that the coefficients are greater than their sample values. Unweighted returns are used. The sample starts in 1900 for the UK, 1919 for Sweden, 1922 for Denmark, 1871 for the US using S&P data, and 1926 for the US using CRSP data.

Table 12. Simulated p-values for joint tests on long-horizon return predictability on sub-samples.

	k	Start sample −1949 $P\left(b_{r,k} < \widehat{b}_{r,k}\right)$	Start sample −1949 $P\left(b_{d,k} < \widehat{b}_{d,k}\right)$	1950 − 2008 $P\left(b_{r,k} < \widehat{b}_{r,k}\right)$	1950 − 2008 $P\left(b_{d,k} < \widehat{b}_{d,k}\right)$
UK					
	1	0.00	0.05	27.22	29.26
	5	44.84	29.63	20.69	91.54
	10	9.79	19.97	88.05	99.23
	15	17.22	13.90	97.29	99.49
	20	6.06	10.11	94.76	90.35
Sweden					
	1	0.56	1.79	0.01	0.06
	5	-	-	0.07	2.36
	10	-	-	0.40	2.06
	15	-	-	1.52	1.50
	20	-	-	7.98	3.48
Denmark					
	1	0.20	9.70	2.91	18.73
	5	-	-	0.32	6.86
	10	-	-	0.39	5.62
	15	-	-	0.77	2.88
	20	-	-	12.22	11.44
US (S&P)					
	1	0.00	0.00	16.10	34.70
	5	2.59	1.98	11.60	35.87
	10	13.55	46.31	41.42	65.36
	15	58.42	23.53	98.54	97.80
	20	76.96	70.31	97.02	94.35
US (CRSP)					
	1	39.45	53.95	36.95	61.01
	5	-	-	25.18	45.96
	10	-	-	50.24	59.27
	15	-	-	82.38	73.90
	20	-	-	71.62	60.87

Notes: Each column gives the simulated probability (%) based on 10,000 simulations that the coefficients are smaller than their sample values. Unweighted dividend growth is used. The sample starts in 1900 for the UK, 1919 for Sweden, 1922 for Denmark, 1871 for the US using S&P data, and 1926 for the US using CRSP data.

Table 13. Simulated p-values for joint tests on long-horizon dividend growth predictability on sub-samples.

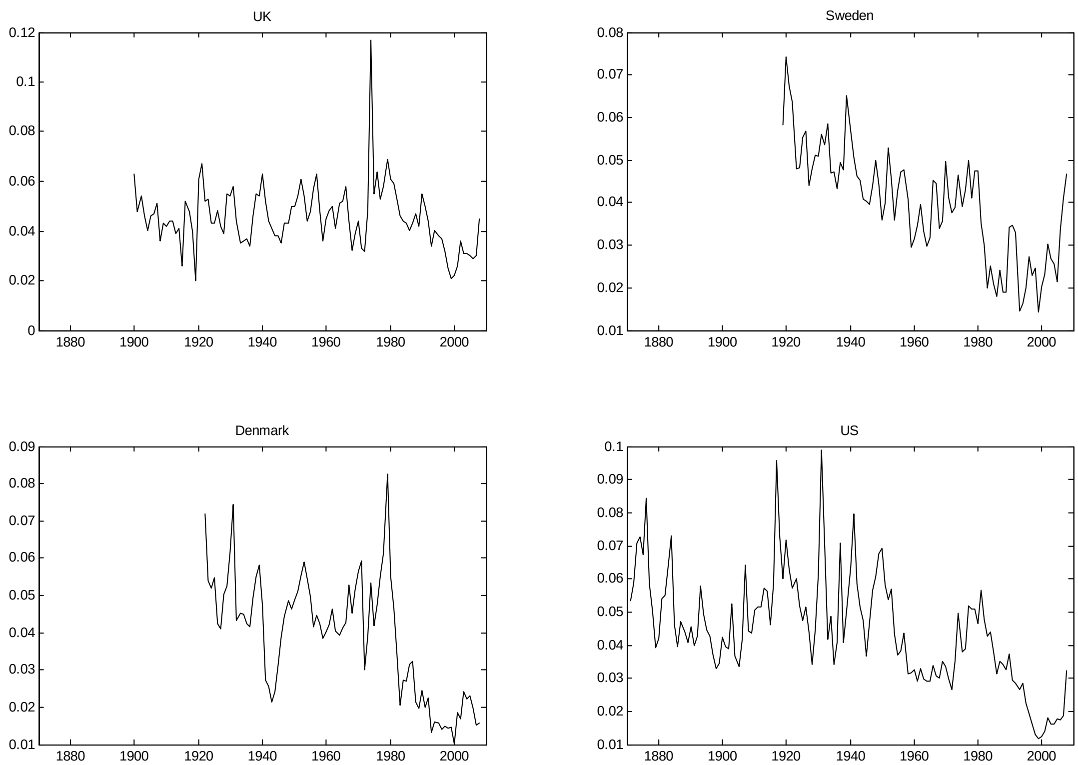
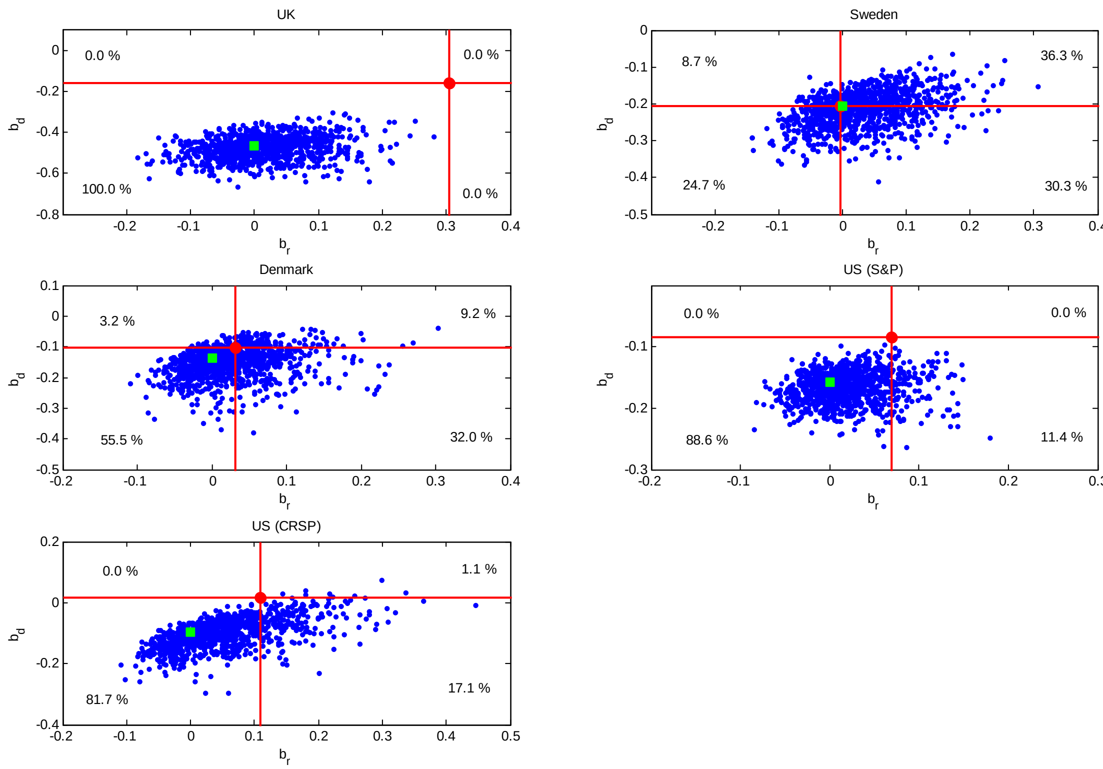
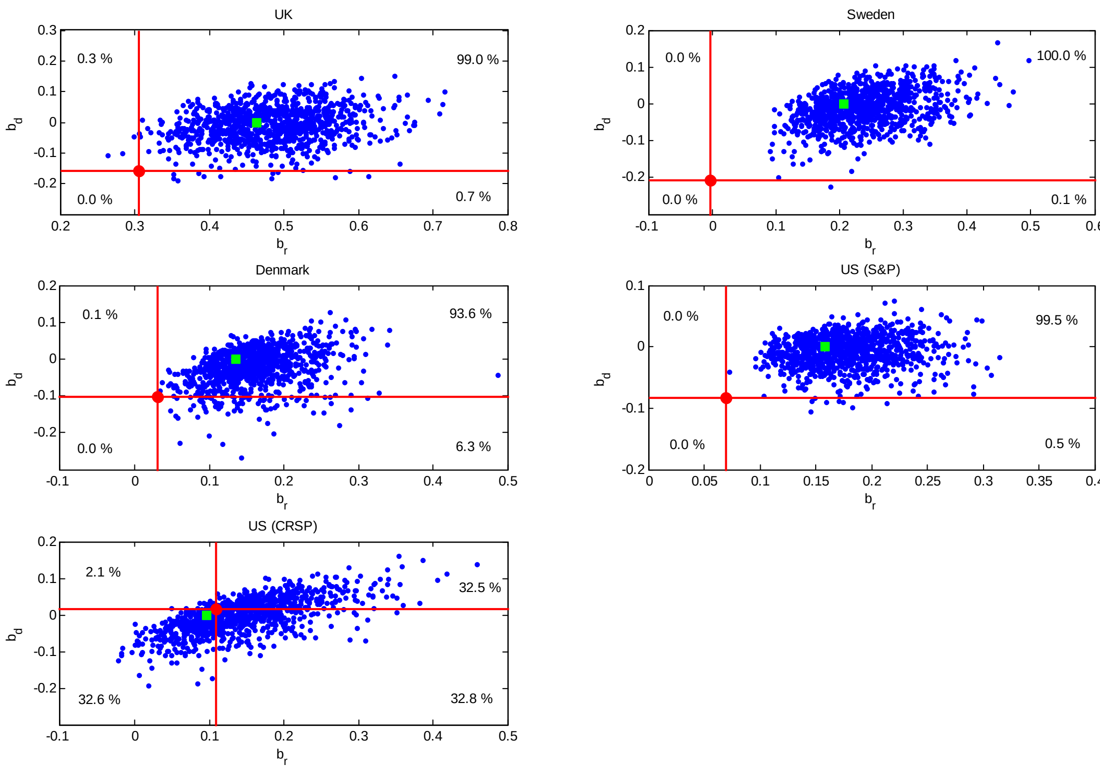


Figure 1. Time-series plot of the dividend-price ratio.



Notes: The lines and large dots give the sample estimates. The square gives the null. 1,000 simulations are plotted for clarity. The number in each quadrant is the fraction of 10,000 simulations that fall within the quadrant.

Figure 2. Joint distribution of the return and dividend growth coefficients under the null hypothesis of no return predictability, $b_r = 0$.



Notes: The lines and large dots give the sample estimates. The square gives the null. 1,000 simulations are plotted for clarity. The number in each quadrant is the fraction of 10,000 simulations that fall within the quadrant.

Figure 3. Joint distribution of the return and dividend growth coefficients under the null hypothesis of no dividend growth predictability, $b_d = 0$.

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