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Cash Flow-Predictability: Still Going Strong

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Abstract

The common perception in the literature is that current dividend yields are uninformative about future dividends, but contain some information about future stock returns. In this paper, we show that this finding reverses when looking at a broad panel of countries outside the U.S.. In particular, we demonstrate that aggregate dividend growth rates are highly predictable by the dividend yield and that dividend predictability is clearly stronger than return predictability in medium-sized and smaller countries that account for the majority of countries in the world. We show that this is true both in the time-series dimension (time variation in dividend yields strongly predicts future dividend growth rates) and in the cross-country dimension (sorting countries into portfolios depending on their lagged dividend yield produces a spread in dividend growth rates of more than 20% p.a.). In an economic assessment of this finding, we show that cash flow predictability is stronger in smaller and medium-sized countries because these countries also have more volatile cash flow growth and higher idiosyncratic return volatility.

JEL-Classification: G12, G15, F31

Keywords: dividend yield, predictability, international stock markets, value, growth, idiosyncratic volatility

1 Introduction

What drives fluctuations in dividend yields? A stylized fact based on aggregate U.S. data is that expected cash flows are more or less constant so that variation in dividend yields is almost exclusively due to variation in expected returns. Cochrane (2008, pp. 1533-1534) states this very clearly (emphasis not added):

> "Finally, the regressions [...] imply that *all* variation in the market price-dividend ratios corresponds to changes in expected excess returns – risk premiums – and *none* corresponds to news about future dividend growth."

This finding implies that stock prices vary due to changes in expected returns and not because of news to expected cash flows.[1] In this paper, we show that a very different conclusion emerges if one looks at international data. Indeed, the main finding of this paper is that dividend yield fluctuations contain a lot of interesting information about expected aggregate dividend growth rates in international stock markets and that dividend predictability is particularly strong in smaller countries and countries with volatile dividend growth rates.

Our starting point is a simple extension of the "dynamic Gordon growth formula" of Campbell and Shiller (1988b). The formula that we drive has both time-series and cross-sectional implications. In the time-series dimension, it shows that a high dividend yield of a country's stock market is driven by expectations about high stock returns in US Dollar (USD), low expectations about future dividend growth in foreign currency, and/or an expected depreciation of the foreign currency relative to the USD. In the cross-sectional dimension, the decomposition illustrates that stock markets of countries that have high dividend yields relative to other countries should provide investors with high returns (in USD), low dividend growth rates in the foreign currencies, and/or a depreciating foreign currency relative to the USD. We investigate both the time-series and cross-sectional implications of this decomposition using international data. We note that the

[1] To be precise, the point in Cochrane (2008) is not that dividend growth rates cannot be predicted at all. The point is that dividend growth rates are unpredictable *by the current-period dividend yield* alone such that dividend yields fluctuate because of changes in expectations of future discount rates only. In the next section, we review the literature that finds predictability of dividend growth rates using other variables than the dividend yield or filtering approaches that use the entire history of dividend growth rates and dividend yields to forecast cash flows and returns.

exchange rate effect is new in relation to the standard Campbell-Shiller decomposition, but arises naturally when analyzing international stock market data.

In the time-series dimension, we analyze which of the three components (returns, dividend growth, exchange rate changes) are predictable by the dividend yield. We use data from 50 markets during the 1973-2009 period and pay special attention to the question of whether differences in stock market sizes affect the conclusions we draw. To do so, we form two aggregate global stock portfolios, an equal-weighted and a value-weighted average of the 50 countries in our sample, and run predictive regressions of these portfolios' future dividend growth rates (and returns and exchange rate changes) on current-period dividend yields.

We find that dividend growth is highly predictable in the equal-weighted portfolio but not predictable at all in the value-weighted portfolio. Likewise, when we calculate long-run effects in the manner proposed by Cochrane (2008), we find that a large fraction of dividend yield-variation is due to expected movements in long-run dividend growth rates when analyzing the equal-weighted portfolio, but that long-run dividend growth accounts for only a small fraction of dividend yield variation when analyzing the value-weighted portfolio. Finally, we simulate the distribution of predictive coefficients under the joint null of no return *and* dividend growth predictability, similar to Cochrane (2008) and Chen (2009). Despite significant return predictability in the value-weighted portfolio, this joint null cannot be rejected due to a lack of dividend predictability. Contrary to this, the presence of dividend growth predictability in the equal-weighted portfolio gives strong statistical evidence against the joint null. Since the equal-weighted portfolio puts more weight on smaller markets than the value-weighted portfolio by construction, the observed dividend growth predictability in the equal-weighted portfolio arises because dividend growth is significantly more predictable in medium-sized and smaller countries relative to large countries. In fact, we find results very similar to those for the U.S. market (i.e. that dividend growth is not predictable), when we study our value-weighted portfolio that is dominated by the U.S. and other large markets.[2]

We also investigate the cross-sectional dimension of the extended Campbell Shiller decomposition. In particular, we investigate whether countries with relatively high dividend yields also

[2]We focus on dividend growth predictability in the paper, but we also present the results on the predictability of returns and exchange rate changes. We find that returns are more predictable in the value-weighted portfolio, but the differences to the equal-weighted portfolio are not as pronounced as they are for dividend growth predictability. We find exchange rate changes to be unpredictable by the dividend yield.

yield relatively higher returns, lower dividend growth rates, and/or higher appreciation rates of USD against the foreign currencies. To examine the cross-sectional economic magnitudes of dividend growth and return predictability, we sort countries into portfolios based on their (lagged) dividend yields.[3] Our procedure works as follows: At the end of the first quarter in each year, we sort countries into five portfolios based upon their relative dividend yields (the 20% of the countries with low dividend yields are allocated to portfolio 1, the next 20% to portfolio 2, and so on, such that the 20% of countries with the highest dividend yields are in portfolio 5). This sorting allows us to obtain a stable and balanced panel of returns, which isolates the effect of predictability by the dividend yield. In addition, it provides us with a measure of the economic significance of our results.

We document large economic effects in this cross-country dimension. For instance, we find that the average dividend growth rate of countries with the lowest dividend yields is an impressive 22.30% p.a., whereas high dividend yield countries have experienced average aggregate dividend growth rates of only 1.75% p.a.. This difference of 20.55 percentage points per annum is highly significant, both economically and statistically.[4] We document that the observed dividend growth predictability truly stems from the behavior of dividend growth in medium-sized and smaller countries. We establish this result by double-sorting countries into portfolios, first, on the size of a country (the relative market capitalization) and, afterwards, on the dividend yield. The double-sorting shows that dividend growth predictability is strong in small countries (with an annualized difference in dividend growth rates of 28% between growth and value countries), still significant in medium-sized markets (difference of 10% p.a.), but basically non-existent in larger countries (2% p.a.). This finding is robust to controlling for structural differences in unconditional dividend yields across countries.

Finally, we turn towards the question of why dividend growth is more predictable in medium-sized and small countries. We find that cash flow predictability is driven by higher return and dividend growth volatility in these countries. For instance, in the time series dimension, dividend

[3] Our approach is thus very similar to the international country sorts by Lustig and Verdelhan (2007) and Lustig, Roussanov, and Verdelhan (2009) who sort currencies of different countries against the USD into portfolios based on their (lagged) interest rate differential vis-a-vis the U.S.

[4] Again, we are mainly interested in cash flow predictability, but also report results for stock returns and spot rate changes. The difference in average returns between stock markets in high and low dividend yield countries (in portfolios 5 and 1) is about 8% per year and highly significant both economically and statistically. We also find a statistically significant differences of about 2.5% – 4.7% p.a. between spot exchange rate changes in low and high dividend yield countries (portfolios 1 and 5). This difference is in line with the prediction from our international Campbell-Shiller approximation but hardly significant in economic terms.

growth volatility of the equal-weighted portfolio is almost twice as large as in the value-weighted portfolio. In the cross-sectional dimension, we double-sort countries into portfolios based on a proxy of "country volatility" and on the dividend yield. We use three proxies for the volatility of a country: raw dividend growth volatility, idiosyncratic dividend growth volatility, and idiosyncratic return volatility over the past four quarters. Irrespective of the specific volatility proxy employed, we find that dividend growth rates are highly predictable in countries with high recent volatility but not in countries with low recent volatility. The average annual difference between dividend growth rates of a portfolio long in value countries (high dividend yield) and short in growth countries (low dividend yield) is approximately $13-18$ percentage points (depending on which of the volatility measures we use) in the countries with high volatility but basically zero in the countries with low volatility. Thus, our overall conclusion is that we find a lot of dividend growth predictability in small and medium-sized markets outside the U.S. since dividend growth and return volatility is also higher in these countries.

Our results are robust. For instance, we show that the results outlined above hold for both nominal and real dividend growth. We further demonstrate that the same results hold when we sort on earnings yields instead of dividend yields and predict earnings growth instead of dividend growth. Our results also hold in subsamples and when we exclude newly emerging markets for which we only have few observations. Finally, we show that the large differences between the dividend yield-based portfolios are not due to large unconditional, time-invariant structural differences between countries that may pin down the levels of countries' dividend yields.

The structure of the remaining part of the paper is as follows: In the next section, we review the related literature. Afterwards, in Section 3, we present the extension of the Campbell-Shiller one-currency return decomposition to an international setting. The data we use are described in Section 4. We discuss results from regressions of returns, dividend growth rates, and exchange rate changes on dividend yields in Section 5. In Section 6, we present results from sorting countries into different portfolios according to the size of their dividend yields. In Section 7, we investigate the relation between volatility (of returns and dividends) and dividend growth predictability. Section 8 contains robustness results and a final section concludes. An appendix available on our webpages contains the additional results and all tables that we refer to in the robustness section.

2 Related literature

It is commonly viewed as a stylized empirical fact that variations in dividend yields on the CRSP value-weighted market portfolio are exclusively due to variation in discount rates, as verified in a long list of papers including Campbell and Shiller (1988a,b), Campbell (1991), Cochrane (1991, 2008), Campbell and Ammer (1993), Lettau and Ludvigson (2005), Ang and Bekaert (2007), and Chen (2009).[5]

The fact that U.S. aggregate dividends cannot be predicted by the dividend yield does not mean that aggregate U.S. dividend growth rates cannot be predicted at all, however.[6] For instance, Lettau and Ludvigson (2005) find that dividend growth rates are predictable by an estimated consumption-dividends-labor income ratio (denoted $\widehat{cdy}$), but not by the dividend yield itself. Likewise, the general finding of no U.S. dividend growth predictability does not mean that dividend growth rates never were predictable: Chen (2009) convincingly demonstrates that aggregate U.S. dividend growth rates were predictable by the dividend yield in early periods of the industrialization. Since WWII, however, dividend growth rates are not predictable by the dividend yield. Likewise, it is possible that dividend smoothing reduces the information in dividends about future cash flows and makes dividend growth rates unpredictable, as demonstrated by Chen, Da, and Priestley (2009). Bansal and Yaron (2007) argue that aggregate dividends paid out by all firms on the market are predictable, even if the normally-used dividends-per-share time series is not. Finally, Koijen and van Binsbergen (2009) use a latent-variables approach and show that dividends are predictable in this framework that incorporates the whole history of lagged price-dividend ratios and dividend growth rates for forecasting future dividend growth. In sum, the literature has shown that even if aggregate dividend growth rates are not predictable by the dividend yield in recent U.S. data, it is likely that they are predictable when using other methods or other predictors, such as the estimated $\widehat{cdy}$-ratio or the history of dividend growth rates and price-dividend ratios, when using earlier data, when excluding data on firms that smooth dividends, or when using aggregate dividends.

In this paper, we use the current dividend yield as the only predictor, use recent data,

[5]Other papers that investigate return and/or cash flow predictability with dividend yields include, among others, Cochrane (1992), Ang (2002), Goyal and Welch (2003), Lewellen (2004), Campbell and Thompson (2008), and Larrain and Yogo (2008).

[6]Also, there is a completely different finding on the level of individual firms: Vuolteenaho (2002) shows that firm-level cash flows are highly predictable, but that this cash flow predictability washes out in the aggregate.

do not exclude certain types of firms, and use the usual dividends-per-share dividend yield to demonstrate that dividend yields contain a lot of information about future dividend growth rates in international data. Our contribution is to show that one does not find dividend growth predictability by the dividend yield in recent data for large and highly developed economies, such as the U.S., but in data for many other, often medium-size and smaller, economies.

A few papers have looked at the international dimension of dividend-growth predictability before us. For instance, in his survey, Campbell (2003) reports dividend growth rate predictability for some selected developed countries but not for the U.S. Ang and Bekaert (2007) look at the U.S., the U.K., France, and Germany, i.e. large markets, and conclude that "[...] the evidence for linear cash flow predictability by the dividend yield is weak and not robust across countries or sample periods" (p. 670). A recent paper by Engsted and Pedersen (2009) investigates long time series for four countries (U.S., U.K., Denmark, and Sweden) and shows that dividend yields do not predict dividend growth rates in the U.K. and U.S. (large countries), but do so in Denmark and Sweden (small countries).[7] In relation to Campbell (2003), Ang and Bekaert (2007), and Engsted and Pedersen (2009), we provide evidence for many more countries, which allows us to verify systematic differences between large and small countries in recent data. We also investigate the economic gains from following value strategies, i.e. invest according to the size of dividend yields in different countries, and report large economic gains to such trading strategies. Finally, Asness, Moskowitz, and Pedersen (2008) also study the return gains to value strategies in international data. Again, however, they mainly study large and developed markets, whereas a key feature of our paper is the inclusion of smaller and emerging markets and our focus on dividend growth rates and not only returns.

3 An international Campbell-Shiller approximation

Our main question of interest is whether dividend growth rates can be predicted by the dividend yield in international data. With international data, we have to take care that we measure dividend growth rates and returns in a consistent way. To make sure that we do so, we provide a simple extension of the Campbell and Shiller (1988b,a) "dynamic Gordon formula" that makes

[7] Engsted and Pedersen (2009) also show that Chen's (2009) results depend upon the use of nominal dividends, such that other results are found if using real dividends. Hence, we show that our results hold for both real and nominal dividends.

the formula relevant for returns in different currencies.

Our starting point is the return of a *U.S. investor* who invests in a foreign stock market. The gross return in U.S. Dollar of an investment in a foreign country's stock market, denoted R, is:

$$R_{t+1} = \frac{P^f_{t+1} + D^f_{t+1}}{P^f_t} \cdot \frac{S_{t+1}}{S_t} \tag{1}$$

where P^f, D^f are prices and dividends in foreign currency and S is the exchange rate (USD per foreign currency unit – a higher S means a depreciation of the USD).

Rewriting Eq. (1) as:

$$\frac{P^f_t}{D^f_t} = \frac{1}{R_{t+1}} \left(1 + \frac{P^f_{t+1}}{D^f_{t+1}}\right) \frac{D^f_{t+1}}{D^f_t} \frac{S_{t+1}}{S_t} \tag{2}$$

and approximating in the usual Campbell-Shiller way by linearizing around the average price-dividend ratio $\overline{P^f/D^f}$ gives:

$$d^f_t - p^f_t \simeq r_{t+1} - \triangle d^f_{t+1} - \triangle s_{t+1} + k + \rho \left(d^f_{t+1} - p^f_{t+1}\right) \tag{3}$$

where lower-case letters denote logs, k is a constant term related to the average dividend yield in a country, and $\rho \equiv \overline{P^f/D^f}(1 + \overline{P^f/D^f})^{-1}$ denotes the usual linearization constant.

Iterating this first-order difference equation in $(d^f_t - p^f_t)$ forward, taking conditional expectations, and imposing the standard transversality condition results in the almost standard relationship:

$$d^f_t - p^f_t \simeq \text{const.} + E_t \left[\sum_{j=1}^{\infty} \rho^{j-1} (r_{t+j} - \triangle d^f_{t+j} - \triangle s_{t+j})\right]. \tag{4}$$

Eq. (4) shows that a high dividend yield in a foreign country's stock market, measured in foreign currency, reflects expectations of high future returns in USD, low future dividend growth rates in foreign currency, and/or higher future depreciation rates of the foreign currency against the USD. These effects can be measured both in the time-series for an individual stock market and in the whole cross-section of all foreign stock markets. In the time series, Eq. (4) shows that an increase in the dividend yield of an asset implies that investors have lowered their expectations about the future growth rates of dividends measured in the foreign currency, have raised their expectations about future returns measured in USD, and/or expect the foreign currency to depreciate in the future.

In the cross-section, Eq. (4) reveals that stock markets of countries (or a portfolio of countries) with higher dividend yields must be expected to yield higher returns in USD, lower dividend growth rates, and/or higher rates of depreciation of the foreign currency on average. We test both the time-series and the cross-sectional implications of Eq. (4) using international data.[8]

The exchange rate term is new in relation to the usual Campbell-Shiller approximation that looks at one country/currency only. The exchange rate term reflects the fact that U.S. investors are only willing to pay lower valuation multiples for foreign stocks (a low p_t^f per unit of d_t^f, i.e. a high dividend yield in foreign currency) if they expect the foreign currency to depreciate when they cash-in their investment in future periods, i.e. if they expect $\triangle s_{t+j} < 0$.

4 Data

We analyze a total of 50 countries for which dividend yields, earnings yields, and price and total return data are available and employ a quarterly frequency. The countries are: Argentina, Australia, Austria, Belgium, Brazil, Bulgaria, Canada, Chile, China, Colombia, Czech Republic, Denmark, Finland, France, Germany, Greece, Hong Kong, Hungary, India, Indonesia, Ireland, Israel, Italy, Japan, Luxembourg, Malaysia, Mexico, Netherlands, New Zealand, Norway, Pakistan, Peru, Philippine, Poland, Portugal, Romania, Russia, Singapore, Slovenia, South Africa, South Korea, Spain, Sri Lanka, Sweden, Switzerland, Taiwan, Thailand, Turkey, United Kingdom, and United States. This sample covers the 32 industrialized countries as defined by the IMF and 18 additional developing countries. The total sample period runs from the first quarter of 1973 to the first quarter of 2009. Data for some countries are available for the total sample period, whereas other countries enter the sample later. We present the results from a host of robustness checks later in the paper which verify that our main results are not affected by certain kinds of countries being in the dataset throughout the whole sample period (mainly "developed" countries) and others not (mainly "emerging" markets).

We use the share price indices and total return indices from M.S.C.I. We use dividends and dividend yields from Datastream, as the available M.S.C.I data span a much shorter subperiod.

[8] In the cross-section, this prediction actually concerns dividend yields relative to the constant term in Eq. (4) above. Applying such a fixed-effects control, we find, however, that this effect does not matter much for our results below.

All our results reported below are nearly unchanged when we also use returns from Datastream, so that our results are not driven by combining the two data sources. The advantage of using the Datastream data is that we do not have to impute dividends from total returns.[9]

The dividend yield of a country is calculated as the total amount of dividends paid out by constituents of that country as a percentage of the total market value of the constituents, i.e., as $DY_t = 100 \cdot \sum_n D_t N_t / \sum_n P_t N_t$, where DY = aggregate dividend yield on day t, D_t = dividends per share on day t, N_t = number of shares in issue on day t, P_t = unadjusted share price on day t, n indexes constituents, and N_t = number of constituents in index. The dividend yield is thus an average of the individual yields of the constituents weighted by market value.

Descriptive statistics for total USD returns, dividend growth, spot rate changes (of the home currency against the USD), the average dividend yield, and information on data availability for the individual countries are reported in Table 1, Panel A.

Table 1 about here

A couple of comments seem relevant. First of all, the M.S.C.I./Datastream data exhibit tendencies close to those well-know from other datasets. For instance, the reported average annualized log return on the U.S. market of 8.37% and average annualized dividend growth rate of 6.19% are very close to the annual log return and dividend growth rate on the S&P 500 (from Robert Shiller's homepage) over the same period of 8.61% and 6.08%, respectively. Second, there are large differences in the average dividend growth rates across countries. For instance, among those countries for which we have full-sample information, we find the highest average dividend growth rates in Denmark (10.11%), Belgium (9.87%), Italy (11.06%), and Hong Kong (11.33%), i.e., mainly small countries, whereas the lowest average dividend growth rates are found in Germany (5.66%), Japan (3.36%), and the U.S. (6.19%), i.e., very large countries. For the countries that enter the sample at later points in time, there are very large spreads in the average dividend growth rates, ranging from as high as 62.82% for Russia to as low as -29.94%

[9] See e.g. Chen (2009) or Koijen and van Binsbergen (2009) for the impact of assumptions about dividend reinvestments that are paid out throughout the year.

for Bulgaria (however, for Bulgaria, the sample is very short, too).[10]

For our empirical analyses below, we form two kinds of aggregate portfolios from our individual country data: A value-weighted global portfolio and an equal-weighted global portfolio. We use each market's capitalization (at the end of the previous quarter) as a fraction of total market capitalization (at the end of the previous quarter) to value-weight. In other words, in the value-weighted portfolio we use dynamic weights, such that a market that grows in size relative to another market will also be given a larger weight. The value-weighted portfolio is highly dominated by large countries such as the U.S. (roughly 40% market share on average), Japan (about 20%), or the U.K. (roughly 10%) implying that results for the value-weighted portfolio should be expected to closely resemble results from the earlier literature (see e.g. Ang and Bekaert, 2007, who find no clear evidence for linear cash flow predictability in these countries). Results for the equal-weighted portfolio, on the other hand, more closely resemble the behavior of the bulk of smaller and medium-sized markets: In the equal-weighted portfolio, the share given to the U.S. is only $1/15 = 6.67\%$ in the beginning of the sample period (we have data for 15 countries in 1973) versus $1/50 = 2\%$ at the end of the sample period. Descriptive statistics are reported in Table 1, Panel B. As expected, we see that the equal-weighted portfolio has a higher standard deviation for returns, dividend growth, as well as spot rate changes, and a higher dividend yield on average when compared to the value-weighted portfolio.

5 The time-series statistical evidence: Predictive regressions

We first test the implications of Eq. (4) in the time-series dimension, i.e., evaluate whether *variation over time* in the dividend yield of a portfolio *forecasts* high returns on the portfolio, low dividend growth, and/or appreciations of the USD. As portfolios, we employ either the equal- or the value-weighted global equity portfolios discussed above. We run three time-series regressions: future values of dividend growth rates measured in foreign currency on current-period dividend yields, future values of stock returns in USD on current-period dividend yields, and future values

[10] One of our robustness checks reported below is to exclude countries for which we have less than 15 years of data (Brazil, Bulgaria, Czech Republic, Hungary, Korea, Romania, Russia, and Slovenia) and to redo our tests on the resulting smaller sample. The results of these tests are described in Section 8. Excluding these somewhat extreme countries does not affect the results reported below.

of exchange rate changes on current-period dividend yields:

$$r^{USD}_{t+h} = \alpha^{(h)}_r + \beta^{(h)}_r (d_t - p_t) + \varepsilon^{(h)}_{t+h} \tag{5}$$

$$\triangle d^f_{t+h} = \alpha^{(h)}_d + \beta^{(h)}_d (d_t - p_t) + \varepsilon^{(h)}_{t+h} \tag{6}$$

$$\triangle s_{t+h} = \alpha^{(h)}_s + \beta^{(h)}_s (d_t - p_t) + \varepsilon^{(h)}_{t+h} \tag{7}$$

where t indexes time and h denotes the forecast horizon. We consider both short-horizon forecasts for the next quarter ($h = 1$) and multi-step forecasts over longer forecast horizons of $h = 2, 4, 8$ quarters.

In our regressions, we base our statistical inference about the regressions' slope coefficients both on Newey and West (1987) HAC standard errors (we employ h lags for robustness) and, in addition, on a moving-block bootstrap to account for a possible Stambaugh (1999) bias and problems due to overlapping observations. The bootstrap procedure is detailed in the appendix to this paper. We also report R^2s implied by a VAR(1) (denoted R^2_{IH}) as in Hodrick (1992) so that we can compare direct R^2s from overlapping horizons with R^2s implied by regressions based on non-overlapping observations. The specific procedure is briefly summarized in the appendix, too.

5.1 Short-horizon regressions

Our results are clear-cut: When we use value-weights, we do not find significant dividend growth rate predictability by the dividend yield. However, when we use equal weights, there is clear evidence of dividend growth predictability. The results are reported in Table 2 and the evidence for short-horizon (h equals one quarter) predictability is summarized by:

$$\text{Value weights:} \qquad \Delta d^f_{t+1} = \text{constant} + \underset{[0.57]}{0.25}\,(d_t - p_t) \qquad \overline{R}^2 = 0.21$$

$$\text{Equal weights} \quad : \quad \Delta d^f_{t+1} = \text{constant} - \underset{[-3.64]}{3.61}\,(d_t - p_t) \qquad \overline{R}^2 = 6.92,$$

where the numbers in brackets below the coefficient estimates are Newey-West HAC based t-statistics. The dividend yield is thus a significant forecaster of future dividend growth in equal-weighted portfolio, whereas the value weighted portfolio's dividend yield does not forecast cash flows of the value-weighted portfolio is insignificant. The extent to which the dividend yield captures future dividend growth rates seems noteworthy, since the R^2 is almost 7% at the non-overlapping quarterly horizon.

By construction, the strong difference between the results using the value-weighted and the equal-weighted portfolio is due to larger weights given to the smaller markets in the equal-weighted portfolio. Hence, cash flow predictability is still going strong – not in the very large markets such as the U.S., U.K., or Japan that dominate the value-weighted portfolio, but in the majority of medium-sized and smaller markets that dominate the equal-weighted portfolio.

We find it interesting that the predictability of dividend growth remains significant after aggregating each individual country into a global portfolio. Chen and Zhao (2008) argue that it does not seem to be a diversification effect that drives out dividend-growth predictability when moving from the firm-level to the aggregate level as reported by Vuolteenaho (2002). We also find that cash flow predictability does not wash out in the aggregate: Both indexes we study are highly diversified, but dividend growth reemerges when we weight down the U.S. market, as we do in the equal-weighted portfolio.

We comment on the predictability of returns and exchange rate changes below.

5.2 Long-horizon regressions

Eq. (4) shows that dividend yields should capture movements of future returns, dividend growth rates, and spot rate changes over longer horizons than one quarter, too. Hence, we now present results for longer forecasting horizons. We investigate long-horizon predictability in two ways: From direct long-horizon regressions (as in e.g. Lettau and Ludvigson, 2005; Ang and Bekaert, 2007) and from implied long-horizon results based on VAR(1) models (as in e.g. Cochrane, 2008; Chen, 2009).

5.2.1 Direct long-horizon regressions

Table 2, columns $h = 2, 4, 8$, reports results for the direct long-horizon regressions. We find that long-horizon dividend growth rates are predictable in the equal-weighted portfolio but not in the value-weighted portfolio, as above for one-period forecasts. For instance, the two-years ahead change in the dividend growth rate of the equal-weighted portfolio is significantly predictable by its current-period portfolio dividend yield with an R^2 of 17%. In the value-weighted portfolio which puts more weight on the large markets, dividend growth rates are not predictable by current dividend yields, neither at the single horizon nor at multiple horizons.

Table 2 about here

Returns seem to be more predictable in the value-weighted portfolio when we look at R^2s and Newey-West t-statistics. Our findings for the value-weighted portfolios thus reflect the findings in the literature that uses U.S. data: Dividend growth rates are not predictable, whereas returns are. It should be noted, though, that the statistical significance of our results for return predictability are dependent on the standard errors we use. Indeed, the bootstrapped standard errors are much larger than Newey-West standard errors in the return regressions due to the fact that we are dealing with relatively few observations here such that finite-sample biases (Stambaugh, 1999) become relevant. In fact, the strongest evidence in terms of statistical significance obtains for dividend growth predictability in the equal-weighted portfolio, whereas results for returns (and spot rates) are (more or less) insignificant after the bootstrap adjustment. For the value-weighted portfolio, these results seem to imply that the dividend yield does not forecast returns, dividend growth, or spot rates. However, this finding does not take into account that predictive coefficients in the above regressions are linked through the definition of returns in the above Campbell-Shiller decomposition. We turn to this observation in the next section.

5.2.2 Cochrane long-horizon regressions

Cochrane (2008) notices that the coefficients from predictive regressions, like the ones presented in Table 2 above, are related via the definition of returns. Cochrane uses this insight to derive restrictions on the predictive coefficients and to decompose the long-run variation in dividend yields into the fractions attributable to long-run variation in returns and dividend growth rates, respectively. An advantage of Cochrane's framework is that it only needs the one-period predictive regressions when analyzing long-horizon relations, i.e., the procedure does not rely on overlapping observations as the direct long-horizon regressions shown above necessarily do.

Cochrane works with U.S. data and the one-currency definition of returns. We investigate international data and, hence, have to adjust the VAR proposed by Cochrane to include changes in exchange rates:

$$\begin{aligned}
r_{t+1} &= a_r + b_r\,(d_t - p_t) + \varepsilon^r_{t+1} && (8)\\
\Delta d^f_{t+1} &= a_d + b_d\,(d_t - p_t) + \varepsilon^d_{t+1} && (9)\\
\Delta s_{t+1} &= a_s + b_s\,(d_t - p_t) + \varepsilon^s_{t+1} && (10)\\
d_{t+1} - p_{t+1} &= a_{dp} + \phi\,(d_t - p_t) + \varepsilon^{dp}_{t+1}. && (11)
\end{aligned}$$

Eq. (10) is new compared to the system studied by Cochrane (2008). The inclusion of the exchange rate equation in the VAR means that the restriction implied by the VAR changes from its one-currency case of $b_r = 1 - \rho\phi + b_d$ to its two-currency (home and foreign) case:

$$b_r = 1 - \rho\phi + b_d + b_s. \tag{12}$$

As in Cochrane (2008), ρ is the linearization constant which is close to one (in our case ≈ 0.99 on a quarterly frequency). Dividing with $(1 - \rho\phi)$ on both sides of Eq. (12), we find the implied restriction of the long-run coefficients:

$$\begin{aligned}
1 &= \frac{b_r}{1-\rho\phi} - \frac{b_d}{1-\rho\phi} - \frac{b_s}{1-\rho\phi}\\
1 &= b^l_r - b^l_d - b^l_s
\end{aligned}$$

which can be compared to the one-currency case of $1 = b^l_r - b^l_d$ that Cochrane studies. As Cochrane (2008) shows, the long-run coefficients b^l measure the fraction of dividend yield variation due to long-run movements in expected future returns, dividend growth, and exchange rate changes, respectively.

We estimate the system of Eqs. (8) - (11) using both our equal- and value-weighted portfolios. We employ annual data here to avoid seasonality effects in dividend growth rates.[11] We report the results in Table 3, Panel A.

Table 3 about here

[11] Dividends are paid out infrequently and tend to have strong seasonality patterns, so it is common to work on annual data (e.g. Cochrane, 2008). However, results for quarterly VARs are qualitatively identical, though coefficients are estimated less precisely. Results for quarterly data are available upon request.

We find that the fraction of dividend-yield variation due to long-run dividend growth rate variation is quite sizeable at 34% ($b^l_d = -0.34$) and significant (t-statistic = 3.1) in the equal-weighted portfolio but insignificant (t-statistic = 0.22), smaller in absolute size, and of the "wrong" sign at about -11% (b^l_d =0.11) in the value-weighted portfolio. For the long-run return coefficient (b^l_r), the effect is the exact opposite: The fraction of dividend-yield variation due to return variation is large, about 108% ($b^l_r = 1.08$), and significant (t-statistic = 3.2) in the value-weighted portfolio, but much smaller (0.69), though significant (t-statistic = 3.1), in the equal-weighted portfolio. Thus, when we tilt the portfolios towards very large countries, expected returns dominate dividend-yield variation and expected dividend growth does not matter. Contrary to our findings for the direct predictive regressions in the previous section, there is thus a strong case for return predictability in large markets. We also find that expected dividend growth is much more important for dividend yield fluctuations in the equal-weighted portfolio where smaller countries get a larger weight. As in Table 2, exchange rate variations do not matter for dividend growth fluctuations (the b^l_s-coefficients are small and insignificant in both portfolios).

5.2.3 Simulation evidence

In Table 2 and the left part of Table 3 (coefficient estimates from the VAR), we have studied the ability of the dividend yield to predict returns, dividend growth, and exchange rate changes one-by-one. There is significant dividend growth predictability for the equal-weighted portfolio but little direct significant evidence for return predictability in either the equal- or value-weighted portfolio.

To further learn about whether returns and/or dividends are predictable, we follow Cochrane (2008) and investigate the joint distribution of predictive regression coefficients. While Cochrane is interested in the null of no return predictability, we are interested in the joint null that there is no return and no dividend growth predictability, though. That is, we want to test whether one can jointly reject both types of predictability in international stock markets. We study this joint null in order to better discriminate between the drivers of dividend yield variation in the equal- versus value-weighted portfolios.[12]

We first note that predictive regression coefficients are linked by the identity in Eq. (3).

[12] Hence, although the setup is similar, our results will not be directly comparable to Cochrane's (or Chen's, 2009, for that matter) since we study a different null.

This identity, taken together with our extended VAR(1) in Eqs. (8) - (11), implies the following relationships between coefficients and regression errors:

$$
\begin{aligned}
b_r &= 1 + b_d + b_s - \rho\phi \\
\varepsilon^r_{t+1} &= \varepsilon^d_{t+1} + \varepsilon^s_{t+1} - \rho\varepsilon^{dp}_{t+1}.
\end{aligned} \tag{13}
$$

These relations imply that one does not have to estimate all four equations in the VAR(1), but one can recover estimates for one equation by means of the other three. We choose to simulate dividend growth rates and impose the joint null $\{b_r = 0 \,\cup\, b_d = 0\}$ so that our system reads:[13]

$$
\begin{pmatrix} r_{t+1} \ \Delta d^f_{t+1} \\ \Delta s_{t+1} \\ d_{t+1} - p_{t+1} \end{pmatrix} = \begin{pmatrix} 0 \\ 0 \\ \rho\phi - 1 \\ \phi \end{pmatrix} (d_t - p_t) + \begin{pmatrix} \varepsilon^r_{t+1} \\ \varepsilon^r_{t+1} - \varepsilon^s_{t+1} + \rho\varepsilon^{dp}_{t+1} \\ \varepsilon^s_{t+1} \\ \varepsilon^{dp}_{t+1} \end{pmatrix}. \tag{14}
$$

Following the procedure in Cochrane (2008), we draw the first observation for the dividend yield from the unconditional density $d_0 - p_0 \sim \mathcal{N}[0, \sigma^2_{\varepsilon^{dp}}/(1-\rho\phi)]$. Residuals $\varepsilon^d_{t+1}, \varepsilon^s_{t+1}, \varepsilon^{dp}_{t+1}$ are drawn from a multivariate normal with covariance matrix equal to the sample estimate. We simulate 25,000 artificial time-series for the system with a length of 300 quarters and discard the first 156 observations as the burn-in sample so that we are left with time-series of 144 quarters as in the actual data. We then estimate the VAR in Eqs. (8) - (11) on these simulated time-series and investigate the distribution of estimated coefficients $\widehat{b}_r, \widehat{b}_d, \widehat{b}_s$ and t-statistics t_r, t_d, t_s. Finally, in order to compare with Panel A of Table 3, we employ annual data.

We report rejection probabilities based on the *marginal* distribution of coefficients in Panel B of Table 3, i.e., the frequencies with which simulated coefficients (or t-statistics) exceed their estimated values in the original data. Results are clear-cut. Both for the equal- as well as the value-weighted portfolio, there is a relatively small chance of 1% and 2%, respectively, to see a simulated return coefficient b_r as large as in the actual data. Thus, no return predictability is easily rejected for both portfolios. However, there is a sharp difference regarding dividend yield predictability. For the portfolio with equal weights, basically all simulated dividend growth coefficients b_d (or t-statistics t_d) are too high, i.e., the probability of observing a more negative

[13] The choice of simulating dividend growth rates has no material effect on our results reported below.

dividend growth coefficient than $\widehat{b}_d = -11.07$ as in the original data is about 1.3%, so that no dividend predictability can be rejected easily for the equal-weighted portfolio. Results for the value-weighted portfolio are different, since observing the estimated value of $\widehat{b}_d = 1.59$ is not uncommon in the simulated data and 47% of all simulated coefficients are smaller than this value. Thus, there is no evidence for dividend growth predictability for the value-weighted portfolio.[14]

Finally, we show results for *joint* coefficient distributions in Figure 1. Here we cross-plot the simulated b_r and b_d coefficients (red dots) along with the sample estimates of these coefficients (blue large dot and lines) and the null (black triangle). The numbers in the four quadrants correspond to the fraction of all simulated coefficients that fall into the respective quadrant. For the equal-weighted portfolio, there is only a 1.98% (1.29% + 0.69%) probability of jointly observing a more positive b_r and/or more negative b_d, whereas the same probability is 48.66% (46.75% + 1.91%) for the value-weighted portfolio. For the latter portfolio, it can be seen from the figure that the failure to reject the joint null of no return and no dividend growth predictability clearly comes from the failure to reject no dividend growth predictability as noted above. Thus, the presence of dividend growth predictability in the equal-weighted portfolio gives strong statistical evidence against the joint null, whereas the lack of dividend growth predictability in the value-weighted portfolio implies that the joint null cannot be rejected for this portfolio, despite of clear return predictability.

Figure 1 about here

6 The cross-country economic evidence: Portfolios

In the previous section, we have demonstrated that there is strong *statistical* evidence that movements in dividend yields over time reflect expectations of movements in future dividend growth rates in medium-sized and smaller countries. We have also explained that this contrasts with the common perception in the literature, based almost solely on U.S. data, that practically all variation over time in dividend yields is due to variation in expected returns. In this section,

[14]Results for the marginal distribution of spot rate coefficient indicate that there is no spot rate predictability. We also did not find other illuminating aspects in the simulated spot rate coefficients, no matter whether we looked at marginal or joint distributions.

we focus on dividend-predictability in the cross-section. By doing so, we can also measure the *economic* significance of our results by investigating portfolio sorts based on dividend yields. We show that there are large and interesting economic differences between countries with high and low dividend yields, respectively, and between countries with high and low dividend and return volatility.

To verify these patterns, we sort countries into portfolios and investigate cross-sectional patterns in returns, dividend growth, and exchange rate changes. We use two different portfolio formation strategies: In one we directly sort countries into different portfolios on the basis of dividend yields, but regardless of the sizes of the countries (and then value- or equal-weight within the resulting portfolios). In the other strategy we double-sort by first allocating countries into different portfolios on the basis of the sizes of the countries and then sorting them according to the sizes of the dividend yields within the different size portfolios.

6.1 Sorting directly on dividend yields

We construct the portfolios in the following way: Each year (at the end of the first quarter) we rank all countries with available data according to the size of their dividend yield. We then allocate countries to five portfolios where we include the 20% of the countries with the lowest dividend yields in portfolio 1, the next 20% of the countries in portfolio 2, etc., such that we will have the 20% of countries with the highest dividend yields in portfolio 5. We then aggregate, using equal or value weights, the dividend yields from each country into a portfolio dividend yield. Finally, we track each portfolio over the next four quarters and calculate the equal-weighted or value-weighted return, dividend growth rate, and spot exchange rate change and re-balance portfolios annually.

From our five portfolios, we construct a long-short portfolio, which is long in the high dividend yield countries in portfolio 5 and short in low dividend countries in portfolio 1. This long-short portfolio captures the dividend growth (or returns or exchange rate changes) an investor would obtain if he followed an international value strategy. The returns to this international value strategy can be interpreted similarly to the carry trade portfolios studied in e.g. Lustig, Roussanov, and Verdelhan (2009) who investigate returns to shorting the money market in low interest rate countries and, simultaneously, investing in the money market of high interest rate countries. Our strategy is similar in that we go short and long in the stock market (and not the money market) of a country and that we sort equity portfolios on dividend yields instead of exchange rates sorted on interest rates. Furthermore, Fama and French (1998) study value and growth portfolios in several countries internationally.

The portfolio approach has several advantages compared to the predictive regressions employed in Section 5. First, we can directly focus on returns, cash flow growth, and exchange rate change patterns that occur through predictability by the dividend yield, since portfolio sorts isolate these effects and average out other factors (see e.g. Cochrane, 2007; Lustig and Verdelhan, 2007). Second, we can investigate return and cash flow predictability without having to rely on predictive regressions and their associated econometric problems.

We plot the time series of the five portfolios' dividend yields in Figure 2. There are large differences between the portfolios. For instance, the spread between the dividend yields of portfolios 1 and 5 is generally in the range of 2–5 percentage points, irrespective of the way we weight the countries together. A closer look at portfolio compositions reveals that countries switch frequently between portfolios and that we are not dealing with a relatively constant set of high-dividend yield countries in portfolio 5 and low dividend yield countries in portfolio 1. More information on portfolio turnover and portfolio compositions is documented in the web appendix to this paper in Section A.3.

Figure 2 about here

Patterns across portfolios. What would an investor have gained by investing in the different portfolios? We report results illustrating this in Table 4. Consider the portfolios where we use equal weights within each portfolio first. The first thing to notice is that the differences between the average dividend growth rates on the different portfolios are large (Panel B). For instance, the average annualized dividend growth rate of the portfolio of countries with the highest dividend yield has been 1.75% only. This can be compared to the average annualized dividend growth rate of the countries with the lowest dividend yield, which has been 22.30%. This spread in dividend growth rates of more than 20% p.a. is highly significant both statistically (t-statistic of -5.04 based on Newey-West HAC standard errors) and in economic terms. Similar to the time-series results above, we find that dividend growth predictability stems from the smaller markets. Indeed, in the portfolios where we use value weights within each portfolio, the average dividend growth rate of the low dividend-yield portfolio (portfolio 1) is only 1.67%-points lower than the average dividend growth rate of the high dividend-yield portfolio (portfolio 5) and insignificantly different from zero.

Table 4 about here

The amount of return predictability captured by the trading strategy is also sizeable. Panel A of Table 5 shows that the difference between the average returns of the highest dividend-yield portfolio compared to the lowest dividend-yield portfolio is 8.68 percentage points per annum.

It is also "well-behaved" with skewness close to zero and kurtosis close to three.[15] When compared to other well-known zero-cost portfolios, the average return of 7.96% is large. For instance, the average annualized return to the international long-short carry trade portfolio in foreign exchange markets in Lustig and Verdelhan (2007) and Lustig, Roussanov, and Verdelhan (2009) is 5.33% and around 8% per annum, respectively. The average 1926-2009 return to a U.S. value-growth long-short portfolio is 4.8% (based on the HML factor), and U.S. equity premium is 7.38%.

Regarding exchange rates, we find that even when the exchange rate effects of the individual portfolios are not significant, the spread between the high and the low dividend yield portfolios is so large that the "5-1" portfolio contains significant exchange rate predictability, reaching 4.68% for the value-weighted portfolio. An annualized predictable exchange rate growth rate of 4.68% is noteworthy in light of the many studies in the literature that document the absence of short-term exchange rate predictability (see e.g. Meese and Rogoff, 1983; Kilian and Taylor, 2003).[16]

All in all, the conclusion is that there is a significant return differences between high and low dividend-yield portfolio both for equal- and value-weights. We find significant dividend growth predictability when using equal-weights, and a small degree of exchange rate predictability that

[15] In unreported results, we show that basically the same patterns holds when we do not convert foreign stock returns to USD or when we look at price changes only (i.e., not at total returns). Results are available upon request.

[16] Lustig, Roussanov, and Verdelhan (2009) show that there is a lot of short-term predictability in exchange rate *excess returns*, i.e., spot rate changes adjusted for interest rate differentials. This is different from pure exchange rate predictability, however.

is most clearly seen in the value-weighted portfolios.

Predictability over time. In Figure 3, we visualize the cumulated returns, dividend growth rates, and exchange rates from the long-short portfolio. The cumulated return of this zero-cost strategy is in the order of 200-300% over the full sample period. We find it particularly interesting that the long-short portfolios perform well even during the financial crisis of 2007-2009. Furthermore, much of the return predictability in the value-weighted portfolio seems to come from the strong performance of value strategies after the late 80s, whereas the equal-weighted value strategy's cumulated excess returns are much smoother.

FIGURE 3 ABOUT HERE

From Panel B in Figure 3, the sizeable difference since the early 1980s between the dividends accumulating to the long-short portfolio of the equal-weighted and the value-weighted portfolios become clear: Dividends accumulated to the long-short portfolio of equal-weighted portfolios is in the order of −700 percent, whereas it is "only" in the order of −100 percent in the value-weighted portfolios. Panel C shows that exchange rates are mainly predictable in larger countries, as the economic effect from the value-weighted portfolio is particularly clear. For the equal-weighted portfolio, exchange rate predictability seems to die out in the early 90s. This may be due to an increased tendency for smaller countries to switch to managed exchange rates instead of free floating.

6.2 Double sorts on size and dividend yields

In this section, we present cross-sectional results for portfolios sorted on country size in order to further investigate the importance of market size for dividend predictability.

To do so, we double-sort countries into nine portfolios. In the first step, we sort the countries into three groups based on their market capitalization (measured in USD), i.e., into small markets, medium-sized markets, and large markets. Each group contains one third of all available countries at a given point in time. At the next step, we sort countries into three portfolios based on their dividend yields within each size group, such that we get a growth, medium, and value portfolio within each size category. Again, each subgroup contains one third of all countries within a size group (i.e. one ninth of all countries). As with the simple portfolio sorts above, we use values at the end of the first quarter for sorting and rebalance annually.

Table 5 reports the annualized average quarterly total returns (left part of the table), dividend growth rates (middle part), and exchange rate changes (right part). We also report the means of long-short portfolios along two dimensions: (a) three zero-cost value minus growth portfolios (i.e., long in the value portfolio and short the growth portfolio, "V – G"), one within each size group, and (b) three zero-cost large minus small portfolios ("L–S"), one within each dividend yield group. The value in the lower right corner of each panel of the table is the difference of the value minus growth (V–G) portfolio between the large and small size group of countries.

TABLE 5 ABOUT HERE

From Table 5, it is clear that dividend growth predictability is a salient characteristic of small and medium-sized markets. Looking at the Value minus Growth portfolios ("V– G" column), we see that the average annualized dividend growth rates of the small growth countries (small countries with low dividend yield) is 28.08 percentage points higher than that of the small value countries. This should be contrasted with the V–G dividend growth of -10.04 percentage points p.a. in the group of medium-sized countries and the tiny and insignificant -2.3 percentage points in average dividend growth rates between the Large Value and Large Growth countries. This is direct evidence that dividend growth predictability strongly depends on the size of a market. Also, our results demonstrate that expected cash flow growth is a stronger driver of dividend yields in smaller markets. This result is different from the result in Vuolteenaho (2002), who finds that expected return news are more important for small (U.S.) firms than for large ones. Therefore, using aggregate data from individual countries does not simply lead to the same results as using data on individual firms.

Regarding total returns, we find that Value countries deliver higher returns on average, and that this pattern is somewhat more clear in large countries.

7 Why are dividends more predictable in small countries?

We have now arrived at the last punch line of our paper: Why are dividends growth rates more predictable by the dividend yield in smaller countries? One explanation for the absence of dividend growth predictability in aggregate U.S. data is put forward by Chen, Da, and Priestley (2009). They argue that corporate payout policy and especially dividend smoothing and the change to repurchases instead of dividend distribution by U.S. firms in the postwar era is a driving factor behind these results. In other words, less volatile dividend growth reduces the possibility to predict dividend growth.

Looking at differences between the equal- and value-weighted portfolios, we do indeed see in Panel B of Table 1 that dividend growth is more volatile in the equal-weighted portfolio than in the value-weighted portfolio by a factor of almost two: The standard deviation of dividend growth is 6.10% p.a. in the equal-weighted portfolio but only 3.10% p.a. in the value-weighted portfolio. Also, we see that dividend yields are much less autocorrelated in the equal-weighted portfolio ($\phi \approx 0.7$) compared to the value-weighted portfolio ($\phi \approx 0.9$) in Table 3. Thus, on the face of it, there seems to be some evidence that higher dividend growth volatility and less persistent dividend yield processes favor dividend growth predictability in the time-series setting. More powerful tests can be conducted by exploiting cross-sectional information, however, since we have a panel of countries where volatility varies both in the cross-section as well as in the time-series domain. Therefore, we examine whether countries with more volatile cash flow environments and less dividend smoothing are also the countries with higher dividend growth predictability by relying on extended portfolio sorts.

Our findings on this issue are shown in Table 6. The table looks similar to Table 5, but we only report results for dividend growth and instead of double-sorting on dividend yields and size, we sort on dividend yields and different measures of a stock market's volatility. We use two measures of dividend volatility: raw dividend volatility and idiosyncratic dividend volatility. Raw dividend volatility is computed as the sum of absolute quarterly log changes of dividends over the last year, while idiosyncratic dividend volatility is calculated from a regression of each country's log dividend growth on the aggregate, global dividend growth rate, and then summing the absolute residuals over the last four quarters. In addition, we sort on idiosyncratic return volatility. This is calculated from a regression of each country's total market return on the aggregate, global stock return, and then summing the absolute residuals over the last four quarters. We include idiosyncratic return volatility here to capture the general information environment of a market and since it has been shown to be related to the volatility of fundamental cash flows (see Irvine and Pontiff, 2009, on the latter point).

We follow the same procedure as above and sort countries into three equal-sized groups depending on their (lagged) volatility and then sort on dividend yields within each volatility group. Within each of the nine groups we then calculate the average dividend growth rates. Finally, we calculate for each volatility category the difference in average dividend growth rates between the countries in the value and growth portfolios (in columns "V – G"), and the difference between the countries in the High and Low volatility category (in row "H – L").

Several patterns stand out in Table 6. First, and regardless of how volatility is measured, high volatility countries have higher dividend growth rates than low volatility countries (rows "H–L"). Second, high dividend yield countries have higher dividend growth rates than low dividend yield countries on average (columns "V – G"). Third, but most important, the largest difference in average dividend growth rates between value and growth countries occur in countries with higher lagged volatility. The dividend growth differential between value and growth countries is highly significantly different from zero and about -15%, -17%, and -22% p.a. for the group of countries that have experienced the highest levels of lagged volatility, but insignificant and around zero for the group of countries with low lagged volatility (ranging from -2.87% p.a. for idiosyncratic return volatility to 0.91% p.a. for idiosyncratic dividend volatility). Countries with intermediate values of lagged volatility are somewhere in between with significant dividend growth rate differences between value and growth portfolios of about -9% to -11%.

Table 6 about here

We conclude that the reason why we see a lot of dividend growth predictability in small countries is that these countries also tend to have more volatile dividends and returns and these effects are picked up by dynamically sorting countries into portfolios based on lagged volatility movements as we have done in this section.

8 Robustness

We have tested whether our results are robust along many different dimensions. In order to save space, we have delegated the description of these robustness tests to the Appendix. In this section, we briefly indicate what we have done and the main findings.

First of all, we have evaluated whether our results are robust towards the use of excess returns instead of simple returns and real dividend growth expressed in USD instead of nominal dividend growth in foreign currency units. It is important to check whether our results also hold for real dividends, since Engsted and Pedersen (2009) find that the results in Chen (2009) are sensitive to the choice of real or nominal dividends. We find that our main result that dividends are more predictable in smaller countries also holds when using real dividends and excess returns (both in its time-series and cross-sectional dimension). These results are in Appendix A.1.

Second, we have checked whether our results are driven by recently added small emerging markets. They are not. To verify this, we conducted our time-series regressions and cross-sectional portfolio formations using a dataset consisting exclusively of countries for which we have more than 15 years of data. The main result from these exercises is that dividends are more predictable in the equal-weighted portfolios (both in the time-series and the cross-section) than in the value-weighted portfolios, but the results are naturally somewhat less pronounced than the ones reported in Tables 2 and 5 that included all countries. We explain these results in Appendix A.2.

Third, we have constructed portfolios by using standardized dividend yields instead of the level of dividend yields themselves (Appendix A.4). We do this in order to rule out the potential critique that our portfolio results could be due to constant structural differences between the sizes of dividend yields in different countries. We find that even when we take out the unconditional means of the countries' dividend yields, and standardize the resulting demeaned dividend yields, there are large cross-sectional differences between the dividend growth rates of the equal-weighted portfolios, but considerably less in the value-weighted portfolios. For these portfolios based on standardized dividend yields, we have also conducted subsample analysis (Appendix A.5).

Finally, we have evaluated whether one can use earnings instead of dividends to sort countries into portfolios (in the cross-section) and whether earnings growth is predictable by the earnings yield in the time-series dimension. We find that the degree of earnings predictability is as strong as the degree of dividend predictability is, both in the time-series and the cross-sectional dimension. This is in Appendix A.6.

9 Conclusion

The common perception in the literature is that dividend yields do not predict dividend growth rates in the "standard setting" based on U.S. aggregate data.[17] We show that extending the sample to include aggregate data from other countries changes the picture painted by U.S. data quite a bit. Indeed, we show that cash flow predictability accounts for a sizeable fraction of dividend yield variability in countries outside the U.S., and most pronounced so in smaller countries. This predictability is large and significant, both in the time-series dimension and the cross-country dimension, and both in a statistical sense and an economic sense. We are particularly intrigued by the economic magnitudes of the average differences in dividend growth predictability that we see in the cross-country dimension. We demonstrate that cash flow predictability in international aggregate data is different from the firm-level evidence from the U.S. and we link dividend growth predictability to the volatility environment of countries cross-sectionally.

The results in this paper point towards interesting directions for future research. First, there is a large cross-sectional return spread in portfolios sorted on lagged dividend yields which call for an explanation. For this, one needs an asset-pricing model that ties the returns on the different portfolios to differences in their exposures to observable systematic risk factors. We are currently working on investigating such an asset-pricing model, and the results will be reported in future work. Second, it may be interesting to understand more clearly why dividend smoothing is so different across countries and over time since dividend smoothing is a decision by firms and not an exogenous feature of different countries per se. Finally, and related to the last point, it would be interesting to investigate whether our findings of higher dividend volatility in smaller and sometimes emerging countries are akin to the findings in the literature on the Great Moderation that volatility of consumption falls when economics develop and economic policies improve (Blanchard and Simon, 2001).

[17] Other variables have been found to predict dividend growth rates (Lettau and Ludvigson, 2005). Likewise, dividend growth rates were predictable in earlier time periods (Chen, 2009). The point here is that dividend growth predictability by means of the current dividend yield is generally thought to be non-existing.

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Appendix

I. Bootstrap simulations

Bootstrap t-statistics for the slope coefficients in our predictive regressions are based on a moving block-bootstrap (Goncalves and White, 2005). More specifically, the procedure works as follows. We first block-bootstrap returns and dividend yields for each country and set the block length equal to $3h$, so that longer blocks are chosen for longer forecast horizons to account for the larger degree of serial correlation in overlapping returns at longer forecast horizons. We generate 10,000 bootstrap samples and estimate our regressions on these artificial data.

This procedure yields the bootstrap distribution of the estimated coefficients $\beta_r, \beta_d, \beta_s$ from which we estimate the bootstrap standard error (around the coefficient estimates of the original sample) for each predictive coefficient. The t-statistic reported in the tables t^{BS} is based on these bootstrapped standard errors.

II. Hodrick (1992) implied R^2s

The calculation of implied R^2s for our predictive regressions follows Hodrick (1992). The (2×1) vector of interest X_{t+1}, where X contains either (log) returns, dividend growth, or spot rate changes and the log dividend yield, is assumed to follow a VAR(1)

$$X_{t+1} = AX_t + u_{t+1}$$

where A is a (2×2) coefficient matrix. Note that X is demeaned. The predictive R^2 for a forecast horizon h implied by the VAR, denoted R^2_{IH} in the tables, is given by

$$R^2_{IH} = 1 - \frac{\mathbf{e1}' W_h \mathbf{e1}}{\mathbf{e1}' V_h \mathbf{e1}}$$

where

$$V_h = hC(0) + \sum_{j=1}^{h-1} (h-j)[C(j) + C(j)']$$

and $C(j)$ denotes the $j-$th order autocovariance of X_{t+1}. Furthermore

$$W_h = \sum_{j=1}^{h} (I-A)^{-1}(I-A^j)V(I-A^j)'(I-A)^{-1\prime}$$

and V denotes the covariance matrix of residuals $V = E(u_{t+1}u'_{t+1})$ and I is a conformable identity matrix. Further details can be found in Hodrick (1992).

Table 1: Descriptive statistics

This table shows descriptive statistics for all 50 countries in our sample (Panel A) and for an equal- as well as a value-weighted portfolio of these countries (Panel B). The second column shows the date of the first observation in our sample, the next six columns show means and standard deviations of annualized (log) returns (total returns in USD), (log) dividend growth, and (log) spot rate changes. The column labeled "DY" shows the average dividend yield and the final column reports the number of available observations.

Panel A: Individual countries									
		Returns		Dividends		Spot rates			
	First obs	MEAN	STD	MEAN	STD	MEAN	STD	DY	OBS
ARGENTINA	1993 Q4	1.79	42.52	14.71	73.45	-8.2	21.54	2.96	62
AUSTRALIA	1973 Q1	8.41	25.22	9.47	8.52	-1.86	12.01	4	145
AUSTRIA	1973 Q1	7.02	27.22	7.7	19.09	2.01	12.05	2.6	145
BELGIUM	1973 Q1	9.28	24.99	9.87	14.84	0.92	11.9	3.83	145
BRAZIL	1994 Q3	11.32	44.59	25.79	49.52	-6.25	23.75	0.9	59
BULGARIA	2005 Q3	-38.76	66.65	-29.94	43.97	1.54	12.82	3.26	15
CANADA	1973 Q1	8.09	20.92	6.5	10.16	-0.6	6.19	2.22	145
CHILE	1989 Q3	14.53	28.18	11.59	24.75	-4.42	11.15	3.16	79
CHINA	1993 Q3	-1.97	42.94	9.04	46.81	0	0.42	3.67	63
COLOMBIA	1993 Q1	13.13	38.93	20.1	51.91	-7.4	11.98	3.06	65
CZECH REP	1995 Q1	12.96	30.76	20.27	54.1	1.64	13.08	4.04	57
DENMARK	1973 Q1	10.26	21.04	10.11	16.21	0.45	11.64	3.58	145
FINLAND	1988 Q2	8.07	33.91	11.52	31.28	-0.72	12.32	2.01	84
FRANCE	1973 Q1	9.53	24.2	8.98	12.52	-0.05	11.4	3.09	145
GERMANY	1973 Q1	9.22	22.72	5.66	10.8	2.12	12	2.6	145
GREECE	1990 Q1	5.18	36.97	16.62	25.5	-2.74	11.31	3.74	77
HONG KONG	1973 Q1	9.37	34.48	11.33	10.89	-0.87	4.49	2.82	145
HUNGARY	1995 Q1	11.81	40.13	17.79	46.4	-5.17	13.38	3.69	57
INDIA	1993 Q1	6.93	36.12	15.86	19.71	-2.62	6.54	2.67	65
INDONESIA	1990 Q2	-3.79	53.18	21.55	54.49	-9.79	33.45	2.07	76
IRELAND	1988 Q1	2.42	25.45	7.39	11.02	0.1	10.82	1.51	85
ISRAEL	1993 Q1	5.25	25.73	16.87	25.43	-1.89	6.71	2.71	65
ITALY	1973 Q1	6.6	27.08	11.06	17.37	-2.52	11.48	2.85	145
JAPAN	1973 Q1	6.68	22.81	3.93	5.29	3.36	12.51	2.74	145
KOREA	2005 Q3	-9.46	39.05	5.6	13.42	0.23	4.56	1.25	15
LUXEMBOURG	1992 Q1	-69.29	65.87	5.56	13.42	-7.72	7.17	1.84	69
MALAYSIA	1988 Q1	5.92	34.72	8.19	13.43	-1.66	12.16	2.16	85
MEXICO	1989 Q3	14.24	33.6	16.95	36.56	-8.9	14.35	2	79
NETHERLAND	1973 Q1	11.46	19.85	6.27	7.62	1.69	11.84	2.59	145
NEW ZEALAND	1988 Q1	3.1	22.72	4.84	16.56	-1.29	10.95	4.27	85
NORWAY	1973 Q1	7.64	29.37	10.8	27.07	-1.19	11.25	2.56	145
PAKISTAN	1993 Q1	0.79	42.84	15.61	37.41	-6.95	7.48	4.69	65
PERU	1994 Q1	12.73	35.01	26.61	53.45	-2.46	3.75	1.88	61
PHILIPPINES	1989 Q1	2.19	37.01	13.71	31.88	-4.16	9.91	3.15	81

(continued on next page)

Table 1 (continued)

	First obs	Returns MEAN	Returns STD	Dividends MEAN	Dividends STD	Spot rates MEAN	Spot rates STD	DY	OBS
POLAND	1994 Q2	-0.04	38.52	23.56	44.73	-3.03	14.15	1.38	60
PORTUGAL	1990 Q1	3.5	23.7	-1.79	52.11	-0.29	11.67	4.64	77
ROMANIA	2006 Q1	-45.12	68.07	39.82	46.91	-3.9	20.27	1.85	13
RUSSIA	1995 Q1	12.12	63.52	62.82	149.48	-0.56	2.22	3.03	57
SINGAPORE	1973 Q1	5.9	30.65	6.59	16.07	1.71	6.21	2.61	145
SLOVENIA	2002 Q3	10.51	34.03	8.81	37.42	3.3	10.72	1.35	27
SOUTH AFRICA	1993 Q1	8.56	29.22	15.88	11.1	-4.85	16.55	2.87	65
SPAIN	1987 Q2	9.67	22.4	9.77	11.29	-0.14	12.14	2.58	88
SRI LANKA	1993 Q1	1.55	36.93	10.86	44.15	-5.82	4.52	2.58	65
SWEDEN	1982 Q1	12.74	28.04	13.95	21.09	-1.42	12.05	1.17	109
SWITZERLAND	1973 Q1	10.31	18.03	6.91	11.79	3.15	12.46	2.13	145
TAIWAN	1988 Q3	-1.4	39.11	13.36	33.01	-0.78	5.7	2.01	83
THAILAND	1988 Q1	3.46	41.28	6.56	35.38	-1.58	12.61	2.95	85
TURKEY	1989 Q3	9.9	63.85	34.18	40.11	-34.05	25.62	3.86	79
UK	1973 Q1	9.16	23.48	8.2	5.88	-1.38	11.34	4.29	145
US	1973 Q1	8.37	14.93	6.19	3.77	—	—	3.12	145

Panel B: Global portfolios

	First obs	Returns MEAN	Returns STD	Dividends MEAN	Dividends STD	Spot rates MEAN	Spot rates STD	DY	OBS
Equal weights	1973 Q1	8.57	20.51	10.63	6.10	-1.15	7.60	3.11	145
Value weights	1973 Q1	9.12	16.00	6.66	3.29	1.05	5.11	2.76	145

Table 2: Predictive regressions

This table shows estimates of the following (long-horizon) predictive regressions

$$r_{t+h}^{USD} = \alpha_r^{(h)} + \beta_r^{(h)}(d_t - p_t) + \varepsilon_{t+h}^{(h)}$$
$$\triangle d_{t+h}^{f} = \alpha_d^{(h)} + \beta_d^{(h)}(d_t - p_t) + \varepsilon_{t+h}^{(h)}$$
$$\triangle s_{t+h}^{f} = \alpha_f^{(h)} + \beta_s^{(h)}(d_t - p_t) + \varepsilon_{t+h}^{(h)}$$

for two global portfolios, namely the equal-weighted (left part of the table) or value-weighted market portfolio constructed from aggregating all individual sample countries.

Equal weights					Value weights				
Dependent variable: Total returns – USD									
h	1	2	4	8	h	1	2	4	8
β_r	2.40	8.19	21.29	33.55	β_r	2.34	5.93	14.27	28.04
t^{NW}	[0.66]	[1.60]	[2.31]	[1.89]	t^{NW}	[1.37]	[1.96]	[2.36]	[2.20]
t^{BS}	[0.79]	[1.48]	[1.64]	[1.04]	t^{BS}	[1.37]	[1.67]	[1.62]	[1.07]
$\bar{R}^2$	0.00	0.01	0.05	0.08	$\bar{R}^2$	0.00	0.02	0.08	0.17
R^2_{IH}	0.04	0.04	0.05	0.08	R^2_{IH}	0.06	0.06	0.08	0.14
Dependent variable: Dividend growth									
h	1	2	4	8	h	1	2	4	8
β_d	-3.61	-6.52	-12.06	-20.36	β_d	0.25	0.68	1.40	3.20
t^{NW}	[-3.64]	[-3.41]	[-3.08]	[-2.22]	t^{NW}	[0.57]	[0.79]	[0.75]	[0.79]
t^{BS}	[-3.46]	[-2.86]	[-2.35]	[-1.90]	t^{BS}	[0.54]	[0.65]	[0.56]	[0.48]
$\bar{R}^2$	0.07	0.10	0.15	0.17	$\bar{R}^2$	0.00	0.00	0.01	0.02
R^2_{IH}	0.13	0.18	0.27	0.35	R^2_{IH}	0.03	0.03	0.02	0.02
Dependent variable: Spot rate changes									
h	1	2	4	8	h	1	2	4	8
β_s	-0.44	-0.60	0.11	2.24	β_s	-0.03	-0.01	0.28	0.93
t^{NW}	[-0.34]	[-0.24]	[0.02]	[0.21]	t^{NW}	[-0.06]	[-0.01]	[0.14]	[0.22]
t^{BS}	[-0.32]	[-0.20]	[0.02]	[0.13]	t^{BS}	[-0.06]	[-0.01]	[0.10]	[0.12]
$\bar{R}^2$	-0.01	-0.01	-0.01	-0.01	$\bar{R}^2$	-0.01	-0.01	-0.01	-0.01
R^2_{IH}	0.01	0.01	0.01	0.01	R^2_{IH}	0.01	0.00	0.00	0.00

Table 3: VAR-based long-run coefficients and simulation results

This table shows Cochrane (2008)-type results based on a VAR(1) of returns (r), dividend growth (Δd), spot rate changes (Δs), and dividend yields ($d-p$). The VAR is

$$
\begin{aligned}
r_{t+1} &= a_r + b_r(d_t - p_t) + \varepsilon^r_{t+1} \\
\triangle d^f_{t+1} &= a_d + b_d(d_t - p_{i,t}) + \varepsilon^d_{t+1} \\
\triangle s_{t+1} &= a_s + b_s(d_t - p_{i,t}) + \varepsilon^s_{t+1} \\
d_{t+1} - p_{t+1} &= a_{dp} + \phi(d_t - p_{i,t}) + \varepsilon^{dp}_{t+1}
\end{aligned}
$$

Panel A shows predictive coefficients (b_r, b_d, b_s) as well as return decompositions based on VAR-implied long-run predictive coefficients (b^l_r, b^l_d, b^l_s)where long-run coefficients are calculated as $b^l_r = b_r/(1-\rho\phi)$ and similarly for b^l_d and b^l_s. b^l_r, $-b^l_d$, and $-b^l_s$ approximately sum up to one and show the fractions of dividend yield variation that can be attributed to time-varying expected returns, time-varying dividend growth, and time-varying spot rate changes. Standard errors (in parentheses) for the VAR coefficients (b_r, b_d, b_s) are Newey-West HAC, whereas standard errors for the long-run coefficients (b^l_r, b^l_d, b^l_s) are based on a moving block-bootstrap. Panel B shows Monte Carlo simulation results for simulating the above VAR under the joint null of no return and dividend growth predictability. Numbers shown are the frequencies with which simulated coefficient estimates (left part) and t-statistics (right part) exceed their estimated value in the original data. The simulation is based on 25,000 repetitions.

Panel A: VAR coefficients and long-run coefficients						
Equal weights						
b_r	b_d	b_s	ϕ	b^l_r	b^l_d	b^l_s
22.69	-11.07	-0.48	0.69	0.69	-0.34	-0.01
(10.01)	(4.43)	(6.53)	(0.09)	(0.22)	(0.11)	(0.21)
Value weights						
b_r	b_d	b_s	ϕ	b^l_r	b^l_d	b^l_s
14.21	1.59	0.23	0.90	1.08	0.11	0.02
(6.75)	(2.35)	(2.33)	(0.07)	(0.34)	(0.25)	(0.26)
Panel B: Simulation results						
Equal weights						
b_r	b_d	b_s		t_r	t_d	t_s
0.01	0.99	0.53		0.02	1.00	0.49
Value weights						
b_r	b_d	b_s		t_r	t_d	t_s
0.02	0.53	0.40		0.05	0.42	0.44

Table 4: Portfolio sorts

This table shows results for portfolios sorts. In the second quarter of each year we sort countries into five portfolios depending on their dividend yield at the end of the first quarter. Portfolio 1 contains the 20% of countries with the lowest dividend yield, whereas portfolio 5 contains the high dividend yield countries. These portfolios are rebalanced annually. The left part shows results for equal weights within portfolios, whereas the right part shows results for using value weights within portfolios. Panel A shows total returns in USD for the five portfolios, the average return ("Avg.") and the excess return of the long-short portfolio 5-1. Panel B shows results for dividend growth rates, whereas Panel C shows results for spot rate changes.

Equal weights								Value weights							
Panel A: Total returns – USD															
PF	1	2	3	4	5	Avg.	5-1	*PF*	1	2	3	4	5	Avg.	5-1
Mean	4.50	7.86	9.35	8.81	12.47	8.68	7.96	Mean	4.67	6.20	7.94	7.89	11.25	7.35	6.58
	[0.99]	[1.86]	[2.55]	[2.38]	[3.16]	[2.32]	[3.19]		[1.01]	[1.61]	[2.39]	[2.43]	[2.94]	[1.90]	[1.90]
Std	23.06	22.35	20.64	19.99	22.72	19.83	15.73	Std	22.58	20.64	18.10	17.31	23.63	15.46	21.46
Skew	-1.30	-0.61	-1.15	-1.07	-0.78	-1.24	-0.06	Skew	-0.36	-0.19	-0.88	-0.91	-0.62	-0.84	0.05
Kurt	7.31	4.60	7.66	4.97	4.31	6.46	3.21	Kurt	4.97	3.10	5.54	4.39	4.41	5.21	3.51
Panel B: Dividend growth															
PF	1	2	3	4	5	Avg.	5-1	*PF*	1	2	3	4	5	Avg.	5-1
Mean	22.30	11.63	9.35	10.52	1.75	11.17	-20.56	Mean	6.68	8.25	8.59	8.31	5.01	6.81	-1.67
	[6.57]	[8.44]	[6.55]	[7.33]	[0.72]	[9.13]	[-5.04]		[5.18]	[6.19]	[7.26]	[7.49]	[3.85]	[-1.00]	[-1.00]
Std	17.39	8.97	8.02	8.45	12.23	6.39	21.01	Std	5.89	7.09	6.07	5.84	7.23	3.10	9.06
Skew	2.10	0.94	0.12	1.67	-4.66	1.19	-2.22	Skew	2.43	0.34	0.41	0.94	-0.66	0.59	-0.58
Kurt	9.21	5.03	5.34	8.16	35.34	6.26	10.13	Kurt	12.66	4.87	3.74	6.76	16.01	5.50	11.31
Panel C: Spot rate changes															
PF	1	2	3	4	5	Avg.	5-1	*PF*	1	2	3	4	5	Avg.	5-1
Mean	-0.08	0.00	-0.54	-2.03	-2.72	-1.07	-2.64	Mean	2.64	0.91	-0.09	-1.00	-2.04	0.49	-4.68
	[-0.04]	[0.00]	[-0.41]	[-1.43]	[-1.62]	[-0.77]	[-2.17]		[1.37]	[0.57]	[-0.08]	[-0.72]	[-1.15]	[-2.17]	[-2.17]
Std	9.12	8.70	7.90	7.57	8.57	7.43	5.96	Std	10.85	8.57	6.83	7.61	10.22	4.99	11.57
Skew	0.01	-0.38	-0.45	-0.61	-0.28	-0.37	-0.12	Skew	0.36	0.07	-0.01	-0.78	-1.08	0.03	-1.08
Kurt	3.88	4.12	4.38	5.27	4.36	4.03	4.52	Kurt	3.43	4.37	3.80	8.55	6.42	3.13	5.22

Table 5: Double sorts on size and dividend yields

This table shows result from double sorts on size (total market capitalization) and dividend yields. Countries are first sorted into three groups according to their size (small, medium, and large countries). Within each group, countries are allocated to three portfolios depending on their dividend yield (growth, medium, value portfolios). We report average annualized total returns (left part), dividend growth rates (middle part), and spot rate changes (right part) for each of the nine portfolios. Row "L – S" shows results for the large minus small portfolio within each dividend yield group, whereas column "V – G" shows results for the value minus growth portfolio within each size group. T-statistics in squared brackets are based on Newey-West HAC standard errors.

	Total returns – USD				Dividend growth				Spot rate changes			
	Growth	Med.	Value	V – G	Growth	Med.	Value	V – G	Growth	Med.	Value	V – G
Small	8.85	7.59	13.79	4.93	29.32	9.77	1.24	-28.08	0.63	-5.12	-0.81	-1.44
	[2.07]	[1.36]	[3.08]	[1.28]	[5.56]	[1.76]	[0.46]	[-4.74]	[0.36]	[-1.78]	[-0.46]	[-0.81]
Med.	4.51	11.44	5.64	1.12	16.36	11.13	6.32	-10.04	-0.41	0.49	-2.64	-2.23
	[0.95]	[3.13]	[1.40]	[0.35]	[7.44]	[5.99]	[2.77]	[-3.48]	[-0.22]	[0.39]	[-1.76]	[-1.42]
Large	3.95	8.72	10.35	6.40	9.60	8.79	7.30	-2.30	1.25	-0.37	0.12	-1.13
	[0.93]	[2.49]	[3.07]	[2.34]	[5.91]	[6.95]	[8.14]	[-1.42]	[0.79]	[-0.26]	[0.08]	[-0.92]
L – S	-4.90	1.13	-3.44	1.47	-19.72	-0.98	6.07	25.78	0.62	4.76	0.93	0.31
	[-1.63]	[0.26]	[-0.86]	[0.34]	[-3.68]	[-0.18]	[2.34]	[4.47]	[0.52]	[1.61]	[0.58]	[0.15]

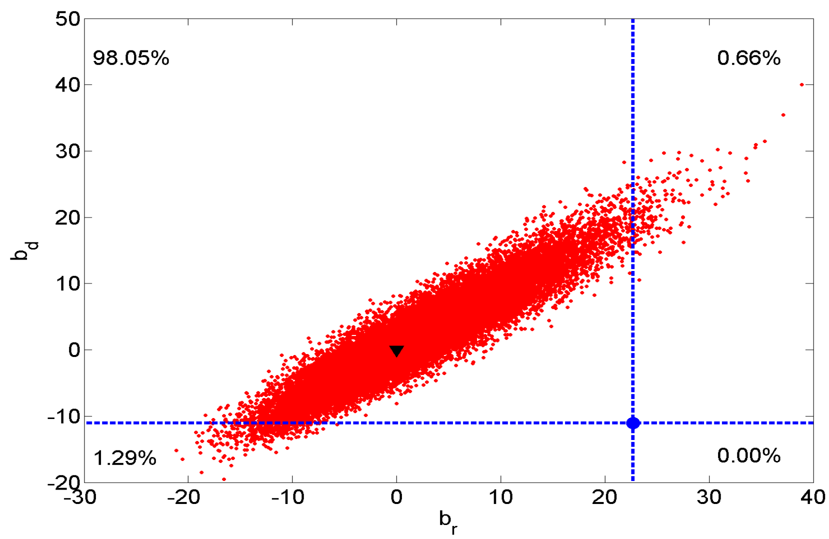
Table 6: Dividend growth across portfolios: Double sorts on volatility and dividend yields

The setup is the same as in Table 5, but we do not sort on size but on measures of volatility. Also, we only show results for dividend growth rates in this table. The left part shows double sorts on raw dividend volatility (sum of absolute quarterly log changes of dividends over the last year), the middle panel shows results for idiosyncratic dividend volatility, whereas the right panel shows results for idiosyncratic return volatility. Idiosyncratic volatilities are obtained by first regressing each country's (log) dividend growth (or total market return) on the aggregate, global dividend growth rate (or return), and then summing the absolute residuals over the last four quarters. The three volatility categories are shown in rows ("Low" to "High" volatility), whereas the value–growth dimension is shown in columns ("Growth" to "Value"). T-statistics in squared brackets are based on Newey-West HAC standard errors.

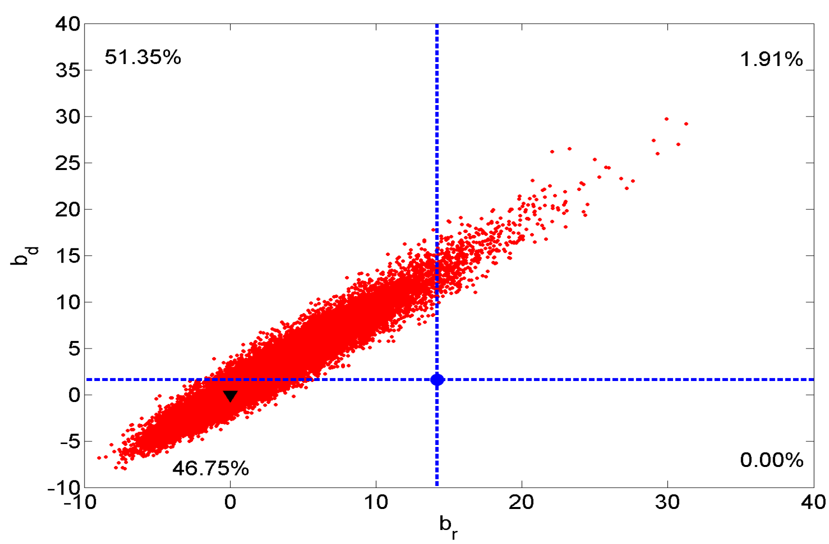
	Dividend volatility				Idiosyncratic dividend volatility				Idiosyncratic return volatility			
	Growth	Med.	Value	V – G	Growth	Med.	Value	V – G	Growth	Med.	Value	V – G
Low	7.50	6.19	4.91	-2.59	6.60	7.52	7.51	0.91	9.86	9.61	6.99	-2.87
	[4.00]	[4.60]	[5.04]	[-1.43]	[4.81]	[6.20]	[6.68]	[0.58]	[5.49]	[7.32]	[7.15]	[-1.63]
Med.	13.47	10.98	4.61	-8.86	14.27	8.67	5.13	-9.14	14.15	10.07	3.17	-10.98
	[7.17]	[6.71]	[1.67]	[-3.06]	[7.03]	[4.98]	[2.22]	[-3.51]	[6.48]	[5.12]	[1.76]	[-3.96]
High	24.42	12.53	8.97	-15.44	24.83	13.57	7.63	-17.20	23.59	14.99	1.87	-21.72
	[6.41]	[3.39]	[3.17]	[-3.48]	[6.69]	[5.44]	[2.38]	[-3.41]	[6.16]	[6.39]	[0.50]	[-4.24]
H – L	16.92	6.33	4.07	-12.85	18.23	6.05	0.12	-18.11	13.73	5.38	-5.12	-18.85
	[4.50]	[1.80]	[1.55]	[-2.84]	[5.24]	[2.54]	[0.04]	[-3.73]	[3.56]	[2.24]	[-1.41]	[-3.71]

Figure 1: Simulated coefficients

Simulated coefficients b_r (horizontal axis) and b_d (vertical axis) for equal and value-weighted portfolios, based on 25,000 repetitions of a Monte Carlo simulation. The small dots show simulated coefficient estimates, the large blue dot (and dashed lines) shows coefficient estimates in the actual data and the black triangle shows the null of no return and dividend growth predictability. The four percentage points in each graph show the frequencies of observed simulated coefficients in the four quadrants.



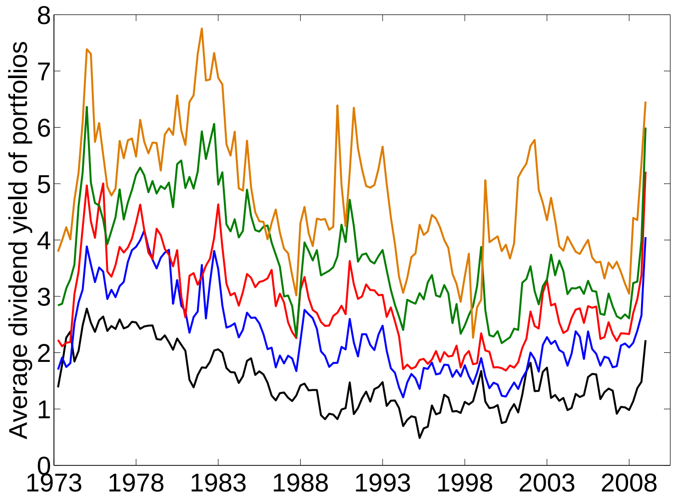
(a) Equal weights



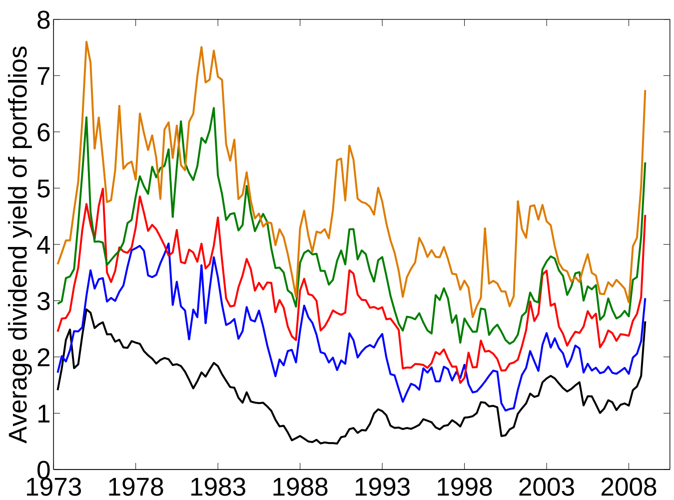
(b) Value weights

Figure 2: Average dividend yields

Average dividend yields for five portfolios sorted on dividend yields. The sample period is 1973Q1 to 2009Q1.



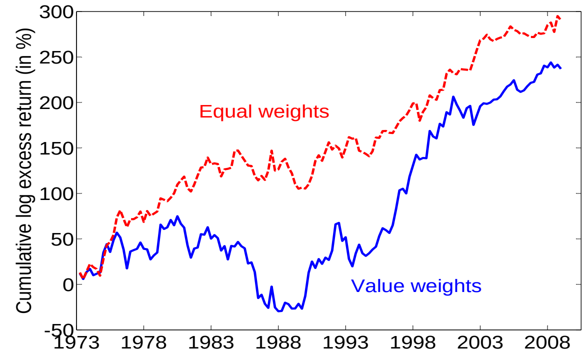
(a) Equal weights



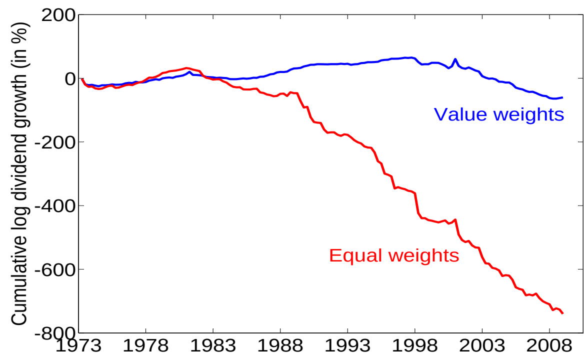
(b) Value weights

Figure 3: Cumulative returns, dividend growth, and spot rate changes of long-short portfolios

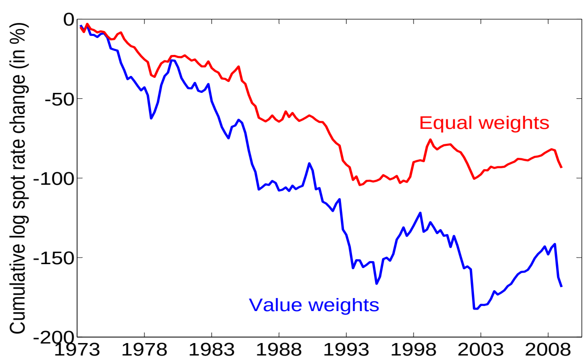
Cumulative returns, dividend growth, and spot rate changes of the long-short portfolio (portfolio 5 minus portfolio 1). Solid, blue lines show results for the full sample (all countries), whereas dashed, red lines show results for the sample of larger markets.



(a) Returns



(b) Dividend growth



(c) Spot rate changes

Appendix with robustness checks

A.1 Real dividends and excess returns: Predictive regressions

In our analyses, we have used the definition of returns and dividends implied by the Campbell-Shiller approximation of all variables, i.e., simple stock returns in USD and nominal dividends in foreign currency units. Chen (2009) also uses nominal variables in his analysis. Engsted & Pedersen (2009) scrutinize Chen's (2009) results and find that if using real dividends, one obtains results that are different from those of Chen (2009).

In order to evaluate whether our results are robust towards a change from nominal to real dividends, we have converted all dividend series into USD and then deflate all dividend series with U.S. inflation (CPI inflation). The reason we do this is that inflation data for many countries are not available over sufficient time spans. We therefore opt to express dividends in USD and use data on U.S. inflation. Also, this conversion is better suited to assess the actual gains or losses of a U.S.-based investor.[18] We run predictive regressions like those in Table 2, but use real USD dividend growth, and USD excess returns (in excess over the U.S. risk-free rate). The results are shown in Table A.I.

Basically, we find the same patterns for real variables, as we reported in Table 1 where we used nominal variables: Real dividend growth rates are highly predictable by the dividend yield when using equal weights, but not when using value weights. For instance, at the 2 years horizon, the R^2 is 21% for the real dividend-growth predicting regression in the equally weighted portfolio versus only 5% in the value-weighted portfolio. Hence, we find that our overall result holds for both real and nominal dividends.

A.1.1 Real dividends and excess returns: portfolios

We also calculated the average growth rates of real dividends and the average excess returns (in excess of the risk-free rate) that an investor would have obtained if he had constructed portfolios and trading strategies on the basis of the levels of dividend yields, in the same way as explained in Section 6. These appear in Table A.II. Basically, our main result is that the real returns resulting from such portfolio formations are large. For instance, the average *excess* return from investing in the zero-cost long-short portfolio based on equal-weights has on average been 7.96% compared to 9.10% if using value-weights such that the results are dominated by larger countries. Even more impressive, the average *real* dividend growth an investor would have obtained if following the

[18] Purchasing Power Parity arguments imply that there is no difference between using foreign inflation and dividends in foreign currency and using dividend in USD and U.S. inflation.

long-short trading strategy is -15.85% based on the equal-weighted portfolios versus the much smaller -6.64% in the long-short portfolio based on value-weights.

Hence, the overall result of the paper that there is significant dividend growth predictability in smaller markets, and that it is also economically significant, also holds for real dividends.

A.2 Excluding small countries with less than 15 years of data

Table 1 with summary statistics showed that we have relatively few observations for some of the countries (for instance, we only have 15 observations for Bulgaria and Korea, 13 for Rumania, 27 for Slovenia etc.). In addition, the dividend growth rates of these countries are often very volatile (most extreme is Russia). Consequently, one might worry that our main result that dividend growth rates are more predictable in small countries could be partly driven by these newly emerging economies. Of course, this could be interesting in itself. On the other hand, however, such a finding may imply that our results would loose importance as soon as the countries mature. Hence, we conducted our investigations on the subset of the countries for which we have at least fifteen years of data, thereby excluding the newly added emerging markets. We report the results from the time-series regressions in Table A.III and from the portfolio formations in Table A.IV.

The time-series tests reveal that dividend growth rates are predictable in the equal-weighted portfolio but not in the value-weighted portfolio, like in our results in Table 2. Hence, even if excluding the countries for which we have only few years of data, dividend growth rates appear more predictable in small countries. At the same time, however, it should be mentioned that our results are not as "spectacular" as when using the full sample of countries. For instance, the R^2 is "only" 5% in the restricted sample of Table A.III versus the approximately 7% reported in Table 2. Likewise, the R^2 increases to 17% at the two-years horizon in Table 2 but only to 9% in Table A.III. The main thing to notice, however, is that in Tables 2 and A.III, dividends are not predictable in the value-weighted portfolio.

Regarding the portfolios, Table A.IV reveals that the average dividend growth rate of the long-short portfolio constructed from the equal-weighted portfolios is -15.70%-points versus 0.25%-points when using the value-weighted portfolios. Qualitatively, this is the same pattern as the one we reported in Table 4 where we used all countries. Quantitatively, the results are less dramatic here, though. In Table 4, the average dividend growth rates of the long-short portfolios were -20.56%-points using equal-weighted portfolios and -1.67%-points using value-weighted portfolios.

All in all, we conclude that even if we exclude countries for which we have observations for less than fifteen years (mainly small countries), we find that dividend growth rates are more predictable in small countries, both in the time-series and in the cross-section.

A.3 Portfolio transitions

One concern with the above results on portfolio sorts could be that one may simply picking up structural cross-sectional differences between countries due to different, but rather constant, payout policies or tax codes, and not time-series predictability by the dividend yield.

In Figure A.1, we thus illustrate the transitions that occur between the portfolios for a few selected countries with a long data history. Take the U.S. for example which starts as a high dividend yield country in the 70s and 80s and ends out as a low dividend yield country. An opposite pattern can be observed for Italy. Other countries such as the U.K. or Australia are predominantly high dividend yield countries over the whole sample but switch around frequently between portfolios 4 and 5. Germany shows the opposite pattern and flips around between portfolios 1, 2, and 3. All in all, many transitions between the different portfolios occur, even in large markets.

Corroborating the visual impression from Figure A.1, we find the following average turnover frequencies (per annum): 46.5% (Portfolio 1), 48.2%, 54.0%, 53.4%, and 39.5% (Portfolio 5). Therefore, roughly 40-50% of the portfolio composition changes per year. This is important as it implies that the patterns we pick up in Table 4 are not just reflections of constant structural differences between different countries. In a robustness check in Section A.4, we further verify that we get the same kind of results as the ones we see in Table 4 if we sort on standardized dividend yields that eliminate unconditional cross-sectional differences between countries.

A.4 Standardizing dividend yields

The findings we present in Table 4 are not merely an illustration of constant structural differences between the payout policies (and returns) of firms in different countries. As an example, imagine that one country has a dividend yield that fluctuates around an average of, say, 2%, while another country has a dividend yield that fluctuates around, say, 5% because of differences in tax structures or other institutional differences. In such a case, the pattern we pick up in Table 4 would not be due to interesting transitions between the portfolios over time and, perhaps even more importantly, it would not be entirely clear either that such structural differences should imply that one country has higher expected returns than another.

To show that this is not the case, we calculate the characteristics of portfolios based on standardized dividend yields. The way we proceed is to standardize the dividend yields by demeaning each country's dividend yield and divide it by its own standard deviation. We then form portfolios in the same way as described in Section 6, but use standardized dividend yields.

We report the annualized mean returns, standard deviations, and other summary statistics from these trading strategies in Table A.V. As is clear, our basic result goes through also when sorting on standardized dividend yields. In particular, the average quarterly annualized return to the zero-cost long-short portfolio is still very high: Around nine percent when based on value-weighted portfolios and around 11% when based on equal-weighted. As before, the dividend growth averages are markedly different between the equal-weighted and the value-weighted portfolios. Looking at equal-weighted portfolios, for instance, the average annualized dividend growth rate is -23.33% in the portfolio of countries with the lowest dividend yields (portfolio 1), but only 0.93% in the countries with the highest dividend yields (in portfolio 5). This is an annualized difference of 22.40 percentage points. For the value-weighted portfolios dominated by large countries, the difference is "only" 8 percentage points.

Finally, exchange rate changes are, again, generally not predictable by the dividend yield; only the exchange rate change of the long-short portfolio (All countries) is marginally statistical significant.

A.5 Subsample analysis

We also checked whether there are differences between the two subsamples that we consider (1973-1990 and 1990-2009) for our portfolio sorts.[19] We show results for the standardized portfolio sorts directly in Appendix Table A.VI. We only look at "large countries", i.e., countries with full data histories, so that we are comparing the same sample countries over the sub-samples. The main result is that, like in the previous table, that there is not a big difference between the results from the subsamples with respect to the dividend growth rates: The average dividend growth rates of the long-short portfolios were -10.57% in the early subsample and -9.38% in the later subsample. On the other hand, there is some difference between the two subsample regarding the returns. For instance, the average return on the long-short portfolio is 8.42% in the early subsample, but only 3.04% in the later subsample. Again, exchange rate changes in the portfolios are not predictable.

A.6 Earnings yields and earnings growth: Portfolio sorts

We also sort countries into portfolios based on their earnings yields instead of dividend yields. Results are reported in Table A.VII in the appendix. Like for dividends, we find large economic effects resulting from the sorting procedure. The annualized growth in earnings in the countries having the highest earnings yield before portfolio formation is a negative 1.90% for the equal-weighted portfolio, whereas it is 19.70% for the portfolio of countries with the lowest earnings yield before portfolio formation. This means that the growth rate of earnings in the zero-cost long-short equal-weighted portfolio is an impressive -21.60% in annualized terms. If constructing the long-short portfolio on the basis of value-weighted portfolios, the result is an average dividend growth rate of only 1.74%

[19] We do not look at predictive regressions in sub-samples since our sample is too short and aggregate dividend yields show non-stationary behavior over shorter subsamples.

We find that returns in USD from being long in the countries with the highest earnings yield and short in the countries with the lowest earnings yield has provided investors on average with a return of 8.01% (in annualized terms based on equal-weighted portfolios; 7.04% when based on value-weighted). This is as high as if investing in the zero-cost long-short dividend yield-based portfolio shown in the main part of this paper. Regarding exchange rates, we find, similar to sorting on dividend yields, that the average exchange rate changes in the individual portfolios are not statistically different from zero, but that the exchange rate changes in the long-short portfolios are significantly predictable.

Overall, our results hold when using both earnings and dividends, and, hence, demonstrate that both earnings growth and dividend growth predictability are alive and well, particularly in smaller markets.

Table A.I: Predictive regressions: Excess returns and real dividend growth

The setup is the same as in Table 2, but here we use excess returns (total returns in USD in excess of the U.S. riskfree rate) and real dividend growth (dividend growth rates converted to USD and deflated by U.S. CPI inflation).

Equal weights					Value weights				
Dependent variable: Excess returns (in USD)									
h	1	2	4	8	h	1	2	4	8
β_r	1.16	5.42	15.54	21.60	β_r	1.22	3.60	9.49	18.17
t^{NW}	[0.32]	[1.01]	[1.59]	[1.13]	t^{NW}	[0.70]	[1.13]	[1.48]	[1.33]
t^{BS}	[0.37]	[0.89]	[1.12]	[0.59]	t^{BS}	[0.68]	[0.97]	[0.99]	[0.64]
$\bar{R}^2$	-0.01	0.00	0.02	0.03	$\bar{R}^2$	0.00	0.00	0.03	0.07
Dependent variable: Real dividend growth (in USD)									
h	1	2	4	8	h	1	2	4	8
β_d	-4.67	-9.23	-18.90	-35.83	β_d	-0.91	-1.77	-3.70	-6.82
t^{NW}	[-2.87]	[-3.13]	[-3.27]	[-2.73]	t^{NW}	[-1.41]	[-1.48]	[-1.66]	[-1.46]
t^{BS}	[-2.89]	[-2.70]	[-2.35]	[-1.93]	t^{BS}	[-1.40]	[-1.32]	[-1.27]	[-0.85]
$\bar{R}^2$	0.04	0.08	0.15	0.21	$\bar{R}^2$	0.00	0.01	0.03	0.05

Table A.II: Excess returns and real dividend growth

The setup is the same as in Table 4, but here we provide results for excess returns (in USD, in excess over the risk-free rate) in Panel A, and real dividend growth (in USD) in Panel B.

Panel A: Equal weights								Panel B: Value weights							
Excess returns – USD								Excess Returns – USD							
PF	1	2	3	4	5	Av.	5-1	*PF*	1	2	3	4	5	Avg.	5-1
Mean	-1.23	2.13	3.62	3.07	6.73	2.94	7.96	Mean	-1.03	5.61	3.56	4.57	8.06	3.39	9.10
	[-0.27]	[0.51]	[0.99]	[0.82]	[1.69]	[0.78]	[3.19]		[-0.25]	[1.45]	[1.21]	[1.38]	[2.42]	[1.25]	[2.61]
Std	23.13	22.33	20.66	20.07	22.82	19.88	15.73	Std	21.70	20.79	17.07	20.53	21.27	14.15	21.77
Skew	-1.22	-0.57	-1.06	-1.02	-0.73	-1.15	-0.06	Skew	-0.12	-0.11	-0.36	-0.38	-0.77	-0.39	0.24
Kurt	6.87	4.35	7.19	4.64	4.10	5.99	3.21	Kurt	4.15	3.36	2.82	3.87	4.05	3.06	5.45
SR	-0.05	0.10	0.18	0.15	0.30	0.15	0.51	SR	-0.05	0.27	0.21	0.22	0.38	0.24	0.42
Real dividend growth – USD								Real dividend growth – USD							
PF	1	2	3	4	5	Av.	5-1	*PF*	1	2	3	4	5	Avg.	5-1
Mean	15.54	8.52	4.60	8.12	-0.30	7.31	-15.85	Mean	7.21	4.57	1.84	2.40	0.57	1.68	-6.64
	[3.84]	[3.93]	[2.42]	[4.00]	[-0.11]	[3.77]	[-3.86]		[2.80]	[2.09]	[0.97]	[1.48]	[0.30]	[1.54]	[-2.25]
Std	18.94	13.67	11.94	11.83	13.81	10.00	20.96	Std	12.17	12.66	11.22	10.26	13.83	5.95	17.30
Skew	1.05	0.46	0.28	1.14	-2.41	0.27	-1.77	Skew	0.80	0.11	0.31	0.49	0.68	0.04	0.46
Kurt	4.82	2.98	4.82	6.88	14.14	3.47	7.64	Kurt	6.77	3.81	6.12	3.97	18.18	3.09	12.58

Table A.III: Predictive regressions: Excluding small countries

The setup is the same as in Table 2, but we exclude countries with less than 15 years of available data.

	Equal weights					Value weights			
	Dependent variable: Total returns – USD								
h	1	2	4	8	h	1	2	4	8
β_r	2.41	7.65	21.23	35.06	β_r	2.35	5.89	14.26	28.41
t^{NW}	[0.64]	[1.43]	[2.42]	[1.96]	t^{NW}	[1.39]	[1.95]	[2.38]	[2.25]
t^{BS}	[0.77]	[1.34]	[1.69]	[1.07]	t^{BS}	[1.40]	[1.68]	[1.63]	[1.10]
$\bar{R}^2$	0.00	0.01	0.05	0.08	$\bar{R}^2$	0.00	0.02	0.08	0.18
	Dependent variable: Dividend growth								
h	1	2	4	8	h	1	2	4	8
β_d	-2.79	-4.90	-8.72	-13.02	β_d	0.32	0.81	1.68	3.67
t^{NW}	[-3.23]	[-3.17]	[-2.87]	[-1.94]	t^{NW}	[0.72]	[0.95]	[0.90]	[0.92]
t^{BS}	[-3.06]	[-2.60]	[-2.16]	[-1.66]	t^{BS}	[0.68]	[0.80]	[0.67]	[0.57]
$\bar{R}^2$	0.05	0.07	0.10	0.09	$\bar{R}^2$	0.00	0.01	0.01	0.02
R^2_{IH}	0.13	0.18	0.27	0.35	R^2_{IH}	0.03	0.03	0.02	0.02
h	1	2	4	8	h	1	2	4	8
β_s	-0.35	-0.59	0.21	2.19	β_s	-0.03	-0.02	0.25	0.87
t^{NW}	[-0.26]	[-0.23]	[0.04]	[0.20]	t^{NW}	[-0.05]	[-0.02]	[0.12]	[0.21]
t^{BS}	[-0.25]	[-0.20]	[0.03]	[0.13]	t^{BS}	[-0.05]	[-0.02]	[0.09]	[0.11]
$\bar{R}^2$	-0.01	-0.01	-0.01	-0.01	$\bar{R}^2$	-0.01	-0.01	-0.01	-0.01

Table A.IV: Portfolio sorts: Excluding small countries

The setup is the same as in Table 4, but here we exclude countries with less than 15 years of available data.

Panel A: Equal weights								Panel B:Value weights							
Total returns – USD								Total returns – USD							
PF	1	2	3	4	5	Avg.	5-1	*PF*	1	2	3	4	5	Avg.	5-1
Mean	3.56	8.22	10.29	8.26	12.37	8.58	8.81	Mean	4.47	7.24	8.51	7.58	11.42	7.38	6.95
	[0.81]	[2.04]	[2.88]	[2.20]	[3.28]	[2.40]	[3.22]		[1.00]	[1.90]	[2.47]	[2.34]	[3.13]	[2.42]	[1.96]
Std	22.38	21.68	20.08	20.29	21.96	19.16	16.42	Std	21.69	20.46	18.50	17.26	22.34	15.24	20.92
Skew	-0.87	-0.52	-0.87	-1.05	-0.74	-1.03	-0.05	Skew	-0.07	-0.28	-0.99	-0.87	-0.49	-0.72	0.06
Kurt	4.74	4.23	5.82	4.97	4.12	5.22	2.81	Kurt	4.10	3.48	6.06	4.22	4.10	4.63	3.59
Dividend growth								Dividend growth							
PF	1	2	3	4	5	Avg.	5-1	*PF*	1	2	3	4	5	Avg.	5-1
Mean	18.54	11.90	9.29	10.63	2.84	10.65	-15.70	Mean	5.67	9.03	9.18	8.07	5.42	6.70	-0.25
	[7.01]	[8.91]	[6.74]	[7.73]	[1.46]	[10.12]	[-4.97]		[4.77]	[6.95]	[7.53]	[7.53]	[4.45]	[9.35]	[-0.16]
Std	13.88	9.10	8.03	7.83	9.47	5.67	16.30	Std	5.54	7.38	6.60	5.66	5.71	3.11	7.34
Skew	1.53	1.42	-0.28	1.28	-2.90	0.81	-1.25	Skew	2.73	0.96	0.59	0.81	-1.91	0.49	-2.03
Kurt	6.01	7.57	4.95	5.90	19.69	5.05	4.79	Kurt	16.29	5.45	4.37	7.11	16.72	5.57	10.76
Spot rate changes								Spot rate changes							
PF	1	2	3	4	5	Avg.	5-1	*PF*	1	2	3	4	5	Avg.	5-1
Mean	-0.42	0.46	-0.42	-2.10	-2.82	-1.07	-2.40	Mean	2.82	1.05	0.02	-1.04	-1.63	0.52	-4.45
	[-0.22]	[0.30]	[-0.32]	[-1.48]	[-1.73]	[-0.77]	[-2.00]		[1.46]	[0.68]	[0.01]	[-0.74]	[-0.99]	[0.62]	[-2.17]
Std	9.36	8.36	7.92	7.48	8.41	7.37	6.05	Std	10.84	8.61	7.20	7.63	9.73	4.98	10.93
Skew	-0.09	-0.19	-0.45	-0.53	-0.21	-0.30	-0.12	Skew	0.37	0.05	-0.56	-0.75	-0.69	0.07	-0.72
Kurt	4.13	3.69	4.53	4.75	4.19	3.70	4.85	Kurt	3.54	4.29	6.11	8.27	4.94	3.02	4.14

Table A.V: Portfolio sorts on standardized dividend yields

This table shows results similar to Table 4, but here we sort on *standardized dividend yields*. Each country's dividend yield is demeaned and divided by its own standard deviation. As above, we re-balance portfolios annually (in the second quarter) and mean returns and standard deviations reported in this table are annualized.

Panel A: Equal weights							
Total returns – USD							
PF	1	2	3	4	5	Avg.	5-1
Mean	2.79	7.90	6.55	11.44	14.12	8.66	11.32
	[0.63]	[1.80]	[1.70]	[3.18]	[3.50]	[2.32]	[3.48]
Std	23.55	23.55	20.18	20.38	22.52	19.83	18.19
Skew	-0.70	-1.13	-1.24	-0.70	-1.01	-1.24	-0.82
Kurt	6.07	5.79	6.94	4.18	4.86	6.46	6.94
Dividend growth							
PF	1	2	3	4	5	Avg.	5-1
Mean	23.33	14.46	10.62	6.31	0.93	11.17	-22.40
	[8.54]	[8.86]	[7.77]	[4.20]	[0.42]	[9.13]	[-6.87]
Std	16.45	9.96	8.52	8.74	11.88	6.39	20.77
Skew	2.39	1.27	1.49	0.08	-4.32	1.19	-2.37
Kurt	10.43	5.95	6.57	7.45	36.36	6.26	11.41
Spot rate changes							
PF	1	2	3	4	5	Avg.	5-1
Mean	0.05	-0.74	-0.12	-1.78	-2.82	-1.08	-2.86
	[0.03]	[-0.48]	[-0.07]	[-1.20]	[-1.91]	[-0.77]	[-2.25]
Std	8.14	8.67	8.66	8.17	7.56	7.44	6.23
Skew	-0.08	-0.56	-0.73	-0.30	-0.39	-0.37	-0.03
Kurt	3.86	5.06	5.41	3.79	4.26	4.02	4.10

Panel B:Value weights							
Total returns – USD							
PF	1	2	3	4	5	Avg.	5-1
Mean	3.40	8.92	6.95	10.29	12.33	7.35	8.93
	[0.85]	[1.93]	[2.10]	[2.81]	[3.43]	[2.38]	[2.74]
Std	21.94	25.00	17.53	20.75	21.08	15.46	20.38
Skew	-0.03	-0.75	-0.72	-0.53	-0.78	-0.84	0.13
Kurt	3.83	5.34	4.21	3.99	4.15	5.21	6.02
Dividend growth							
PF	1	2	3	4	5	Avg.	5-1
Mean	12.02	10.70	7.19	5.58	3.64	6.81	-8.39
	[7.40]	[8.18]	[6.61]	[4.46]	[2.01]	[9.52]	[-3.72]
Std	7.94	7.17	5.48	6.88	11.85	3.10	14.27
Skew	3.22	1.05	0.75	0.34	-0.23	0.59	-0.10
Kurt	22.85	4.75	4.39	7.42	23.14	5.50	16.92
Spot rate changes							
PF	1	2	3	4	5	Avg.	5-1
Mean	0.79	0.99	0.42	-0.53	-1.61	0.49	-2.40
	[0.51]	[0.61]	[0.29]	[-0.40]	[-1.15]	[0.58]	[-1.40]
Std	7.73	9.83	8.84	7.86	7.47	4.99	8.05
Skew	0.64	0.07	-0.15	-0.86	-0.24	0.03	-0.55
Kurt	3.85	3.89	6.08	5.66	4.20	3.13	3.88

Table A.VI: Descriptive Statistics: Portfolios sorted on standardized dividend yields (sub-samples)

The setup is identical to Table A.V, i.e., we sort on standardized dividend yields. The left part shows results for the sample period from 1973 to 1990, whereas the right part shows results for the period 1991 to 2009.

Panel A: Large markets (1973 – 1990)							
Total returns – USD							
PF	1	2	3	4	5	Avg.	5-1
Mean	3.06	14.00	8.99	11.30	16.99	10.94	8.42
	[0.52]	[2.11]	[2.05]	[2.91]	[4.03]	[2.46]	[2.07]
Std	23.72	25.18	18.42	16.55	19.70	17.89	17.87
Skew	0.12	-1.01	-0.32	-0.28	-0.35	-0.65	-0.03
Kurt	2.48	5.75	2.76	2.88	2.82	3.09	2.85
Dividend growth							
PF	1	2	3	4	5	Avg.	5-1
Mean	14.41	11.56	6.61	5.84	3.83	8.54	-10.57
	[9.57]	[8.41]	[5.21]	[5.48]	[2.33]	[8.83]	[-5.47]
Std	7.23	7.04	5.57	4.36	7.07	3.71	11.19
Skew	0.84	-0.08	1.76	-0.36	-0.50	0.54	-0.70
Kurt	3.35	3.66	12.20	5.03	5.01	3.33	4.86
Spot rate changes							
PF	1	2	3	4	5	Avg.	5-1
Mean	2.29	1.06	2.95	-0.91	0.18	1.09	-2.11
	[0.83]	[0.42]	[1.33]	[-0.44]	[0.10]	[0.53]	[-1.00]
Std	9.21	9.78	8.30	8.78	7.54	7.76	6.96
Skew	0.33	0.05	-0.19	-0.07	0.26	0.06	0.07
Kurt	2.38	2.91	2.57	3.67	3.08	2.33	3.87

Panel B: Large markets (1991 – 2009)							
Total returns – USD							
PF	1	2	3	4	5	Avg.	5-1
Mean	4.46	6.11	8.25	7.68	9.10	7.12	3.04
	[0.88]	[1.52]	[1.59]	[1.45]	[2.03]	[1.58]	[0.92]
Std	17.65	15.96	18.09	18.52	18.03	16.07	13.00
Skew	-1.07	-0.47	-1.04	-1.27	-1.11	-1.30	0.34
Kurt	5.16	4.02	4.85	5.99	4.77	6.09	3.94
Dividend growth							
PF	1	2	3	4	5	Avg.	5-1
Mean	12.75	6.70	8.75	6.63	3.37	7.64	-9.38
	[7.32]	[2.95]	[4.64]	[3.69]	[1.48]	[5.27]	[-3.69]
Std	9.32	9.93	7.70	8.09	9.51	6.06	12.20
Skew	0.59	0.08	1.04	0.39	0.06	1.54	-0.57
Kurt	3.69	5.43	4.61	4.42	4.07	6.67	3.15
Spot rate changes							
PF	1	2	3	4	5	Avg.	5-1
Mean	0.11	0.40	-0.29	0.17	-0.43	-0.01	-0.54
	[0.06]	[0.20]	[-0.13]	[0.11]	[-0.21]	[0.00]	[-0.31]
Std	7.11	8.08	9.07	7.45	7.82	7.18	5.90
Skew	-0.24	-0.23	-1.02	-0.47	-0.40	-0.54	-0.05
Kurt	3.69	4.41	6.12	3.35	3.66	3.46	5.14

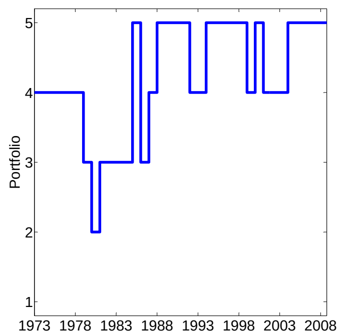
Table A.VII: Descriptive Statistics: Portfolios sorted on earnings yields

The setup of this table is identical to Table 4, but here we sort countries into portfolios based on (lagged) earnings yields (as opposed to dividend yields) and we show average growth rates of (log) earnings (instead of dividends).

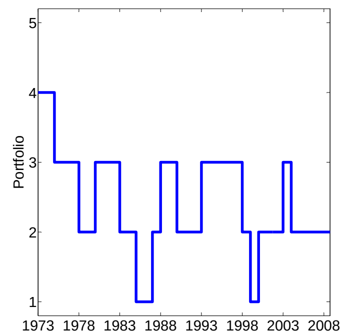
Equal weights								Value weights							
Panel A: Total returns – USD															
PF	1	2	3	4	5	Avg.	5-1	*PF*	1	2	3	4	5	Avg.	5-1
Mean	3.94	5.60	10.51	11.62	11.95	8.66	8.01	Mean	5.27	5.68	8.11	10.93	12.31	7.37	7.04
	[0.86]	[1.46]	[2.94]	[2.99]	[2.89]	[2.33]	[3.09]		1.16	1.83	2.47	3.08	2.87	2.01	2.01
Std	24.08	20.52	20.36	21.01	23.42	19.76	16.37	Std	22.75	18.01	18.04	21.05	25.29	15.45	22.40
Skew	-1.05	-1.19	-1.38	-0.77	-0.74	-1.25	-0.22	Skew	-0.25	-0.37	-1.56	-0.64	-0.79	-0.84	0.29
Kurt	7.29	6.98	7.50	3.67	4.20	6.57	5.60	Kurt	4.66	3.42	8.53	3.73	5.47	5.22	4.68
Panel B: Earnings growth															
PF	1	2	3	4	5	Avg.	5-1	*PF*	1	2	3	4	5	Avg.	5-1
Mean	19.70	15.62	10.15	8.81	-1.90	10.51	-21.60	Mean	6.26	6.16	9.14	8.94	8.00	6.73	1.74
	[8.61]	[7.56]	[5.06]	[3.92]	[-0.81]	[6.61]	[-7.76]		5.18	5.20	9.89	8.80	2.66	0.55	0.55
Std	15.18	12.09	9.05	10.71	14.39	7.17	21.11	Std	5.59	5.69	5.76	6.14	15.33	3.09	15.77
Skew	0.32	1.35	0.24	0.12	-0.94	-0.03	-1.15	Skew	3.66	-0.16	1.46	0.18	-0.48	0.62	-0.31
Kurt	6.53	7.46	3.45	4.74	6.19	3.58	5.87	Kurt	27.22	5.42	7.37	3.93	19.07	5.59	18.98
Panel C: Spot rate changes															
PF	1	2	3	4	5	Avg.	5-1	*PF*	1	2	3	4	5	Avg.	5-1
Mean	0.94	-0.94	-0.21	-1.00	-2.53	-0.83	-3.47	Mean	3.38	0.23	-0.98	-0.14	-1.85	0.53	-5.23
	[0.60]	[-0.64]	[-0.14]	[-0.69]	[-1.48]	[-0.59]	[-3.20]		1.82	0.17	-0.79	-0.10	-0.99	-3.04	-3.04
Std	8.10	8.57	8.56	7.92	8.80	7.43	5.97	Std	10.09	7.73	7.88	8.16	10.00	4.99	10.15
Skew	-0.69	-0.34	-0.12	-0.40	0.11	-0.35	-0.25	Skew	0.29	0.41	-0.50	-0.54	-0.34	0.03	-0.61
Kurt	5.85	4.97	4.55	4.49	3.92	4.08	4.99	Kurt	3.66	5.86	6.74	5.43	4.45	3.16	4.37

Figure A.1: Portfolio composition

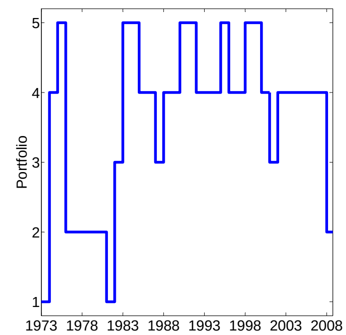
The Figure shows portfolio belongings for some countries. Portfolios (shown on the vertical axis) range from 1 (low dividend yield countries) to 5 (high dividend yield countries). The calculations are based on the sample of all 50 countries.



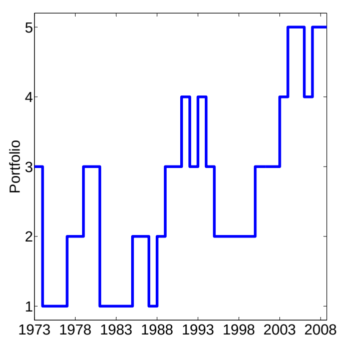
(a) Australia



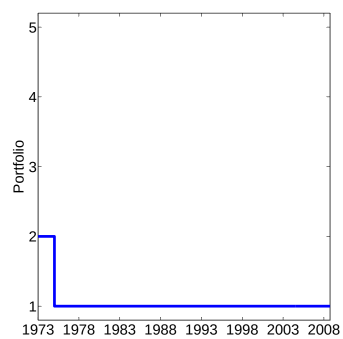
(b) Germany



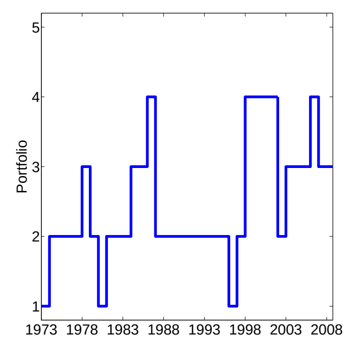
(c) Hong Kong



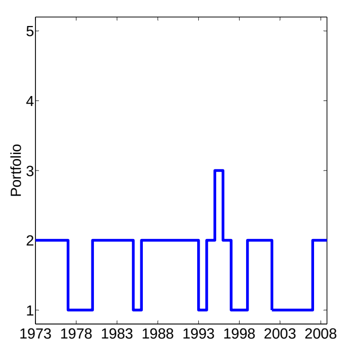
(d) Italy



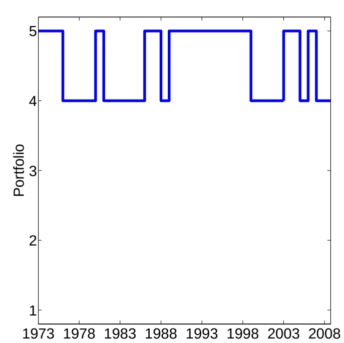
(e) Japan



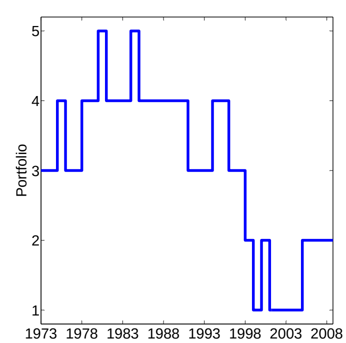
(f) Singapore



(g) Switzerland



(h) U.K.



(i) U.S.

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