Dividend predictability around the world[*]

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Abstract

A large literature examines whether dividend growth rates in the U.S. are predictable by the dividend yield. We provide fresh perspectives to this literature by extending it to a global setting. We show that aggregate dividend growth is highly predictable by dividend yields in medium-sized and smaller countries, but generally not in larger countries. We also show that dividend predictability is weaker in countries where the typical firm is larger and idiosyncratic dividend growth and return volatilities are lower. We find that the reason why dividends in countries with large and more stable firms are more difficult to predict is that these types of firms smooth their dividends more, and dividend smoothing disconnects movements in future dividends from dividend yield fluctuations. We finally show that in countries where the quality of institutions is high, dividend predictability is weaker. These findings indicate that the apparent lack of dividend predictability in the U.S. does not, in general, extend to other countries. Rather, dividend predictability is driven by cross-country differences in firm characteristics, dividend smoothing, and institutions.

JEL-Classification: G12, G15, F31

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1 Introduction

A fundamental question in asset pricing is whether stock prices move because of news to expected returns or news to expected dividend growth. For the aggregate U.S. stock market, a large literature reports that news to discount rates (i.e. expected future returns) account for the major fraction of variations in dividend yields; see, for instance, Campbell and Shiller (1988a,b), Campbell (1991), Cochrane (1991, 2008), Campbell and Ammer (1993), Lettau and Ludvigson (2005), Ang and Bekaert (2007), Cochrane (2008), Cochrane (1992), Ang (2002), Goyal and Welch (2003), Lewellen (2004), Campbell and Thompson (2008), and Larrain and Yogo (2008). Recently, however, a literature has emerged that argues that the finding that U.S. aggregate dividends cannot be predicted by the dividend yield on its own does not mean that aggregate U.S. dividend growth rates cannot be predicted at all.[1] For instance, Lettau and Ludvigson (2005) find that U.S. dividend growth rates are predictable by an estimated consumption-dividends-labor income ratio, but not by the dividend yield itself, Chen (2009) demonstrates that aggregate U.S. dividend growth rates were predictable by the dividend yield in early periods of the industrialization, whereas dividend growth rates are not predictable by the dividend yield after WWII, and Koijen and van Binsbergen (2010) show that U.S. market-wide dividends are predictable when incorporating the whole history of lagged price-dividend ratios and dividend growth rates for forecasting future dividend growth.

[1] Also, there is a completely different finding at 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.

We provide fresh perspectives to this discussion. Instead of looking solely at U.S. data, we study dividend predictability by the dividend yield in an international setting. This allows us to extend and broaden the evidence on dividend predictability and to test new hypotheses regarding its underlying economic drivers.

We provide four new findings. First of all, we systematically evaluate whether the traditional finding from U.S. data, that market-wide dividends are not predictable by the dividend yield on its own, also holds internationally. We find that it does not. Indeed, using a global sample of fifty stock markets over the period from 1973 to 2009, we show that market-wide dividends are highly predictable by the dividend yield in smaller and medium-sized countries, but generally not in large equity markets such as the U.S. To show this, we first run, country by country, traditional regressions of next-year dividend growth rates or returns on this year's dividend yield. We find that in large countries, such as the U.S., the U.K., and Japan, dividends yields are insignificantly related to future dividend growth rates and R^2s are below 10%, whereas in smaller countries, such as Austria, Argentina, and New Zealand, we find that changes in dividend yields are strongly and significantly related to future dividend growth rates and R^2s are sometimes higher than 30%. Next, in order to provide more systematic evidence and take into account that some markets grow in size relative to other markets, we form two aggregate global stock portfolios; an equally-weighted and a value-weighted average of the market indices of the fifty countries in our sample. For each of these two portfolios, we run predictive regressions of their future dividend growth rates on current-period dividend yields. We find that dividend growth is highly predictable in the equally-weighted portfolio but not predictable at all in the value-weighted portfolio. Since the equally-weighted portfolio puts more weight on smaller markets than the value-weighted portfolio by construction, the observed dividend growth predictability in the equally-weighted portfolio arises because dividend growth is significantly more predictable in countries with medium-sized or smaller equity markets compared to countries with large market capitalization, such as the U.S.[2] We conduct a large number of robustness tests that confirm that dividends are more predictable in smaller countries. An an example, we also sort countries into five portfolios based on their (lagged) dividend yields, and then value-weight and equal-weight within each of the five portfolios. This allows us both to illustrate the economic importance of time-series predictability via portfolio return spreads, as advocated by Cochrane (2010), and to derive our results using other methods than univariate time-series regressions (Koijen and van Binsbergen, 2010). We find a lot of economically important dividend predictability in the equal-weighted portfolios but nothing in the value-weighted.

After having documented that dividends are more predictable in countries with smaller market capitalization, we turn to possible explanations for this finding. We first investigate the relation between dividend predictability and dividend smoothing. Chen, Da, and Priestley (2010) find that dividend smoothing reduces dividend predictability because dividend smoothing disconnects dividend payments from fluctuations in dividend yields. If this is true, we should expect to find more dividend smoothing in large countries. To verify this conjecture empirically, we show that dividends are indeed more smooth in large

[2]We focus on dividend growth predictability in the paper, but we also present the results on the predictability of returns. We find that returns are more predictable in the value-weighted portfolio, but the differences to the equally-weighted portfolio are not as pronounced as they are for dividend growth predictability.

equity markets by estimating a version of the Lintner (1956) partial-adjustment model for our equally- and value-weighted portfolios. We find that the estimated smoothing parameter is considerably higher in the value-weighted portfolio and even insignificant in the equal-weigthed portfolio. We also show that dividends react less to changes in earnings in the value-weighted portfolio compared to the equally-weighted portfolio. Both of these findings confirm that dividends in large equity markets are smoothed more. Finally, we relate smoothing to predictability and find that in those countries where dividends are more smooth, dividends are also more difficult to predict by the dividend yield.

Our third contribution is to examine the underlying factors driving these results and link dividend-predictability to differences in firm characteristics across countries. Our hypotheses are motivated by two recent findings (both using U.S. data): First, Vuolteenaho (2002) shows that dividends are highly predictable when looking at U.S. firm level data, and that firm-level dividend predictability varies with firm size, but that aggregate market-wide dividends are unpredictable because cash-flow predictability at the firm level is idiosyncratic and washes out in the aggregate. Second, Leary and Michaely (2010) find that large and mature U.S. firms and firms with stable cash-flow and return processes have a higher tendency to smooth dividends. Based on these findings, a natural hypothesis in our global investigation is that aggregate dividends are more difficult to predict in countries where the typical firm is large and/or has a more stable dividend and return process. In order to analyze the relation between firm size and dividend predictability, we run panel time-series regressions where we interact the dividend yield of the country with the size of the typical firm in the country, measured for instance by average market capitalization. We find strong evidence that dividend growth is less predictable in countries where the typical firm is large.[3] We next investigate the relation between idiosyncratic volatility (of dividends and returns) and dividend predictability. We find that countries with more stable (i.e. less volatile) return and dividend processes have less predictable dividend growth rate processes. We end up concluding that differences in how well market-wide dividends can be predicted across countries is related to differences in firm characteristics across countries.

The use of international data finally allows us to relate cross-sectional determinants in dividend predictability to variations in even more fundamental underlying factors, such as the quality of the legal system in a country or the quality of corporate governance. This is our fourth contribution. Porta *et al.* (2000a) and Pinkowitz *et al.* (2006) find that the level and value of dividends in different countries are related to differences between institutional qualities. Hence, if the value and level of dividends is related to institutional quality, it seems intuitive to relate dividend predictability to institutional quality as well. One could imagine two channels through which institutions might affect dividend policy. On the one hand, if low institutional quality is associated with higher uncertainty for firms in the country, which seems very likely and turns out to be the case, then low institutional quality would imply more predictable dividends, because volatility and predictability are positively related. On the other hand, low institutional quality could also lead to more dividend smoothing, as argued in Leary and Michaely (2010), and thereby low dividend predictability. We test which of the two channels seem to dominate in international data.

[3]We also present results from an extension of our otherwise purely international investigation by verifying that dividend predictability is related to firm size in the U.S. as well: Dividends of large U.S. firms are more difficult to predict than dividends of small U.S. firms.

We find that dividend predictability is stronger in countries where the efficiency of the judicial system is poor and/or the risk of expropriation and the risk of earnings management is high.

Finally, we should mention that 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 a few 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 equity 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 (2010) 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., but do so in Denmark and Sweden. In relation to Campbell (2003), Ang and Bekaert (2007), and Engsted and Pedersen (2010), we provide evidence for many more countries, which allows us to verify systematic differences across countries in recent data, i.e. 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. More importantly, we link dividend predictability across the globe to cross-country differences in firm sizes and volatilities, and dividend smoothing, as well as to underlying institutional characteristics, such as the level of the legal system and corporate governance.

The structure of the remaining part of the paper is as follows: In the next section, we present an simple extension of the Campbell-Shiller one-currency return decomposition to an international setting. The data we use are described in Section 3. In Section 4, we use time-series regression and portfolio-sorting techniques to show that dividends are more predictable in countries with smaller market capitalization. We show that dividends are more smooth in larger equity markets in Section 5. In Section 6, we show that predictability is higher in countries where the typical firm is small and return and/or dividend volatility high, and that firm size and volatility are related to dividend smoothing. In Section7, we relate institutional quality to dividend 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 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 the formula directly applicable 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:

$$R_{t+1} = \frac{P_{t+1}^f + D_{t+1}^f}{P_t^f} \cdot \frac{S_{t+1}}{S_t} \tag{1}$$

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:

$$\frac{P_t^f}{D_t^f} = \frac{1}{R_{t+1}} \left(1 + \frac{P_{t+1}^f}{D_{t+1}^f} \right) \frac{D_{t+1}^f}{D_t^f} \frac{S_{t+1}}{S_t} \tag{2}$$

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

$$d_t^f - p_t^f \simeq r_{t+1} - \triangle d_{t+1}^f - \triangle s_{t+1} + k + \rho \left(d_{t+1}^f - p_{t+1}^f \right) \tag{3}$$

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 $(d_t^f - p_t^f)$ forward, taking conditional expectations, and imposing the standard transversality condition results in the almost standard relationship:

$$d_t^f - p_t^f \simeq \text{const.} + E_t \left[\sum_{j=1}^{\infty} \rho^{j-1} (r_{t+j} - \triangle d_{t+j}^f - \triangle s_{t+j}) \right]. \tag{4}$$

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 with higher dividend yields are 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.[4]

We should stress that dividend growth rates are in local currencies. This means that when we compare dividend predictability across countries, there is no exchange rate effect influencing the results we report.

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 will only pay low 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 USD to having appreciated (so that they receive fewer USD per unit of foreign currency) when they cash-in their investment in future periods, i.e. if they expect $\triangle s_{t+j} < 0$.

[4] 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.

3 Data

We analyze a total of 50 countries for which dividend yields, 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. and dividends and dividend yields from Datastream, as the available M.S.C.I data span a much shorter subperiod. 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 and price returns.[5]

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, 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 where yields are calculated with trailing dividends over the last four quarters.

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. To further illustrate this point, we plot the time series of dividend growth series for the US based on data from Robert Shiller's web page (for the S&P 500) and

[5] See e.g. Chen (2009) or Koijen and van Binsbergen (2010) for the impact of assumptions about dividend reinvestments that are paid out throughout the year.

based on data from Datastream (the data we use in this paper) in Figure 1. Of course, these are two different portfolios composed of different sets of firms, so they should not be identical. Nevertheless, the two dividend series behave rather similarly overall and move quite closely together. Hence, in this case where a well-known alternative time-series is available, we see that the Datastream series reveals very much the same characteristics as those of the S&P 500 making us comfortable using the Datastream indices.

Figure 1 about here

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 countries such as Denmark (10.11%), Belgium (9.87%), 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., countries with very large equity market capitalization. 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% for Bulgaria (however, for Bulgaria, the sample is very short, too).[6]

For our empirical analysis below, we form two kinds of aggregate portfolios from our individual country data: A value-weighted global portfolio and an equally-weighted global

[6]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 qualitatively affect the results reported below.

portfolio. We use each market's capitalization (at the end of the previous quarter) as a fraction of total world-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 equally-weighted portfolio, on the other hand, more closely resemble the behavior of the bulk of smaller and medium-sized markets: In the equally-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. We see that the equally-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.

4 Documenting dividend predictability in small and large countries

4.1 First illustrative results: Predictive regressions for selected individual countries

The first thing we do is to provide some initial results from a few simple country-by-country regressions, i.e. a setting where there is no conversion of returns to USD. The intention with these first regressions is to illustrate the main finding of the paper that dividends are generally more predictable in smaller countries using the standard regressions often performed in the literature.

To this end, we split the total of 50 countries into three size groups based on their market capitalization in 2009 (at the 33.3% breakpoints) and show results for return and dividend predictability for three more or less arbitrary countries from each of these groups in Table 2.[7] The group of large countries is made of the three largest stock markets in terms of market capitalization, namely the U.S., Japan, and U.K. It can be seen that results for these large closely resemble the typical finding for the U.S. stock market. Returns appear to some extent predictable and the coefficient on dividend predictability actually has the "wrong" sign and is positive. The three countries from the intermediate size group (Italy, Netherlands, Finland) show clear dividend growth predictability (which is correctly signed) but little return predictability. Finally, results for the three small countries (Austria,

[7] We require at least fifteen full years of data for a country to be included so that we are not looking at the most extreme left tail of the size distribution.

Argentina, New Zealand) are very similar with clear dividend predictability which is even stronger in magnitude. Hence, while these results are, of course, based on a more or less arbitrary selection of countries from the pool of all countries, they clearly also reveal that there is no economically meaningful dividend growth predictability in large countries but strong dividend predictability in small countries. In the next sections, we document this finding in a more systematic and comprehensive manner.

Table 2 about here

4.2 Comprehensive results: Time-series regressions

We now turn to our study of dividend and return predictability in all countries, using our equal- and value-weighted portfolios. 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. 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 of exchange rate changes on current-period dividend yields:

$$\triangle d^f_{t+h} = \alpha^{(h)}_d + \beta^{(h)}_d (d^f_t - p^f_t) + \varepsilon^{(h)}_{t+h} \tag{5}$$

$$r^{USD}_{t+h} = \alpha^{(h)}_r + \beta^{(h)}_r (d^f_t - p^f_t) + \varepsilon^{(h)}_{t+h} \tag{6}$$

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

where t indexes time and h denotes the forecast horizon. In order to avoid potential seasonality issues with the dividend growth series, we generally work with annual (or multi-annual) forecast horizons, i.e. $h = 4$, 8, 12, and 16 quarters.[8]

In our regressions, we base our statistical inference about the regressions' slope coefficients on Newey and West (1987) HAC standard errors (we employ h lags for robustness, but experimented with different choices to check robustness and the results reported below remained robust), Hodrick (1992) standard errors which were found to be more reliable and accurate by Ang and Bekaert (2007), and a moving-block bootstrap to account for potential finite sample biases (cf. Stambaugh, 1999) and moving average structure of regression errors due to overlapping observations. The computation of Hodrick (1992) standard errors and the bootstrap procedure are detailed in the appendix to this paper. In the table, 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 ap-

[8]We have also checked our results for shorter forecast horizons of $h = 1, 2, 3$ quarters and find that they are very similar to results for $h = 4$ reported below. However, we do not report these results to rule out seasonality issues.

pendix, too.

4.2.1 Results

Consider the annual ($h = 4$) regressions first. The results are reported in Table 3 and the evidence is summarized by:

$$\text{Value weights: } \Delta d^f_{t+4} = \text{constant} + \underset{[0.74]}{1.40} \left(d^f_t - p^f_t \right) \qquad \overline{R}^2 = 0.01$$

$$\text{Equal weights: } \Delta d^f_{t+4} = \text{constant} - \underset{[-3.08]}{12.061} \left(d^f_t - p^f_t \right) \qquad \overline{R}^2 = 0.15,$$

where the numbers in brackets below the coefficient estimates are Newey-West HAC based t-statistics (results are similar for t-statistics based on Hodrick (1992) or moving-block bootstrapped standard errors). Our results are clear-cut: When we use value-weights, we cannot reject that the predictive coefficient is zero and dividends consequently unpredictable by the dividend yield, whereas there is clear evidence of dividend growth predictability when we use equal weights. The extent to which the dividend yield of the value-weighted portfolio captures future dividend growth rates is noteworthy, since the R^2 is around 15%. By construction, the strong difference between the results using the value-weighted and the equally-weighted portfolio is due to larger weights given to the smaller markets in the equally-weighted portfolio. Hence, there is significant evidence for cash flow predictability – 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 equally-weighted portfolio.

Table 3 about here

When we increase the horizon over which we measure dividend growth (increase h), we see from Table 3 that the associated t-statistics tend to decline. Hence, the dividend predictability we document in the equally-weighted portfolio is large at the shorter horizons, and stays large and significant up to two years out. Regardless of the horizon, dividend growth is not predictable in the value-weighted portfolio. Furthermore, we also find the same result when using portfolios' dividends converted to USD and deflated by U.S. CPI inflation (reported in Table A.I in the web Appendix). Hence, dividend predictability seems strong in smaller countries regardless of whether we use nominal dividend growth in local currencies or in real dividend growth in USD.[9]

It seems 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 (and other large markets), as we do in the equally-weighted portfolio.

[9]In Section 8, we describe the many robustness tests we did. In addition to the tests described there, we also ran some robust regressions (LAD-regressions). We conclude from all these robustness and robust regressions that our main result of more dividend predictability in small countries is general and not due to outliers, sample period, choice of countries or currencies etc.

Annual returns seem to be predictable both in the equally-weighted and the value-weighted portfolios. Our findings for the value-weighted portfolio thus reflect the findings in the literature that uses U.S. data: Dividend growth rates are not predictable, whereas returns are. When predicting long-horizon returns, the statistical significance of our results depends on the standard errors we use: 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, long-horizon returns seem to be predictable in both the equal- and the value-weighted portfolios when judged via Newey-West or Hodrick t-statistics, but predictive coefficients are insignificant when judged via block-bootstrapped t-statistics.[10] Exchange rates are not predictable, regardless of the portfolios or horizon we look at.

Recently, Cochrane (2008) has noticed that the coefficients from predictive regressions, like the ones presented in Table 3, are related via the definition of returns. He also notices that sharper statistical tests of return and dividend predictability can be derived when taking the coefficient restrictions implied by the return definition into account. For this reason, we follow Cochrane (2008) and simulated the predictive system in Eqs. (5)-(7) under the joint null that there is no return and no dividend growth predictability. We delegate the detailed description of the set-up and the results from this investigation to the Appendix of this paper, but briefly mention the main result here. We find that the presence of dividend growth predictability in the equally-weighted portfolio gives strong

[10] Several authors have noted that the use of Newey-West standard errors may result in an overstatement of the predictive power, particularly when there is a strong overlap in long-horizon regressions (cf. Ang and Bekaert, 2007). In addition, we experimented with different choices for the cut-off parameter in the Newey-West standard errors, and the results remained robust.

statistical evidence against the joint null of no return and dividend growth predictability, whereas the lack of dividend growth predictability in the value-weighted portfolio gives strong statistical evidence that the joint null cannot be rejected, despite of clear evidence for return predictability in the value-weighted portfolio. In other words, the Cochrane (2008) based simulations of the predictive system confirm, with stronger statistical power, the results from the predictive regressions in Table 3: Dividends are predictable in the equally-weighted portfolios where smaller countries have a larger weight, but not predictable in the value-weighted portfolio where larger countries have a larger weight. Thus, dividends are predictable in countries with small equity markets but not in countries with a large equity market capitalization.

4.3 Portfolio sorts

Cochrane (2010) argues that time regressions and portfolio sorts are two sides of the same coin in the sense that small R^2s from time-series regressions can turn into large economically-significant portfolio spread returns, i.e. make the economic importance of perhaps relatively small time-series R^2s clear. To illustrate this with our data, we sort countries into portfolios and investigate cross-sectional patterns in returns, dividend growth, and exchange rate changes. In addition to illustrating the economic importance of predictability, the portfolio approach also has some advantages compared to the predictive regressions employed in Section 4.2. First, we can directly focus on patterns in returns, dividend growth, and exchange rates 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 due to persistent regressors and overlapping data.

4.3.1 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 equally-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.[11] 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 Lustig and Verdelhan (2007), for instance, who investigate returns to shorting the money market in low interest rate countries and, simultaneously, investing in

[11] In the following, we sometimes refer to portfolio 5 (high dividend yields) as value portfolio and portfolio 1 (low dividend yields) as growth portfolio.

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 within several countries internationally.

Patterns across portfolios. In Table 4, we show what an investor would have gained by investing in the different portfolios. Consider the portfolios where we use equal weights within each portfolio first. The most important thing to notice is that the differences between the average dividend growth rates on the different portfolios are large (Panel A). 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 predictability results in Section 4.2, we find that this 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 B of Table 4 shows that the difference between the average returns of the equally-weighted highest dividend yield portfolio compared to the lowest dividend-yield portfolio is 7.96 percentage points per annum. It is also "well-behaved" with skewness close to zero and kurtosis close to three.[12] Like in the time-series regressions, there is not much difference in return predictability between large and small countries, as the average return of the "5-1" portfolio is 7.35% in the value-weighted case. When compared to other well-known zero-cost portfolios, the average return of close to eight percent 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 (2010) 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 the historical U.S. equity premium is 7.38%.

Further details on the characteristics and the predictive performance over time of these portfolios' dividend growth rates, returns, and exchange rate changes are shown in the web Appendix to this paper. All in all, they illustrate that the differences in dividend predictability we document across countries are economically important and appears in analyses outside running regressions.

[12] 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.

5 Dividend predictability and dividend smoothing

We have shown that dividends are more predictable in countries with smaller equity markets, and that this predictability is economically important. In this section, we show that dividends are also less smooth in smaller countries. This is important because dividend smoothing makes dividends more difficult to predict by the dividend yield as dividend fluctuations (that will be small when dividends are smooth) then get disconnected from dividend yield fluctuations.[13] Hence, if dividends are smooth in countries with large equity markets, dividends will also be difficult to predict in these markets. To show this, we proceed in two steps. We first show that dividends are indeed smoother in countries with large equity markets. Afterwards, we relate smoothing and predictability directly.

We use the equal- and value-weighted portfolios to show that dividend smoothing is higher in countries with larger market capitalization. Our analysis is based on the Lintner (1956) partial-adjustment model:

$$\Delta D_t = \beta_0 + \beta_1 \Delta E_t + \beta_2 \Delta D_{t-1} + \varepsilon_t \tag{8}$$

where ΔD_t is the change in the level of dividends and ΔE_t the change in earnings. In this model, $1 - \beta_2$ measures the speed of adjustment towards the long-run target dividend payout ratio that Lintner assumed managers partially adjust towards. Hence, β_2 measures

[13]As mentioned in the Introduction, Chen, Da, and Priestley (2010) investigate the relation between dividend smoothing and predictability using data on U.S. firms.

the degree of smoothing.[14] The results are:

$$\text{Equal weights: } \Delta D_t = \underset{[1.59]}{0.03} + \underset{[7.95]}{0.69}\Delta E_t + \underset{[1.14]}{0.08}\Delta D_{t-1} \qquad R^2 = 0.58$$

$$\text{Value weights:} \Delta D_t = \underset{[1.27]}{0.02} + \underset{[4.49]}{0.41}\Delta E_t + \underset{[2.04]}{0.22}\Delta D_{t-1} \qquad R^2 = 0.47$$

where the numbers in brackets below coefficient estimates are Newey-West t -statistics. We thus find that the smoothing parameter is significant in the value-weighted portfolio where larger countries dominate. We also find that we cannot reject that dividends are not smoothed (the smoothing parameter is not statistically different from zero) in the equally-weighted portfolio where smaller countries get a larger weight. Equally interesting, the results show that dividends respond more to earnings in smaller countries, as seen through the larger coefficient to ΔE_t in the equally-weighted portfolio. When earnings go up in the equally-weighted portfolio, dividends co-move to a larger extent than in the value-weighted portfolio because dividends are smoothed more in the large countries. An additional way of seeing this is by directly looking at the ratio between volatility of earnings and dividends:

$$S = \sigma(\Delta d)/\sigma(\Delta e) \tag{9}$$

where S is defined as the "smoothing parameter" in Chen, Da, and Priestley (2010). Note that a higher value of S means less smoothing since dividend growth is more volatile relative

[14] Lintner specified his original model with the explanatory variables in levels (i.e. using E_t and D_{t-1} instead of ΔE_t and ΔD_{t-1}). As is common nowadays, we use first differences of earnings and dividends to obtain stationary variables.

to earnings growth for higher values of S.

If dividends are smooth in relation to earnings, $\sigma(\Delta d)$ is low relative to $\sigma(\Delta e)$ and S is consequently small. We find that $S = 0.92$ for the equal-weighted portfolio and $S = 0.64$ for the value-weighted portfolio, again indicating that dividends are more smoothed in countries with larger equity markets.

Finally, we directly relate dividend predictability to dividend smoothing. To do so, we first run predictive dividend growth regressions for each individual country with more than 10 years of data.[15] We employ a forecast horizon of one year and use the log dividend yield as the only predictor. The predictive R^2 from this regression is used as a measure of dividend growth predictability. We then regress the predictive R^2 from the dividend predictability regressions on the smoothing parameter in a simple cross-sectional regression (with White (1980) standard errors), i.e. we estimate:

$$R^2_{\Delta d,i} = \alpha + \beta S_i + \varepsilon_i. \tag{10}$$

We find an estimate of β equal to 0.11 with a t-statistic of 2.32 and a R^2 of 12%. So, there is a positive relation between the smoothing parameter and predictability across countries; in those countries where there is less smoothing (i.e. high volatility of dividends relative to the volatility of earnings), predictability of dividends is stronger.[16] And these countries are in general countries with larger equity markets.

[15]We choose 10 years here to obtain a reasonably large cross-section for the regressions. Using larger cut-offs leads to very similar results, though.

[16]We acknowledge that the predictive R^2 is measured with error. For this reason, we interpret these results with caution.

6 Dividend predictability and firm characteristics

So far, we have shown that dividends are more predictable in smaller countries and that dividends are more smooth in these countries, too. But what drives these empirical findings? Dividend policies are the results of decisions taken by individual firms, so why are the dividends of firms in smaller countries more predictable and smoother? Motivated by the results in Leary and Michaely (2010) that large U.S. firms and U.S. firms with less volatile dividend and return processes smooth more, we investigate two hypotheses in this section: Whether (i) dividends are more predictable in smaller countries because the typical firm in these countries is smaller and whether (ii) dividends are more predictable in smaller countries because the volatility of firms' dividends or returns is higher in smaller countries. In addition, we also provide some evidence on the cross-section of U.S. firms by showing that the dividends of larger U.S. firms are more difficult to predict than those of smaller U.S. firms. We end up discussing the implications of these findings for theories of dividend smoothing.

6.1 Firm size and dividend predictability

We use two measures of the firm size in a country in our investigation of whether differences in firm size can explain the differences in dividend predictability we document across countries: the average size of firms in the country and – in order to capture the size of the right tail of the firm size distribution – the 90% quantile of the country's firm-size distribution. To calculate the average size of firms in a country, we divide a country's total stock market capitalization (converted to USD) by the number of firms in the country. To calculate the 90% quantile of the country's firm-size distribution, we calculate the 90% quantile of the cross-sectional firm size distribution of all available firms' market capitalizations (in USD) in a given country in a given quarter. The latter measure is used since it is robust to extreme outliers and better captures the firm size of the top decile of companies in a country. This could be potentially important since large firms usually account for the bulk of dividend payments, at least in the U.S. (DeAngelo, DeAngelo, and Skinner, 2004).

Finally, since market capitalizations are growing more or less steadily over time we deflate both firm size measures in each quarter by the cross-sectional average (log deviations). Hence, for each country and each quarter, our firm size proxies are capturing the percentage deviation from the average value of all countries.

6.1.1 Results

In order to test whether dividend growth is more predictable in countries where the typical firm is relatively small, we run fixed-effects, unbalanced predictive panel regressions using all countries and observations, but extend the setup in Eqs. (5)-(7) with an interaction term between firm size in country i, FS_i (where FS_i thus represents either the average market capitalization of the firms in the country or the 90% quantile of the country's firm size distribution), and the dividend yield in country i:

$$\triangle d^f_{i,t+h} = \alpha^{(h)}_{i,d} + \beta^{(h)}_d (d^f_{i,t} - p^f_{i,t}) + \beta^{(h)}_{size,d} (d^f_{i,t} - p^f_{i,t}) FS_{i,t} + \varepsilon^{(h)}_{i,t+h} \tag{11}$$

$$r^{USD}_{i,t+h} = \alpha^{(h)}_{i,r} + \beta^{(h)}_r (d^f_{i,t} - p^f_{i,t}) + \beta^{(h)}_{size,r} (d^f_{i,t} - p^f_{i,t}) FS_{i,t} + \varepsilon^{(h)}_{i,t+h} \tag{12}$$

$$\triangle s^f_{i,t+h} = \alpha^{(h)}_{i,s} + \beta^{(h)}_s (d^f_{i,t} - p^f_{i,t}) + \beta^{(h)}_{size,s} (d^f_{i,t} - p^f_{i,t}) FS_{i,t} + \varepsilon^{(h)}_{i,t+h} \tag{13}$$

where i indexes countries and β_{size} measures how the interaction term affects the left-hand side variables. As outlined in Section 4.2, we expect dividend yields to forecast dividend growth with a negative sign. Hence, if firm size is associated with less strong dividend predictability, we would expect $\beta^{(h)}_{size,d}$ to be positive.

We show the results in Table 5.[17] Panel A shows results where we use the average firm size as measure of the size of the typical firm in the country (interaction coefficient labelled β_{fsize}), and Panel B shows results from using the 90% quantile of the firm-size distribution within a country (interaction coefficient labelled β_{q90}). Regardless of the measure of the typical size of a firm in a country, the results are clear: Firm size has a positive impact on the predictive coefficient, i.e. the larger is the typical firm in a country, the closer to zero is the predictive impact of dividend yields on future dividend growth rates (i.e. the less strong is the dividend predictability). We also see that the interaction term is statistically significant for forecast horizons of up to $h = 12$ using Newey-West based t-statistics.

Table 5 about here

[17]In Table A.VII in the web Appendix, we show the results from the predictive panel regressions without the interaction terms. Also, to conserve space, we leave the results for how firm size affects exchange rate predictability aside for now.

In contrast to the clear effect of firm size on dividend predictability, the effect of firm size on return predictability is not clear-cut, but depends on the measure of the size of a typical firm in a country, and in some cases on the way standard errors are computed. For instance, if we use the 90% quantile to measure the typical size of a firm in the country, we do not find any effect from firm size on return predictability. Hence, using this measure of firm size, we cannot conclude that return predictability is strong (or weak) in countries with typically large (or small) firms. On the other hand, when we use the average size of a firm in a country, Panel A shows that firm size sometimes has a negative effect on return predictability, but also that this evidence is weak as it depends on the specific t-statistics that we use. There are two reasons why it is not surprising that the effect of firm size on return predictability is less clear. First, Chen, Da, and Priestley (2010) show theoretically and using simulations that the effect of dividend smoothing on return predictability is unclear (in contrast to the effect of dividend smoothing on dividend predictability that clearly is negative). If large firms smooth more, as we showed in the previous section, it is less surprising that it is difficult to establish a clear link between firm size and return predictability. Second, and given our findings from Table 3, when returns are predictable in both large and small countries, it is also not too surprising that we do not find a clear effect of firm size on return predictability.

6.1.2 Results for U.S. firms

Up to now, we have shown that dividend predictability is stronger in countries with smaller average firm size in an international context. In turns out that there is a similar relation between firm size and dividend predictability in the cross-section of U.S. firms. As this has not been shown before (to our knowledge), but U.S. firms are by far the focus of most earlier studies in this literature, we believe it is relevant to show. To do so, we obtain the ten size portfolios from Kenneth French's web page and use the portfolios with and without reinvested dividends to construct the dividend yield and dividend growth rates of the ten size portfolios.[18] Having done so, we regress changes in dividends of a portfolio on the lagged dividend yields of the portfolio. The results are shown in Table 6.

The results are supportive of our main finding above. There is an almost monotonic negative relation between firm size and dividend predictability. This means that even when it is difficult to find individual significant coefficients in the dividend-predicting regressions in Table 6 (reflecting that it is difficult to predict U.S. dividends as noted above), it is at the same time also clear that there is considerably more evidence against the null of no dividend predictability for small U.S. firms than for large U.S. firms. To underscore this, the table also reports results for a simple χ^2 test based on the null that the predictive slope coefficient of the first size portfolio is higher (i.e. less negative) than the coefficient for the tenth size portfolio. This null is rejected for all forecast horizons and shows that the predictive coefficient is significantly lower for small firms. We find this general pattern interesting in light of the literature on dividend predictability of U.S. stocks and think that it lends credence to our finding based on international data above.

[18] Data are from 1927 to 2009 and annual. An interesting additional conclusion is that the differences we report in the text are even stronger for the first half of the sample period; from 1927-1967. This is of course related to the finding of Chen (2009) that predictability of dividend growth is stronger in the period before 1945.

Table 6 about here

6.2 Volatility and dividend predictability

The next question we deal with is whether dividends are more predictable in countries where the volatility of fundamentals and returns is high. We use three measures of volatility: raw dividend volatility, idiosyncratic dividend volatility, and idiosyncratic return 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. Idiosyncratic return volatility 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).

In Table 7, we present the results from predictive panel regressions (for returns and dividends) where we interact dividend yields with, respectively, one of the measures of dividend volatility or return volatility. If dividend predictability is stronger in countries where volatility is higher, we would expect a negative sign to the interaction term, as this implies an even more negative effect on β_d in countries with higher volatility. Our results clearly indicate that dividend growth rates are more predictable in countries where volatility is higher. For returns, on the other hand, there is generally no relation between volatility and return predictability. Hence, both the typical size of a firm in a country (Table 5) and volatility (Table 7) affect dividend predictability, but not return predictability.

Table 7 about here

In Tables 5 and 7, we have used regressions to show that dividends are more predictable in countries where the typical firm is small and/or volatility high. In robustness tests, we also used portfolio sorts to investigate these issues. We delegate the description of these results to the Internet appendix in order to save space and only mention the results briefly here. We double-sort countries into portfolios by, first, firm size (or volatility) and, next, sort countries into portfolios based on their dividend yield within the size groups. Using these portfolio double sorts, we again find that dividends are more predictable in countries with small typical firms and firms facing high uncertainty. In other words, our regression-based results in Tables 5 and 7 are economically important and do not depend on the specific way we set up our predictive regressions, as they also show up in portfolio sorts.

6.3 Firm characteristics and smoothing

We have shown that dividends are more predictable in small countries which are also countries where the typical firm is small and uncertainty high. We have also shown that dividends are more smoothed in large countries. We now close the circle and deal with the question of whether dividends are more smooth in those countries where the typical firm is small and volatility is large. To do so, we calculate the smoothing parameter $S_i = \sigma_i(\Delta d_i)/\sigma_i(\Delta e_i)$ for each country i and regress the smoothing parameter on the typical size of the firm in a country in a simple cross-sectional regression (with White (1980) standard errors which are robust to heteroscedasticity). We employ average firm size here but using the 90% quantile measure yields very similar results. We also run the same regression with volatility instead of average firm size. We employ idiosyncratic return volatility as our proxy for volatility here to maximize the distance between our explanatory variable and the dependent variable which clearly depends on (raw) dividend volatility itself. The results are shown in Table 8. We find that dividend smoothing is higher in countries with larger typical firm size and lower idiosyncratic return.

Table 8 about here

6.4 Discussion of results

The fact that we find less dividend predictability in large and stable countries, and that smoothing is related to predictability, extends and lends further support to the results in Leary and Michaely (2010). Leary and Michaely (2010) study U.S. firms, whereas we study firms around the globe. Leary and Michaely (2010) conclude that their evidence of less smoothing in small and stable U.S. firms goes against theories of dividend smoothing based on asymmetric information. The asymmetric information explanation for dividend smoothing says that firms that are associated with more uncertainty (for instance small and volatile firms) would tend to smooth more; this is not what Leary and Michaely (2010) and we (indirectly) find. Indeed, we find more dividend predictability in small countries where the typical firm is small and volatile, which indicates less smoothing in these types of countries as well because we find that predictability is related to smoothing. The difference to Leary and Michaely (2010), on the other hand, is that we show the implications of dividend smoothing for dividend predictability and asset-pricing, and we show evidence from many countries. Furthermore, an advantage of exploiting international data is that we can dig one step further and ask whether the differences we report are correlated with differences in deep background characteristics, such as the legal environment facing the firm, as we do in the next section. This is difficult to do using a dataset from one country where the legal system facing firms is basically the same across firms.

7 Fundamental determinants of dividend predictability

Recent papers document a relation between the qualities of institutions in a country and the dividend policies of firms in the country. For instance, La Porta, de Silanes, Shleifer, and Vishny (2000) find that firms in common law countries, where investor protection is often better, pay out higher dividends and Pinkowitz, Stulz, and Williamson (2006) find that the value of dividend payments is higher in countries where investor protection is poorer. When institutional quality and corporate governance influence the amount and value of dividends, it seems relevant to hypothesize that it also affects the predictability of dividends. One could imagine two channels through which corporate governance and institutional quality could affect dividend predictability. On the one hand, it is likely that in countries where institutional quality is low, the uncertainty businesses face is higher (if firms do not know how institutions operate and rule, the uncertainty firms face will be higher). Coupled with our findings of higher dividend predictability in countries where volatility is higher, this would imply that we should expect to see more dividend predictability in countries where institutional quality is low. On the other hand, one could imagine that in countries where governance is poor, smoothing would be higher if agency problems dominate the effect of uncertainty just described. Leary and Michaely (2010) mention that this effect is likely to be more pronounced in situations where corporate governance is weaker. In order to evaluate which of these effects dominate empirically, we investigate in this section the relation between dividend predictability and corporate governance/institutional quality.

We obtain data on institutional characteristics of the different countries from Andrei Schleifer's homepage (the data are based on La Porta, Shleifer, de Silanes, and Vishny, 1997; La Porta, de Silanes, Shleifer, and Vishny, 1998; La Porta, Shleifer, de Silanes, and Vishny, 2000).[19] We complement these institutional data with institutional characteristics from other authors such as the risk of earnings management index from Leuz, Nanda, and Wysocki (2003) or the corruption perception index (taken from Chui, Titman, and Wei, 2010). In sum, the institutional characteristics we use are accounting standards, anti-director rights, corruption perception, efficiency of the judicial system, risk of earnings management, and the risk of expropriation. The characteristics are scaled such that a higher value of the variable means a lower quality of institutions.

[19]We are grateful to Andrei Shleifer for providing the cross-country data on his website `http://www.economics.harvard.edu/faculty/shleifer/dataset`. The specific data set is entitled "Shareholder Rights, Creditor Rights, Size and Breadth of Capital Markets for 49 Countries".

We are interested in the extent to which these variables explain how well dividends can be predicted in different countries. For each institutional-characteristic variable, there is one index value per country. For this reason, we conduct simple cross-country regressions, where the dependent variable is the R^2 (for each country i) from a predictive regression of the dividend growth rate of country i on country i's lagged log dividend yield as above. Hence, the regression we run is:

$$R^2_{\Delta d,i} = \alpha + \beta' x_i + \varepsilon_i,$$

where x_i is one of the institutional characteristics of country i. As a robustness test, and as is common in this kind of regressions (see e.g. Morck, Yeung, and Yu, 2000), we also consider a logarithmic transformation of the R^2s as dependent variable. As above, we employ heteroscedasticity robust standard errors (White, 1980). We show the results in Table 9.

The results reveal that a lower quality of institutions is typically associated with more predictable dividends. Indeed, eleven out of the twelve coefficients we estimate are positive, and efficiency of the judicial system, risk of earnings management, and risk of expropriation are significant. Thus, in countries where the efficiency of the judicial system is poor and earnings management and/or the risk of expropriation is high, dividends tend to be more predictable. The mechanism that seems to be at work is that lower quality of institutions increase uncertainty which reduces dividend smoothing and increase predictability. Accounting standards are not significant, whereas the significance of anti-director rights and corruption depends upon how we measure the dependent variable (as the R^2 or as the log of the R^2).

Finally, we have also experimented with multivariate regressions of dividend predictability R^2s on more than one institutional characteristic but find that it is not easy to statistically discriminate between the different proxies for institutions since they are strongly correlated so that multicollinearity prevents meaningful conclusions from these regressions.

TABLE 9 ABOUT HERE

8 Robustness

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

First of all, we evaluate whether our main results can also be found for a selected number of individual countries drawn from the group of large, medium, and small countries. When looking at a few selected individual countries, we find that dividends are difficult to predict in large countries, such as the U.S., U.K., and Japan, but considerably more predictable in smaller countries, such as Argentina, Austria, and New Zealand.[20] We also took special care in evaluating the robustness of our results with respect to specific kinds of countries. For instance, we excluded the U.K. and the U.S. from the equal- and value-weighted portfolios and ran the regressions in Table 3 in order to see whether these two very large common law countries drive our results. We found that even after excluding the U.K. and the U.S., there is still more dividend predictability in the equal-weighted portfolio.

Second, we evaluate 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. 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).

Third, we check whether our results are driven by recently added small emerging markets. They are not. To verify this, we conduct 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 equally-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 the paper itself. We also took a second approach to this issue: Instead of excluding countries for which we only have less than 15 years of

[20]When looking at individual countries, their relative sizes change over time. China, e.g., was small in the beginning of the sample, but is a quite large country in terms of market capitalization today. This is also a reason why we focus on the value- and equal-weighted countries in the paper itself, instead of looking at all 50 countries one-by-one.

data, we investigate what happens if we run the regression over a period where we have data for basically all countries. For instance, if we start the analysis in 1995, we have data for all 50 countries except Bulgaria, South Korea, Rumania, and Slovenia. Of course, when using data from 1995 and onwards, we have few observation if running our regressions for the equal- and value-weighted portfolio, so we run a panel-regression instead. In this panel-regression, we add an interaction term between the size of the equity market in the country and the dividend yield. We found results as above, i.e. more predictability in small countries, though the results not as strong as those in the paper itself which is probably due to the short sample period.

Fourth, we construct portfolios by using standardized dividend yields instead of the level of dividend yields themselves. 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 equally-weighted portfolios, but considerably less in the value-weighted portfolios. For these portfolios based on standardized dividend yields, we have also conducted subsample analysis.

9 Conclusion

The common perception in the literature is that dividend yields do not predict dividend growth rates in the "standard" regression setting based on U.S. aggregate data.[21] We show that using 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 is most pronounced in countries with smaller market capitalization. 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 show that dividends are more predictable in countries where the typical firm is smaller and returns and dividends are more volatile. We also show that dividends are more predictable in these countries because smaller and more volatile firms smooth dividends less, and dividend smoothing reduces dividend predictability because it breaks the link between fluctuations in the dividend yield and future dividends. We finally show that the institutional characteristics that influence firm size also influence dividend predictability across countries.

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 calls 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 system-

[21] Other variables have been found to predict dividend growth rates (Lettau and Ludvigson, 2005). Likewise, dividend growth rates on the U.S. stock market were predictable in earlier time periods as shown in the work by Chen (2009). The point here is that dividend growth predictability by means of the current dividend yield is generally thought to be non-existing during the post-war period.

atic risk factors. It would also be interesting to have a more well-developed theory for why larger firms smooth dividends more, as we find in international data and Leary and Michaely (2010) find in U.S. data. Especially, it would be interesting to investigate whether our findings of higher dividend volatility in smaller and sometimes emerging countries are related 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).

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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) standard errors

We briefly review the construction of Hodrick (1992) standard errors used in our predictive regressions. Denote the vector of regression coefficients as $\phi_h = (\alpha_h \beta_h')'$ and the variables on the RHS as $x_t = (1, z_t')'$. The asymptotic distribution of ϕ_h when using GMM (Hansen, 1982) is $\sqrt{T}(\widehat{\phi}_h - \phi_h) \sim \mathcal{N}(0, \Omega)$, where Ω is given by $\Omega = Z_0^{-1} S_0 Z_0^{-1}$ and $Z_0 = E(x_t x_t')$. The idea of Hodrick's estimator is to exploit covariance stationarity and, hence, to sum the the explanatory variables into the past instead of summing residuals into the future. To this end, let

$$wk_t = e_{t+1}\left(\sum_{i=0}^{k-1} x_{t-i}\right) \tag{14}$$

where under the null hypothesis $\varepsilon_{t+h} = e_{t+1} + \ldots + e_{t+h}$, so that e_{t+1} denotes the one-step ahead forecast error. Estimates of e_{t+1} are obtained as the residual of a regression of returns on a constant. Finally, the spectral density S_0 is estimated as

$$\widehat{S}_0 = \frac{1}{T}\sum_{t=k}^{T} wk_t wk_t' \tag{15}$$

so that an estimate of Ω can be computed.

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)

$$X_{t+1} = AX_t + u_{t+1} \tag{16}$$

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

$$R^2_{IH} = 1 - \frac{\mathbf{e1}' W_h \mathbf{e1}}{\mathbf{e1}' V_h \mathbf{e1}} \tag{17}$$

where

$$V_h = hC(0) + \sum_{j=1}^{h-1}(h-j)[C(j) + C(j)'] \tag{18}$$

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

$$W_h = \sum_{j=1}^{h}(I-A)^{-1}(I-A^j)V(I-A^j)'(I-A)^{-1\prime} \tag{19}$$

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).

III. Cochrane (2008) simulations

Cochrane (2008) notices that the coefficients from predictive regressions, like the ones presented in Table 3 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:

$$r_{t+1} = a_r + b_r \left(d_t^f - p_t^f\right) + \varepsilon_{t+1}^r \tag{20}$$

$$\Delta d_{t+1}^f = a_d + b_d \left(d_t^f - p_t^f\right) + \varepsilon_{t+1}^d \tag{21}$$

$$\Delta s_{t+1} = a_s + b_s \left(d_t^f - p_t^f\right) + \varepsilon_{t+1}^s \tag{22}$$

$$d_{t+1} - p_{t+1} = a_{dp} + \phi \left(d_t^f - p_t^f\right) + \varepsilon_{t+1}^{dp}. \tag{23}$$

Eq. (22) 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:

$$b_r = 1 - \rho\phi + b_d + b_s. \tag{24}$$

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. (24), we find the implied restriction of the long-run coefficients:

$$1 = \frac{b_r}{1-\rho\phi} - \frac{b_d}{1-\rho\phi} - \frac{b_s}{1-\rho\phi}$$
$$1 = b_r^l - b_d^l - b_s^l$$

which can be compared to the one-currency case of $1 = b_r^l - b_d^l$ 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. (20) - (23) using both our equal- and value-weighted portfolios. We employ annual data here to avoid seasonality effects in dividend growth rates.[22] We report the results in Table Table 10, Panel A.

Table 10 about here

We find that the fraction of dividend-yield variation due to long-run dividend growth rate variation is quite sizeable at 34% ($b_d^l = -0.34$) and significant (t-statistic = 3.1) in the equally-weighted portfolio but insignificant (t-statistic = 0.22), smaller in absolute size, and of the "wrong" sign at about -11% (b_d^l =0.11) in the value-weighted portfolio. For the long-run return coefficient (b_r^l), the effect is the exact opposite: The fraction of dividend-yield variation due to return variation is large, about 108% ($b_r^l = 1.08$), and significant (t-statistic = 3.2) in the value-weighted portfolio, but much smaller (0.69), though significant (t-statistic = 3.1), in the equally-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 equally-weighted portfolio where smaller countries get a larger weight. As in Table 3, exchange rate variations do not matter

[22] 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.

for dividend growth fluctuations (the b_s^l-coefficients are small and insignificant in both portfolios).

Simulation evidence. In Table 3 and the left part of Table 10 (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 equally-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.[23]

We first note that predictive regression coefficients are linked by the identity in Eq. (3). This identity, taken together with our extended VAR(1) in Eqs. (20) - (23), implies the following relationships between coefficients and regression errors:

$$\begin{aligned} b_r &= 1 + b_d + b_s - \rho\phi \\ \varepsilon_{t+1}^r &= \varepsilon_{t+1}^d + \varepsilon_{t+1}^s - \rho\varepsilon_{t+1}^{dp}. \end{aligned} \tag{25}$$

[23] 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.

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:[24]

$$\begin{pmatrix} r_{t+1} \\ \Delta d^f_{t+1} \\ \Delta s_{t+1} \\ d_{t+1} - p_{t+1} \end{pmatrix} = \begin{pmatrix} 0 \\ 0 \\ \rho\phi - 1 \\ \phi \end{pmatrix} (d^f_t - p^f_t) + \begin{pmatrix} \varepsilon^r_{t+1} \\ \varepsilon^r_{t+1} - \varepsilon^s_{t+1} + \rho\varepsilon^{dp}_{t+1} \\ \varepsilon^s_{t+1} \\ \varepsilon^{dp}_{t+1} \end{pmatrix}. \qquad (26)$$

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. (20) - (23) 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 10, we employ annual data.

We report rejection probabilities based on the *marginal* distribution of coefficients in Panel B of Table 10, 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

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

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 growth 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 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 equally-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 in case of the value-weighted portfolio.[25]

We show results for *joint* coefficient distributions in Figure 2. 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 equally-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

[25]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.

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 equally-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 2 ABOUT HERE

Finally, it should be mentioned that we also simulated a bivariate system where we used both returns and dividends in USD. Using these simulations, we found that the actually estimated coefficients and t-statistics for the value-weighted portfolio could easily have been obtained in a scenario where we impose a null of no dividend-growth predictability, whereas the actually estimated coefficients and t-statistics for the equal-weighted portfolio were not likely in a scenario with no dividend-growth predictability. In other words, no dividend predictability seems likely to characterize the value-weighted portfolio, but not the equal-weighted, also when we simulate from bivariate systems.

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

(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
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
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 for individual countries

This table reports predictive regression results for nine individual countries which are grouped depending on their market capitalization in 2009 into three groups of large, medium and small countries. Numbers in brackets are Newey-West t-statistics whereas numbers in parentheses are bootstrap t-values. The upper panel shows results for predicting dividend growth whereas the lower panel shows results for return predictability.

	Large countries			Middle group			Small countries		
	Dividend growth								
	US	UK	Japan	Italy	Finland	Neth.	Austria	Argentina	New Zeal.
β_d	2.23	8.47	1.53	-20.70	-47.55	-5.52	-37.52	-56.75	-69.53
t^{NW}	[1.19]	[2.38]	[1.13]	[-3.11]	[-3.93]	[-2.70]	[-4.42]	[-4.93]	[-7.50]
t^{BS}	(1.23)	(1.84)	(0.83)	(-3.14)	(-3.09)	(-2.02)	(-3.60)	(-3.59)	(-5.43)
R^2	0.05	0.07	0.00	0.15	0.40	0.08	0.28	0.34	0.48
	Total returns								
β_r	10.13	28.76	13.67	19.45	-3.29	13.08	4.83	-18.07	-26.05
t^{NW}	[2.10]	[3.49]	[1.99]	[1.84]	[-0.20]	[1.88]	[0.40]	[-2.78]	[-1.64]
t^{BS}	(1.90)	(3.02)	(1.55)	(1.67)	(-0.19)	(1.64)	(0.32)	(-2.46)	(-1.45)
R^2	0.09	0.12	0.05	0.04	-0.01	0.05	-0.01	0.15	0.02

Table 3: Predictive regressions

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

$$\begin{aligned}\triangle d^f_{t+h} &= \alpha^{(h)}_d + \beta^{(h)}_d (d^f_t - p^f_t) + \varepsilon^{(h)}_{t+h} \\ r^{USD}_{t+h} &= \alpha^{(h)}_r + \beta^{(h)}_r (d^f_t - p^f_t) + \varepsilon^{(h)}_{t+h} \\ \triangle s^f_{t+h} &= \alpha^{(h)}_f + \beta^{(h)}_s (d^f_t - p^f_t) + \varepsilon^{(h)}_{t+h}\end{aligned}$$

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. Numbers in brackets are t-values based on Newey-West (1987, t^{NW}), Hodrick (1992, t^H), or moving block bootstrap standard errors (t^{BS}). $\bar{R}^2$ denotes the adjusted regression R-squared whereasd R^2_{IH} denotes the R-squared implied a VAR(1) as in Hodrick (1991).

Equal weights					Value weights				
Dependent variable: Dividend growth									
h	4	8	12	16	h	4	8	12	16
β_d	-12.06	-20.36	-18.44	-19.29	β_d	1.40	3.20	5.21	6.52
t^{NW}	[-3.08]	[-2.22]	[-1.39]	[-1.39]	t^{NW}	[0.75]	[0.79]	[0.90]	[0.96]
t^H	[-3.19]	[-2.78]	[-1.95]	[-1.64]	t^H	[0.94]	[1.12]	[1.27]	[1.23]
t^{BS}	[-2.61]	[-1.92]	[-1.25]	[-1.24]	t^{BS}	[0.66]	[0.61]	[0.57]	[0.71]
$\bar{R}^2$	0.15	0.17	0.08	0.07	$\bar{R}^2$	0.01	0.02	0.03	0.03
R^2_{IH}	0.27	0.35	0.37	0.37	R^2_{IH}	0.05	0.02	0.02	0.01
Dependent variable: Total returns – USD									
h	4	8	12	16	h	4	8	12	16
β_r	21.29	33.55	44.16	65.97	β_r	14.27	28.04	42.36	55.96
t^{NW}	[2.31]	[1.89]	[1.79]	[2.28]	t^{NW}	[2.36]	[2.20]	[2.46]	[2.93]
t^H	[1.83]	[1.51]	[1.38]	[1.56]	t^H	[2.23]	[2.21]	[2.23]	[2.21]
t^{BS}	[1.90]	[1.18]	[1.02]	[1.32]	t^{BS}	[1.95]	[1.37]	[1.23]	[1.48]
$\bar{R}^2$	0.05	0.08	0.10	0.17	$\bar{R}^2$	0.08	0.17	0.26	0.35
R^2_{IH}	0.05	0.08	0.10	0.11	R^2_{IH}	0.08	0.14	0.20	0.25
Dependent variable: Spot rate changes									
h	4	8	12	16	h	4	8	12	16
β_s	0.11	2.24	5.95	11.27	β_s	0.28	0.93	2.08	3.36
t^{NW}	[0.02]	[0.21]	[0.36]	[0.55]	t^{NW}	[0.14]	[0.22]	[0.33]	[0.44]
t^H	[0.02]	[0.27]	[0.48]	[0.67]	t^H	[0.13]	[0.23]	[0.35]	[0.42]
t^{BS}	[0.02]	[0.15]	[0.25]	[0.40]	t^{BS}	[0.11]	[0.15]	[0.20]	[0.27]
$\bar{R}^2$	-0.01	-0.01	0.00	0.01	$\bar{R}^2$	-0.01	-0.01	0.00	0.00
R^2_{IH}	0.01	0.01	0.01	0.01	R^2_{IH}	0.00	0.00	0.00	0.00

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 average dividend growth rates for the five portfolios, the average of all five portfolios ("Avg.") and the difference between portfolios 5 and 1 (5-1). Panel B shows results for total returns, whereas Panel C shows results for spot rate changes.

Equal weights								Value weights							
Panel A: 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 B: 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 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: Predictive panel regressions with firm size measures

This table shows results for panel predictive regressions of future dividend growth or total returns (over forecast horizon $h = 4, 8, 12, 16$) on lagged (log) dividend yields and an interaction term of (log) dividend yields and average firm size (upper part) or the 90% quantile of the cross-sectional firm size distribution (lower part):

$$\begin{aligned} \triangle d^f_{i,t+h} &= \alpha^{(h)}_{i,d} + \beta^{(h)}_d (d^f_{i,t} - p^f_{i,t}) + \beta^{(h)}_{size,d} (d^f_{i,t} - p^f_{i,t}) FS_{i,t} + \varepsilon^{(h)}_{i,t+h} \\ r^{USD}_{i,t+h} &= \alpha^{(h)}_{i,r} + \beta^{(h)}_r (d^f_{i,t} - p^f_{i,t}) + \beta^{(h)}_{size,r} (d^f_{i,t} - p^f_{i,t}) FS_{i,t} + \varepsilon^{(h)}_{i,t+h} \end{aligned}$$

T-statistics are based on Newey-West (t^{NW} or bootstrapped standard errors (t^{BS}) and the panel regressions employ fixed-effects to focus on time-series effects within countries.

	Dividend growth					Total returns – USD			
	Panel A: Interaction of dividend yield with average firm size								
h	4	8	12	16	h	4	8	12	16
β_d	-16.27	-21.19	-23.21	-25.95	β_r	11.14	24.23	26.07	23.43
t^{NW}	[-4.49]	[-4.02]	[-3.76]	[-3.62]	t^{NW}	[3.68]	[4.95]	[3.99]	[2.87]
t^{BS}	[-3.75]	[-2.93]	[-2.54]	[-2.53]	t^{BS}	[3.29]	[4.09]	[3.23]	[2.26]
β_{fsize}	3.56	5.66	5.13	3.92	β_{fsize}	-2.76	-3.32	-6.23	-12.39
t^{NW}	[2.13]	[2.53]	[1.99]	[1.48]	t^{NW}	[-2.22]	[-1.68]	[-2.41]	[-3.85]
t^{BS}	[1.97]	[1.86]	[1.36]	[0.97]	t^{BS}	[-1.89]	[-1.34]	[-1.71]	[-2.83]
$\bar{R}^2$	0.16	0.19	0.15	0.12	$\bar{R}^2$	0.05	0.1	0.12	0.15

	Panel B: Interaction of dividend yield with 90% quantile of firm size distribution								
h	4	8	12	16	h	4	8	12	16
β_d	-16.73	-23.29	-24.92	-28.25	β_r	16.59	32.15	37.1	37.7
t^{NW}	[-5.15]	[-4.93]	[-4.60]	[-4.27]	t^{NW}	[6.14]	[7.17]	[5.84]	[4.71]
t^{BS}	[-4.15]	[-3.65]	[-3.25]	[-3.01]	t^{BS}	[5.63]	[5.79]	[5.19]	[4.02]
β_{q90}	3.61	4.33	3.68	1.88	β_{q90}	-0.3	0.83	-0.58	-5.78
t^{NW}	[2.18]	[2.19]	[1.83]	[0.78]	t^{NW}	[-0.25]	[0.39]	[-0.19]	[-1.48]
t^{BS}	[1.93]	[1.57]	[1.12]	[0.46]	t^{BS}	[-0.23]	[0.31]	[-0.15]	[-1.18]
$\bar{R}^2$	0.15	0.16	0.12	0.09	$\bar{R}^2$	0.05	0.1	0.11	0.13

Table 6: Dividend predictability in the U.S.

This table shows predictive dividend growth regression for ten size decile portfolios based on CRSP data. The forecast horizon is one to four years and we forecast a size portfolio's dividend growth with the portfolio's log dividend yield as the only predictor. The last column χ^2 shows the test statistic and associated p-value (in parentheses) for the null hypothesis that the predictive coefficient of the portfolio of smallest firms is larger than the predictive coefficient of the portfolio of largest firms. Numbers in brackets are t-statistics based on Newey/West or bootstrapped standard errors.

	Size decile										
	Small	2	3	4	5	6	7	8	9	Large	χ^2
					Forecast horizon: 1 year						
β_d	-0.13	-0.10	-0.14	-0.07	-0.04	-0.04	-0.03	-0.05	-0.01	0.01	5.01
t^{NW}	[-1.48]	[-1.40]	[-1.41]	[-1.17]	[-0.88]	[-0.91]	[-0.56]	[-0.86]	[-0.15]	[0.12]	(0.06)
t^{BS}	[-1.50]	[-1.37]	[-1.45]	[-1.23]	[-0.88]	[-1.01]	[-0.50]	[-0.82]	[-0.15]	[0.11]	
R^2	0.00	0.02	0.04	0.01	0.00	0.00	-0.01	0.00	-0.01	-0.01	
					Forecast horizon: 2 years						
β_d	-0.32	-0.18	-0.17	-0.10	-0.06	-0.09	-0.04	-0.08	-0.02	0.00	11.49
t^{NW}	[-1.80]	[-1.35]	[-1.06]	[-0.95]	[-0.93]	[-1.11]	[-0.69]	[-0.93]	[-0.22]	[0.02]	(0.01)
t^{BS}	[-1.83]	[-1.32]	[-1.25]	[-0.83]	[-0.80]	[-1.21]	[-0.34]	[-0.70]	[-0.17]	[0.02]	
R^2	0.03	0.03	0.03	0.00	0.00	0.01	-0.01	0.01	-0.01	-0.01	
					Forecast horizon: 3 years						
β_d	-0.58	-0.28	-0.27	-0.10	-0.08	-0.11	-0.04	-0.11	-0.01	0.01	11.34
t^{NW}	[-1.97]	[-1.51]	[-1.04]	[-0.83]	[-0.95]	[-0.96]	[-0.65]	[-0.95]	[-0.17]	[0.16]	(0.01)
t^{BS}	[-1.98]	[-1.40]	[-1.15]	[-0.59]	[-0.69]	[-1.03]	[-0.24]	[-0.62]	[-0.11]	[0.09]	
R^2	0.06	0.06	0.04	0.00	0.00	0.00	-0.01	0.02	-0.01	-0.01	
					Forecast horizon: 4 years						
β_d	-0.82	-0.37	-0.24	-0.11	-0.05	-0.08	-0.03	-0.13	0.00	0.04	10.71
t^{NW}	[-2.17]	[-1.77]	[-0.98]	[-0.81]	[-0.62]	[-0.72]	[-0.54]	[-0.93]	[0.03]	[0.48]	(0.01)
t^{BS}	[-2.11]	[-1.49]	[-1.05]	[-0.51]	[-0.36]	[-0.63]	[-0.17]	[-0.54]	[0.02]	[0.23]	
R^2	0.10	0.07	0.02	0.00	-0.01	-0.01	-0.01	0.02	-0.01	-0.01	

Table 7: Predictive panel regressions and volatility measures

The setup of this table is similar to Table 5 but here we interact with measures of country volatility, i.e. (i) lagged dividend volatility (sum of absolute quarterly log changes of dividends over the last year) in Panel A, (ii) lagged idiosyncratic dividend volatility in Panel B, and (iii) idiosyncratic return volatility in Panel C. 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.

	Dividend growth					Total returns – USD			
	Panel A: Interaction of dividend yield with Dividend volatility								
h	4	8	12	16	h	4	8	12	16
β_d	-26.22	-35.25	-35.33	-34.61	β_r	15.17	29.58	38.33	49.49
t^{NW}	[-7.76]	[-7.09]	[-6.43]	[-5.58]	t^{NW}	[6.41]	[7.04]	[6.79]	[7.25]
t^{BS}	[-7.66]	[-6.32]	[-5.34]	[-4.53]	t^{BS}	[5.87]	[6.61]	[6.53]	[7.17]
β_{vol}	-9.08	-33.08	-17.91	-22.14	β_{vol}	1.08	-14.92	-12.04	-19.12
t^{NW}	[-1.38]	[-2.42]	[-3.13]	[-3.98]	t^{NW}	[0.19]	[-1.68]	[-1.24]	[-2.39]
t^{BS}	[-1.56]	[-2.73]	[-2.18]	[-2.88]	t^{BS}	[0.21]	[-1.78]	[-1.18]	[-1.85]
$\bar{R}^2$	0.16	0.21	0.15	0.13	$\bar{R}^2$	0.04	0.08	0.10	0.13

	Panel B: Interaction of dividend yield with idiosyncratic dividend volatility								
h	4	8	12	16	h	4	8	12	16
β_d	-25.03	-33.94	-34.33	-33.51	β_r	14.71	29.57	38.66	50.01
t^{NW}	[-7.84]	[-6.86]	[-6.10]	[-5.30]	t^{NW}	[6.14]	[7.13]	[6.79]	[7.32]
t^{BS}	[-7.58]	[-6.32]	[-5.64]	[-4.34]	t^{BS}	[5.55]	[6.56]	[6.81]	[7.29]
β_{vol}	-16.72	-42.4	-23.74	-29.81	β_{vol}	2.18	-18.16	-14.78	-22.72
t^{NW}	[-1.45]	[-2.24]	[-3.43]	[-4.09]	t^{NW}	[0.33]	[-1.43]	[-1.30]	[-2.15]
t^{BS}	[-1.65]	[-2.70]	[-2.31]	[-3.19]	t^{BS}	[0.37]	[-1.69]	[-1.26]	[-1.67]
$\bar{R}^2$	0.17	0.22	0.15	0.14	$\bar{R}^2$	0.04	0.08	0.1	0.13

	Panel C: Interaction of dividend yield with idiosyncratic return volatility								
h	4	8	12	16	h	4	8	12	16
β_d	-21.17	-29.92	-30.76	-32.71	β_r	16.72	31.19	42.78	51.33
t^{NW}	[-7.68]	[-6.42]	[-5.74]	[-5.17]	t^{NW}	[7.39]	[7.32]	[7.20]	[7.05]
t^{BS}	[-6.78]	[-5.73]	[-4.95]	[-4.42]	t^{BS}	[6.74]	[6.46]	[7.00]	[7.18]
β_{vol}	-47.26	-68.13	-37.24	-30.3	β_{vol}	-10.06	-34.2	-58.89	-46.75
t^{NW}	[-2.44]	[-2.13]	[-2.03]	[-1.70]	t^{NW}	[-1.08]	[-2.05]	[-3.71]	[-2.88]
t^{BS}	[-2.51]	[-2.12]	[-1.67]	[-1.36]	t^{BS}	[-1.22]	[-2.08]	[-3.28]	[-2.54]
$\bar{R}^2$	0.17	0.19	0.13	0.11	$\bar{R}^2$	0.04	0.08	0.11	0.13

Table 8: Dividend smoothing, firm size, and volatility

This table shows results for cross-sectional regressions of a country's dividend smoothing parameter on average firm size and/or idiosyncratic return volatility. The smoothing parameter is defined as the standard deviation of dividend growth of a country divided by the standard deviation of earnings growth. We use logs of the dependent variable in this regression. Numbers in brackets are t-statistics based on White (1980) heteroscedasticity-consistent standard errors.

	(i)	(ii)	(iii)
const.	-0.42	-0.78	-0.88
	[-3.16]	[-5.15]	[-6.07]
Average firm size	-0.15		-0.12
	[-2.14]		[-1.76]
Idiosyncratic return volatility		5.25	4.39
		[4.05]	[2.99]
$\bar{R}^2$	0.10	0.28	0.33

Table 9: Dividend growth predictability and institutional characteristics

This table shows results for cross-sectional regressions of a country's dividend growth predictability on institutional characteristics. The dependent variable is the time-series R^2 from a predictive regression of future dividend growth (over a one year forecast horizon) on the lagged (log) dividend yield for each country and the independent variable is an institutional characteristic of a country: Accounting standards (ACCT), anti-director rights (ANTI), the corruption perception index (CPIX), the efficiency of the judicial system (EFFJUDS), earnings management (EMGT), or the risk of expropriation (EXPR). The explanatory variables are scaled such that a higher value means a lower quality of institutions and the RHS variables are standardized. The upper part shows results for regressions where the dependent variable is the unadjusted time-series R^2 and the lower part of the table shows results for the case of a logistic transformation of the dependent variable. The last row in each part of the table shows the average value of the dependent variable. Numbers in brackets are t-statistics based on White (1980) heteroscedasticity-consistent standard errors.

	Dependent: Time-series R^2					
	ACCT	ANTI	CPIX	EFFJUDS	EMGT	EXPR
const	0.12	0.13	0.15	0.12	0.10	0.12
	[1.36]	[5.61]	[5.91]	[5.32]	[3.82]	[5.55]
slope	0.01	0.05	0.01	0.06	0.06	0.06
	[0.31]	[1.73]	[1.20]	[11.55]	[2.07]	[15.07]
R^2	-0.02	0.08	-0.03	0.14	0.14	0.14
$\overline{y}_i$	0.15	0.15	0.15	0.15	0.14	0.15

	Dependent: Logistic transformation of time-series R^2					
	ACCT	ANTI	CPIX	EFFJUDS	EMGT	EXPR
const	-1.92	-2.43	-2.34	-2.44	-2.69	-2.41
	[-2.42]	[-10.67]	[-10.24]	[-10.96]	[-10.01]	[-11.03]
slope	-0.13	0.37	0.14	0.37	0.48	0.36
	[-0.37]	[2.70]	[3.30]	[8.79]	[2.83]	[9.64]
R^2	-0.02	0.04	-0.02	0.05	0.09	0.04
$\overline{y}_i$	-2.23	-2.31	-2.29	-2.25	-2.37	-2.23

Table 10: 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

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

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_r^l, b_d^l, b_s^l)where long-run coefficients are calculated as $b_r^l = b_r/(1-\rho\phi)$ and similarly for b_d^l and b_s^l. b_r^l, $-b_d^l$, and $-b_s^l$ 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_r^l, b_d^l, b_s^l) 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 replications.

Panel A: VAR coefficients and long-run coefficients						
Equal weights						
b_r	b_d	b_s	ϕ	b_r^l	b_d^l	b_s^l
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_r^l	b_d^l	b_s^l
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

Figure 1: A comparison of U.S. dividend growth rates

The figures shows (annualized) dividend growth rates (in %) for the aggregate US stock market based on data from Robert Shiller for the S&P500 (blue solid line) and on Datastream for the aggregate U.S. market (red dashed line). The sample period is 1973Q1 to 2009Q1.

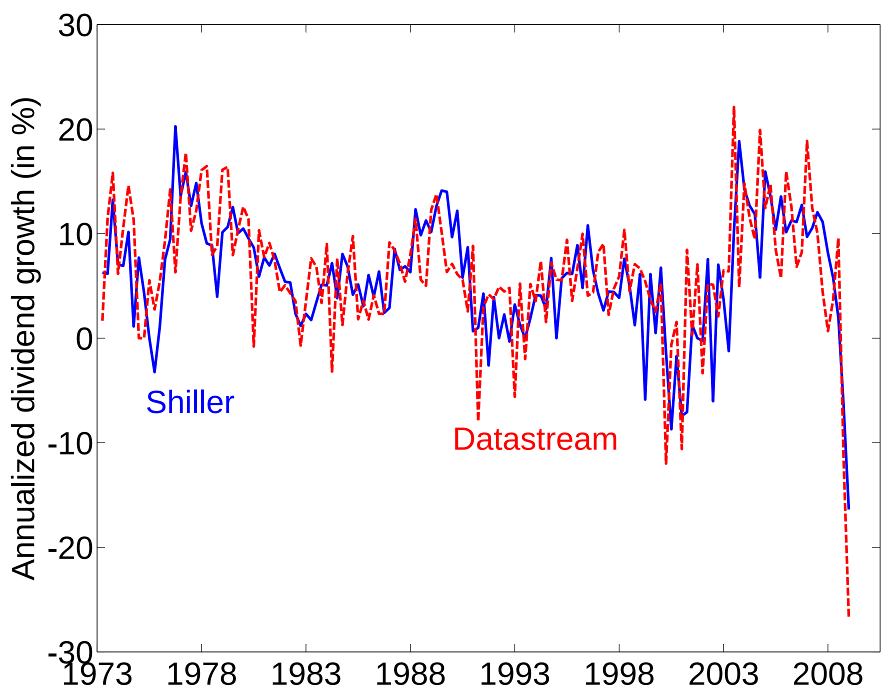
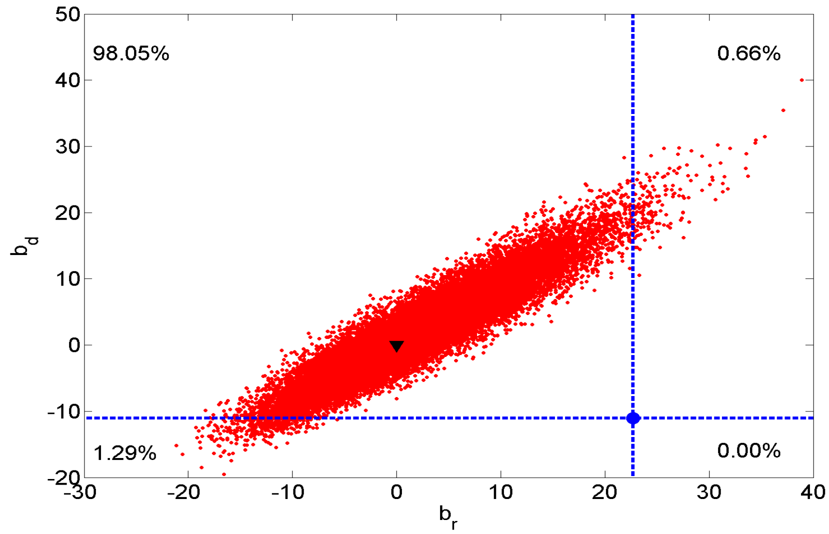
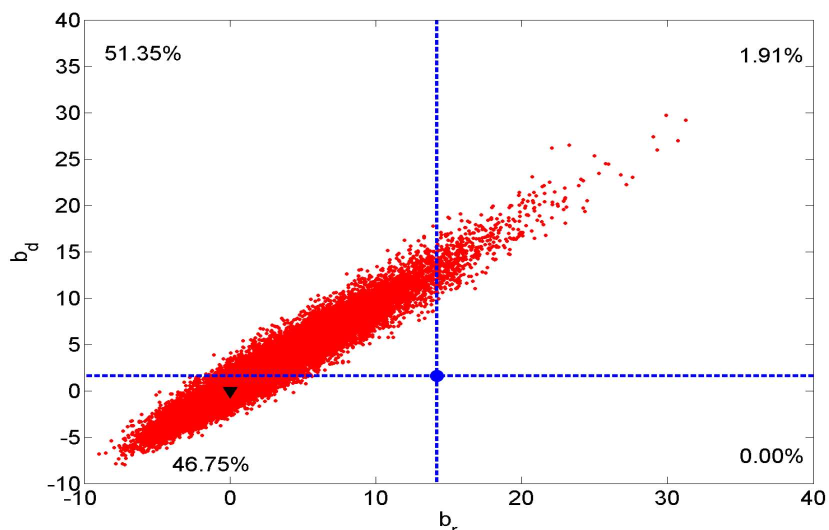


Figure 2: Simulated coefficients

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

Supplementary Appendix to accompany

Dividend predictability around the world

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 and Pedersen (2010) 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.[26] We run predictive regressions like those in Table 3, 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

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

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 4.3. 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 long-short trading strategy is −15.85% based on the equally-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.

Predictability over time. In Figure A.2, we visualize the cumulated returns, dividend growth rates, and exchange rates from the long-short portfolio. From Panel B in Figure A.2, the sizeable difference since the early 1980s between the dividends accumulating to the long-short portfolio of the equally-weighted and the value-weighted portfolios become clear: Dividends accumulated to the long-short portfolio of equally-weighted portfolios is in the order of –700 percent, whereas it is "only" in the order of –100 percent in the value-weighted portfolios. This again illustrates the strong degree of dividend predictability in small countries.

Considering returns, the cumulated return of the 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 equally-weighted value strategy's cumulated excess returns are much smoother. 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 equally-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.

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 equally-weighted portfolio but not in the value-weighted portfolio, like in our results in Table 3. 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 3. Likewise, the R^2 increases to 17% at the two-years horizon in Table 3 but only to 9% in Table A.III. The main thing to notice, however, is that in Tables 3 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 equally-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 equally-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 Panel predictive regressions

In the main text, we investigate panel predictive regressions with interaction terms (dividend yields interacted with average firm size and volatility). As a benchmark for these results we also present unbalanced panel predictive regressions *without* interaction terms in A.VII. The specification underlying these results is

$$
\begin{aligned}
r_{i,t+1;t+h} &= \alpha_{i,r}^{(h)} + \beta_r^{(h)}(d_{i,t}^f - p_{i,t}^f) + \varepsilon_{i,t+1;t+h}^{(h)} \\
\triangle d_{i,t+1;t+h}^f &= \alpha_{i,d}^{(h)} + \beta_d^{(h)}(d_{i,t}^f - p_{i,t}^f) + \varepsilon_{i,t+1;t+h}^{(h)} \\
\triangle s_{i,t+1;t+h}^f &= \alpha_{i,f}^{(h)} + \beta_s^{(h)}(d_{i,t}^f - p_{i,t}^f) + \varepsilon_{i,t+1;t+h}^{(h)}
\end{aligned}
$$

We find results similar to our main findings for equally weighted portfolios in the text which makes sense since we weight each country more or less equal in the panel regressions (abstracting from sample size issues): Returns and dividend growth rates are predictable whereas spot rate changes are not.

A.4 Portfolio double sorts

A.4.1 Firm size and dividend predictability

We also present results based on double-sorted portfolios. In the first step, we sort the countries into two groups based on the size of a typical firm in the country, delegating those countries where the typical firm size (average firm size or the 90% quantile of the firm-size distribution in the country) is below the median firm size (across all countries) into one group and those countries where the typical firm size is above the median in the other group. Each group then contains half of all available countries at a given point in time. As the next step, we sort countries into three portfolios based on their dividend yields within each firm-size group, such that we get a growth, medium, and value portfolio within each firm-size category. Again, each subgroup contains one third of all countries within a size group (i.e. one sixth of all countries). As with the simple portfolio sorts in Section 4.3, we use values at the end of the first quarter for sorting and rebalance annually.

Table A.VI reports the annualized average quarterly dividend growth rates (Panel A), total returns (Panel B), and the average firm size proxies used for sorting countries into portfolios at the time of portfolio formation (Panel C). We also report the means of long-short portfolios along two dimensions: (a) two 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.

From Table A.VI, it is clear that dividend growth predictability is a salient characteristic of countries where the typical growth firm is small. For instance, the average annualized dividend growth rates of countries where the typical growth firm is small is 19.53 percentage points higher than in the countries where the typical value firm is small. This can be contrasted with the V–G dividend growth of −6.56 percentage points p.a. in the group of countries with large average firms.

Regarding returns, we find that value countries (i.e. countries with high dividend yields) deliver higher returns on average. We also find a (insignificant) "small-firm" effect (Banz, 1981) in international returns, in that the returns in countries with typically smaller firms are higher than the returns in countries where the typical firm is large (as seen through the mostly positive numbers in the L-S row); however, this international small-firm effect is neither economically not statistically significant.

Finally, looking at the proxies for firm size in Panel C, we find that there is no significant difference across dividend yield categories (columns "Growth", "Med", and "Val") but significant differences between the firm size categories (rows "Large" and "Small"). An examination of these differences seems necessary since we are not jointly conditioning on firm size and dividend yields (due to the relatively small cross-section of countries available here) and it may thus be the case that firm size varies across dividend yield-sorted portfolios within each size category as well. However, our results suggest that this is not the case and that our results on dividend predictability are not contaminated by this.

A.4.2 Volatility and dividend predictability

We also double sort countries based on, first, volatility and, next, dividend yields, like we did when double-sorting on the typical firm size and dividend yields in Table A.VI. We first sort countries into one of two equal-sized groups depending on their (lagged) volatility (low and high volatility) and then sort on dividend yields within each volatility group, i.e. into growth, medium, and value. Within each of the six groups we then calculate the average dividend growth rates. We show the results in Table A.V.

Several patterns stand out. First, high volatility countries in general have higher dividend growth rates than low volatility countries (rows "H–L"). Second, high dividend yield countries have lower 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 -14%, -15%, and -19% p.a. for the group of countries that have experienced the highest levels of lagged volatility, but insignificant for the group of countries with low lagged volatility (ranging from -2.18% p.a. for idiosyncratic dividend volatility to -3.64% p.a. for idiosyncratic return volatility).

A.5 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.6, 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.6 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 4.3, but use standardized dividend yields.

We report the annualized mean returns, standard deviations, and other summary statistics from these trading strategies in Table A.VIII. 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 equally-weighted. As before, the dividend growth averages are markedly different between the equally-weighted and the value-weighted portfolios. Looking at equally-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.7 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.[27] We show results for the standardized portfolio sorts directly in Appendix Table A.IX. 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

[27]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.

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.

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

The setup is the same as in Table 3, but here we use excess returns (total returns in USD in excess of the U.S. riskfree rate) and real USD dividend growth (dividend growth rates converted to USD and deflated by U.S. CPI inflation).

	Equal weights					Value weights			
	Dependent variable: Real USD dividend growth								
h	4	8	12	16	h	4	8	12	16
β_d	-18.67	-31.34	-31.92	-32.83	β_r	-3.15	-4.96	-5.65	-6.49
t^{NW}	[-2.65]	[-2.05]	[-1.38]	[-1.16]	t^{NW}	[-0.92]	[-0.69]	[-0.55]	[-0.53]
t^H	[-2.89]	[-2.64]	[-1.84]	[-1.40]	t^H	[-1.25]	[-1.02]	[-0.80]	[-0.68]
t^{BS}	[-2.32]	[-1.61]	[-0.95]	[-0.83]	t^{BS}	[-0.80]	[-0.50]	[-0.36]	[-0.38]
$\bar{R}^2$	0.14	0.14	0.08	0.06	$\bar{R}^2$	0.02	0.02	0.01	0.01
R^2_{IH}	0.14	0.20	0.22	0.22	R^2_{IH}	0.01	0.01	0.01	0.01
	Dependent variable: Stock excess returns in USD								
h	4	8	12	16	h	4	8	12	16
β_r	15.54	21.60	25.40	39.22	β_r	9.49	18.17	26.98	34.55
t^{NW}	[1.59]	[1.13]	[0.92]	[1.16]	t^{NW}	[1.48]	[1.33]	[1.43]	[1.60]
t^H	[1.34]	[0.97]	[0.79]	[0.92]	t^H	[1.49]	[1.23]	[1.40]	[1.36]
t^{BS}	[1.30]	[0.71]	[0.52]	[0.69]	t^{BS}	[1.25]	[0.83]	[0.72]	[0.84]
$\bar{R}^2$	0.02	0.03	0.02	0.05	$\bar{R}^2$	0.03	0.07	0.11	0.14
R^2_{IH}	0.05	0.08	0.10	0.11	R^2_{IH}	0.08	0.14	0.20	0.25

Table A.II: Excess returns and real dividend growth

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

Panel A: Equal weights								Panel B: Value weights							
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
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

Table A.III: Predictive regressions: Excluding small countries

The setup is the same as in Table 3, but we exclude countries with less than 15 years of available data.

	Equal weights					Value weights			
				Dependent variable: Dividend growth					
h	4	8	12	16	h	4	8	12	16
β_d	-8.95	-13.59	-9.83	-9.56	β_d	1.67	3.64	5.78	7.25
t^{NW}	[-2.74]	[-1.84]	[-0.89]	[-0.77]	t^{NW}	[0.90]	[0.91]	[1.00]	[1.07]
t^{BS}	[-2.28]	[-1.54]	[-0.75]	[-0.68]	t^{BS}	[0.79]	[0.69]	[0.65]	[0.83]
$\bar{R}^2$	0.10	0.09	0.03	0.02	$\bar{R}^2$	0.01	0.02	0.03	0.04
R^2_{IH}	0.21	0.30	0.33	0.33	R^2_{IH}	0.05	0.03	0.02	0.02
				Dependent variable: Total returns – USD					
h	4	8	12	16	h	4	8	12	16
β_r	21.36	35.29	47.22	69.50	β_r	14.25	28.40	42.91	56.66
t^{NW}	[2.46]	[1.96]	[1.88]	[2.40]	t^{NW}	[2.38]	[2.24]	[2.52]	[3.00]
t^{BS}	[1.91]	[1.23]	[1.07]	[1.36]	t^{BS}	[1.98]	[1.40]	[1.27]	[1.52]
$\bar{R}^2$	0.05	0.09	0.11	0.19	$\bar{R}^2$	0.08	0.18	0.27	0.36
R^2_{IH}	0.05	0.08	0.10	0.12	R^2_{IH}	0.08	0.14	0.20	0.25
				Dependent variable: Spot rate changes					
h	4	8	12	16	h	4	8	12	16
β_s	0.28	2.27	5.39	10.23	β_s	0.25	0.86	1.93	3.16
t^{NW}	[0.05]	[0.21]	[0.33]	[0.51]	t^{NW}	[0.12]	[0.21]	[0.31]	[0.42]
t^{BS}	[0.05]	[0.16]	[0.22]	[0.37]	t^{BS}	[0.10]	[0.14]	[0.19]	[0.26]
$\bar{R}^2$	-0.01	-0.01	0.00	0.01	$\bar{R}^2$	-0.01	-0.01	0.00	0.00
R^2_{IH}	0.00	0.00	0.00	0.00	R^2_{IH}	0.00	0.00	0.00	0.00

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							
Dividend growth							
PF	1	2	3	4	5	Avg.	5-1
Mean	18.54	11.90	9.29	10.63	2.84	10.65	-15.70
	[7.01]	[8.91]	[6.74]	[7.73]	[1.46]	[10.12]	[-4.97]
Std	13.88	9.10	8.03	7.83	9.47	5.67	16.30
Skew	1.53	1.42	-0.28	1.28	-2.90	0.81	-1.25
Kurt	6.01	7.57	4.95	5.90	19.69	5.05	4.79
Total returns – USD							
PF	1	2	3	4	5	Avg.	5-1
Mean	3.56	8.22	10.29	8.26	12.37	8.58	8.81
	[0.81]	[2.04]	[2.88]	[2.20]	[3.28]	[2.40]	[3.22]
Std	22.38	21.68	20.08	20.29	21.96	19.16	16.42
Skew	-0.87	-0.52	-0.87	-1.05	-0.74	-1.03	-0.05
Kurt	4.74	4.23	5.82	4.97	4.12	5.22	2.81
Spot rate changes							
PF	1	2	3	4	5	Avg.	5-1
Mean	-0.42	0.46	-0.42	-2.10	-2.82	-1.07	-2.40
	[-0.22]	[0.30]	[-0.32]	[-1.48]	[-1.73]	[-0.77]	[-2.00]
Std	9.36	8.36	7.92	7.48	8.41	7.37	6.05
Skew	-0.09	-0.19	-0.45	-0.53	-0.21	-0.30	-0.12
Kurt	4.13	3.69	4.53	4.75	4.19	3.70	4.85

Panel B:Value weights							
Dividend growth							
PF	1	2	3	4	5	Avg.	5-1
Mean	5.67	9.03	9.18	8.07	5.42	6.70	-0.25
	[4.77]	[6.95]	[7.53]	[7.53]	[4.45]	[9.35]	[-0.16]
Std	5.54	7.38	6.60	5.66	5.71	3.11	7.34
Skew	2.73	0.96	0.59	0.81	-1.91	0.49	-2.03
Kurt	16.29	5.45	4.37	7.11	16.72	5.57	10.76
Total returns – USD							
PF	1	2	3	4	5	Avg.	5-1
Mean	4.47	7.24	8.51	7.58	11.42	7.38	6.95
	[1.00]	[1.90]	[2.47]	[2.34]	[3.13]	[2.42]	[1.96]
Std	21.69	20.46	18.50	17.26	22.34	15.24	20.92
Skew	-0.07	-0.28	-0.99	-0.87	-0.49	-0.72	0.06
Kurt	4.10	3.48	6.06	4.22	4.10	4.63	3.59
Spot rate changes							
PF	1	2	3	4	5	Avg.	5-1
Mean	2.82	1.05	0.02	-1.04	-1.63	0.52	-4.45
	[1.46]	[0.68]	[0.01]	[-0.74]	[-0.99]	[0.62]	[-2.17]
Std	10.84	8.61	7.20	7.63	9.73	4.98	10.93
Skew	0.37	0.05	-0.56	-0.75	-0.69	0.07	-0.72
Kurt	3.54	4.29	6.11	8.27	4.94	3.02	4.14

Table A.V: Double sorts on volatility measures and dividend yields

The setup of this table is identical to Table A.VI but here we double-sort on dividend yields and proxies for dividend volatility (instead of firm size measures). Also, we only report results for dividend growth (left part) and the average value of the characteristic used for sorting countries into portfolios (right part) The row dimension of the table shows volatility groups (high or low) and the column dimension shows portfolios sorted according to lagged dividend yields. The left part of the table is for dividend volatility

	Average dividend growth					Characteristic			
Panel A: Dividend volatility									
	Growth	Med	Value	V – G		Growth	Med	Value	V – G
Low	8.72	7.45	5.58	-3.14	Low	0.37	0.41	0.42	0.05
	[5.09]	[5.64]	[5.17]	[-1.79]					[3.97]
High	21.37	12.22	7.10	-14.28	High	1.82	1.45	1.56	-0.26
	[7.47]	[4.85]	[2.97]	[-4.02]					[-2.32]
H – L	12.65	4.77	1.52	-11.13	H – L	1.46	1.04	1.14	-0.31
	[4.82]	[2.03]	[0.80]	[-3.46]		[10.13]	[12.53]	[9.45]	-[2.72]
Panel B: Idiosyncratic dividend volatility									
	Growth	Med	Value	V – G		Growth	Med	Value	V – G
Low	8.95	8.36	6.77	-2.18	Low	0.39	0.40	0.38	-0.01
	[5.89]	[6.70]	[7.16]	[-1.55]					[-0.67]
High	20.94	12.60	6.08	-14.86	High	1.80	1.46	1.51	-0.29
	[7.36]	[5.89]	[2.51]	[-3.92]					[-2.76]
H – L	11.99	4.24	-0.69	-12.68	H – L	1.41	1.05	1.13	-0.28
	[4.82]	[2.18]	[-0.32]	[-3.63]		[10.09]	[11.36]	[9.62]	[-2.65]
Panel C: Idiosyncratic return volatility									
	Growth	Med	Value	V – G		Growth	Med	Value	V – G
Low	9.91	9.23	6.27	-3.64	Low	0.73	0.76	0.68	-0.05
	[6.78]	[7.31]	[4.71]	[-1.83]					[-2.11]
High	21.55	12.91	2.79	-18.77	High	1.81	1.69	1.76	-0.05
	[7.11]	[6.52]	[0.95]	[-4.48]					[-0.77]
H – L	11.64	3.69	-3.48	-15.12	H – L	1.08	0.93	1.08	-0.00
	[4.03]	[1.94]	[-1.19]	[-3.58]		[16.56]	[16.23]	[19.48]	[-0.01]

Table A.VI: Double sorts on firm size measures and dividend yields

This table shows results for double sorts on (i) average firm size (left part) or (ii) the 90% quantile of the cross-sectional firm size distribution (right part) and the dividend yield. We first split countries along the median of one of the lagged firm size proxies and then sort into three portfolios depending on lagged dividend yields, resulting in six portfolios per sort. Rows correspond to the size dimension whereas columns correspond to the dividend yield dimension of the sorting exercise. Panel A shows average dividend growth rates, Panel B shows average total USD returns, and Panel C shows the average value for the conditioning variable at the time of portfolio formation (i.e. average firm size or the 90% quantile measure). We also show results for differences in portfolios in rows "L – S" and columns "V – G". Numbers in brackets are t-statistics based on Newey-West standard errors for the null of a zero mean.

	Average firm size					90% quantile			
Panel A: Dividend growth									
	Growth	Med	Value	V – G		Growth	Med	Value	V – G
Small	23.28	7.40	3.76	-19.53	Small	20.77	9.16	3.22	-17.55
	[6.44]	[2.34]	[2.08]	[-5.09]		[6.24]	[3.39]	[1.36]	[-4.11]
Large	13.54	9.51	6.98	-6.56	Large	14.08	9.18	6.37	-7.71
	[7.69]	[7.58]	[4.87]	[-2.80]		[7.34]	[6.32]	[4.18]	[-3.05]
L – S	-9.74	2.11	3.22	12.96	L – S	-6.69	0.02	3.15	9.84
	[-2.66]	[0.68]	[2.10]	[3.37]		[-1.88]	[0.01]	[1.49]	[2.25]
Panel B: Returns									
	Growth	Med	Value	V – G		Growth	Med	Value	V – G
Small	8.06	8.15	11.91	3.85	Small	8.30	7.60	10.45	2.14
	[1.91]	[1.88]	[2.81]	[1.13]		[1.98]	[1.79]	[2.55]	[0.66]
Large	5.55	7.35	8.19	2.64	Large	5.54	8.32	9.46	3.92
	[1.24]	[2.07]	[2.56]	[0.85]		[1.20]	[2.41]	[2.99]	[1.30]
L – S	-2.51	-0.80	-3.72	-1.21	L – S	-2.76	0.72	-0.99	1.78
	[-0.88]	[-0.31]	[-1.18]	[-0.30]		[-0.97]	[0.27]	[-0.35]	[0.48]
Panel C: Average values of firm size-related conditioning variable									
	Growth	Med	Value	V – G		Growth	Med	Value	V – G
Small	-9.39	-8.28	-9.61	-0.22	Small	-8.28	-6.99	-8.68	-0.40
				[-0.62]					[-1.04]
Large	-2.72	-2.75	-2.79	-0.07	Large	-1.86	-2.00	-2.07	-0.21
				[-0.31]					[-1.06]
L – S	6.67	5.53	6.82	0.16	L – S	6.43	4.99	6.61	0.19
	[26.72]	[24.85]	[19.18]	[0.42]		[30.86]	[25.71]	[23.18]	[0.46]

Table A.VII: Predictive panel regressions

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

$$\begin{aligned}\triangle d^f_{i,t+1;t+h} &= \alpha^{(h)}_{i,d} + \beta^{(h)}_d (d^f_{i,t} - p^f_{i,t}) + \varepsilon^{(h)}_{i,t+1;t+h} \\ r_{i,t+1;t+h} &= \alpha^{(h)}_{i,r} + \beta^{(h)}_r (d^f_{i,t} - p^f_{i,t}) + \varepsilon^{(h)}_{i,t+1;t+h} \\ \triangle s^f_{i,t+1;t+h} &= \alpha^{(h)}_{i,f} + \beta^{(h)}_s (d^f_{i,t} - p^f_{i,t}) + \varepsilon^{(h)}_{i,t+1;t+h}\end{aligned}$$

for the panel of all 50 countries and different forecast horizons h. A subscript $t+1;t+h$ means cumulative returns or changes over the next h quarters. We use a fixed-effects panel setting, i.e. we use individually demeaned time-series for the dependent and independent variables. t^{NW} are t-statistics based on Newey-West HAC standard errors whereas t^{BS} shows bootstrap t-statistics (moving block bootstrap with 10,000 repetitions).

Panel A: Dividend growth					Panel B: Total returns – USD					Panel C: Spot rate changes				
h	4	8	12	16	h	4	8	12	16		4	8	12	16
β_d	-29.52	-42.25	-40.77	-38.96	β_r	15.24	26.36	34.88	45.44	β_s	-0.97	-1.45	-2.82	-4.11
t^{NW}	[-7.22]	[-6.36]	[-6.49]	[-6.15]	t^{NW}	[6.50]	[5.13]	[5.57]	[6.37]	t^{NW}	[-1.18]	[-0.85]	[-1.06]	[-1.11]
t^{BS}	[-7.29]	[-5.90]	[-5.17]	[-4.38]	t^{BS}	[6.08]	[4.90]	[5.69]	[6.65]	t^{BS}	[-1.07]	[-0.80]	[-0.98]	[-1.07]
$\bar{R}^2$	0.18	0.21	0.16	0.13	$\bar{R}^2$	0.04	0.07	0.09	0.12	$\bar{R}^2$	0	0	0	0
R^2_{IH}	0.15	0.18	0.17	0.15	R^2_{IH}	0.02	0.03	0.03	0.02	R^2_{IH}	0	0	0	0

Table A.VIII: 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								Panel B:Value weights							
Dividend growth								Dividend growth							
PF	1	2	3	4	5	Avg.	5-1	*PF*	1	2	3	4	5	Avg.	5-1
Mean	23.33	14.46	10.62	6.31	0.93	11.17	-22.40	Mean	12.02	10.70	7.19	5.58	3.64	6.81	-8.39
	[8.54]	[8.86]	[7.77]	[4.20]	[0.42]	[9.13]	[-6.87]		[7.40]	[8.18]	[6.61]	[4.46]	[2.01]	[9.52]	[-3.72]
Std	16.45	9.96	8.52	8.74	11.88	6.39	20.77	Std	7.94	7.17	5.48	6.88	11.85	3.10	14.27
Skew	2.39	1.27	1.49	0.08	-4.32	1.19	-2.37	Skew	3.22	1.05	0.75	0.34	-0.23	0.59	-0.10
Kurt	10.43	5.95	6.57	7.45	36.36	6.26	11.41	Kurt	22.85	4.75	4.39	7.42	23.14	5.50	16.92
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	2.79	7.90	6.55	11.44	14.12	8.66	11.32	Mean	3.40	8.92	6.95	10.29	12.33	7.35	8.93
	[0.63]	[1.80]	[1.70]	[3.18]	[3.50]	[2.32]	[3.48]		[0.85]	[1.93]	[2.10]	[2.81]	[3.43]	[2.38]	[2.74]
Std	23.55	23.55	20.18	20.38	22.52	19.83	18.19	Std	21.94	25.00	17.53	20.75	21.08	15.46	20.38
Skew	-0.70	-1.13	-1.24	-0.70	-1.01	-1.24	-0.82	Skew	-0.03	-0.75	-0.72	-0.53	-0.78	-0.84	0.13
Kurt	6.07	5.79	6.94	4.18	4.86	6.46	6.94	Kurt	3.83	5.34	4.21	3.99	4.15	5.21	6.02
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	0.05	-0.74	-0.12	-1.78	-2.82	-1.08	-2.86	Mean	0.79	0.99	0.42	-0.53	-1.61	0.49	-2.40
	[0.03]	[-0.48]	[-0.07]	[-1.20]	[-1.91]	[-0.77]	[-2.25]		[0.51]	[0.61]	[0.29]	[-0.40]	[-1.15]	[0.58]	[-1.40]
Std	8.14	8.67	8.66	8.17	7.56	7.44	6.23	Std	7.73	9.83	8.84	7.86	7.47	4.99	8.05
Skew	-0.08	-0.56	-0.73	-0.30	-0.39	-0.37	-0.03	Skew	0.64	0.07	-0.15	-0.86	-0.24	0.03	-0.55
Kurt	3.86	5.06	5.41	3.79	4.26	4.02	4.10	Kurt	3.85	3.89	6.08	5.66	4.20	3.13	3.88

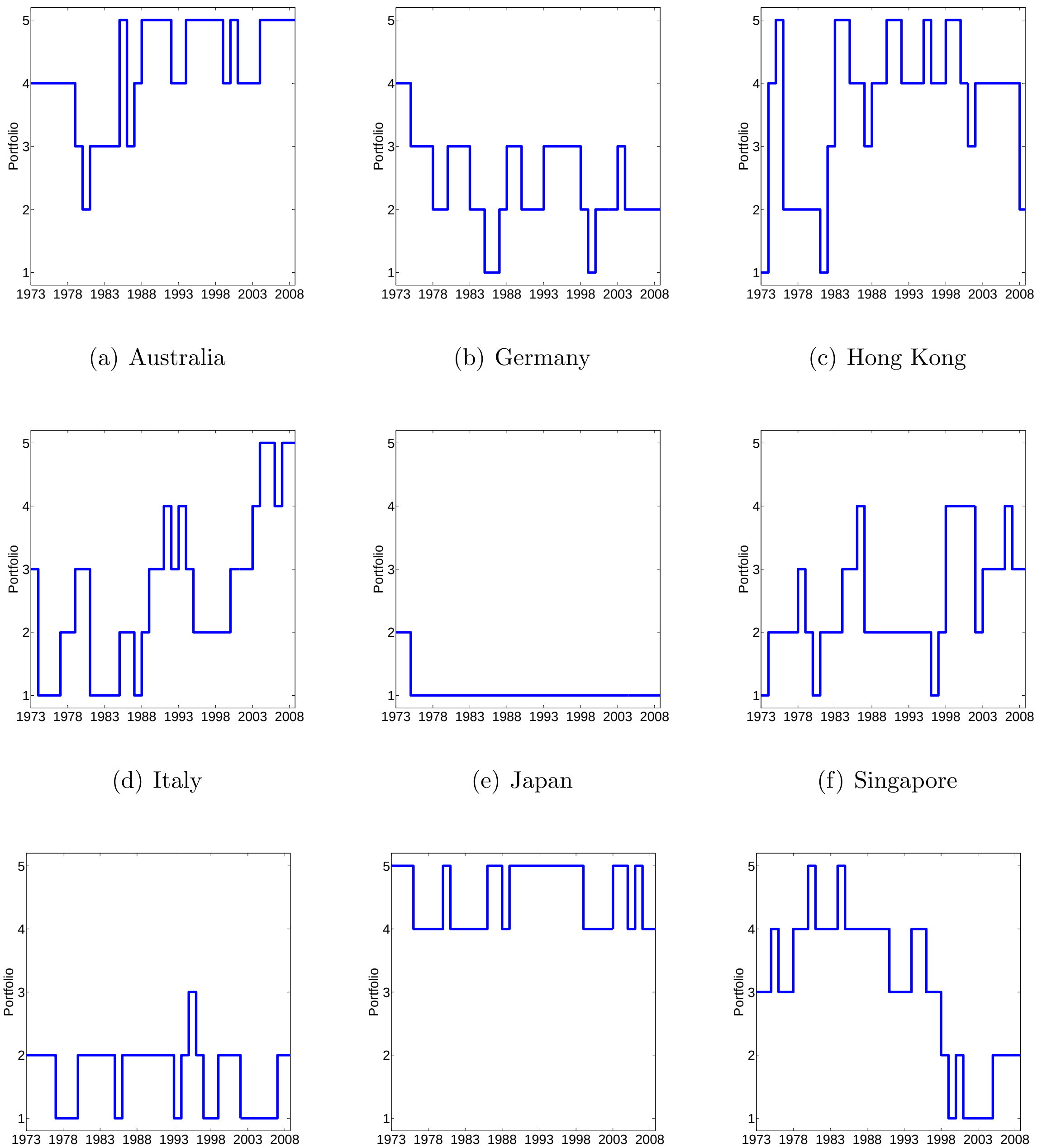
Table A.IX: Descriptive Statistics: Portfolios sorted on standardized dividend yields (sub-samples)

The setup is identical to Table A.VIII, 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)								Panel B: Large markets (1991 – 2009)							
Dividend growth								Dividend growth							
PF	1	2	3	4	5	Avg.	5-1	*PF*	1	2	3	4	5	Avg.	5-1
Mean	14.41	11.56	6.61	5.84	3.83	8.54	-10.57	Mean	12.75	6.70	8.75	6.63	3.37	7.64	-9.38
	[9.57]	[8.41]	[5.21]	[5.48]	[2.33]	[8.83]	[-5.47]		[7.32]	[2.95]	[4.64]	[3.69]	[1.48]	[5.27]	[-3.69]
Std	7.23	7.04	5.57	4.36	7.07	3.71	11.19	Std	9.32	9.93	7.70	8.09	9.51	6.06	12.20
Skew	0.84	-0.08	1.76	-0.36	-0.50	0.54	-0.70	Skew	0.59	0.08	1.04	0.39	0.06	1.54	-0.57
Kurt	3.35	3.66	12.20	5.03	5.01	3.33	4.86	Kurt	3.69	5.43	4.61	4.42	4.07	6.67	3.15
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	3.06	14.00	8.99	11.30	16.99	10.94	8.42	Mean	4.46	6.11	8.25	7.68	9.10	7.12	3.04
	[0.52]	[2.11]	[2.05]	[2.91]	[4.03]	[2.46]	[2.07]		[0.88]	[1.52]	[1.59]	[1.45]	[2.03]	[1.58]	[0.92]
Std	23.72	25.18	18.42	16.55	19.70	17.89	17.87	Std	17.65	15.96	18.09	18.52	18.03	16.07	13.00
Skew	0.12	-1.01	-0.32	-0.28	-0.35	-0.65	-0.03	Skew	-1.07	-0.47	-1.04	-1.27	-1.11	-1.30	0.34
Kurt	2.48	5.75	2.76	2.88	2.82	3.09	2.85	Kurt	5.16	4.02	4.85	5.99	4.77	6.09	3.94
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	2.29	1.06	2.95	-0.91	0.18	1.09	-2.11	Mean	0.11	0.40	-0.29	0.17	-0.43	-0.01	-0.54
	[0.83]	[0.42]	[1.33]	[-0.44]	[0.10]	[0.53]	[-1.00]		[0.06]	[0.20]	[-0.13]	[0.11]	[-0.21]	[0.00]	[-0.31]
Std	9.21	9.78	8.30	8.78	7.54	7.76	6.96	Std	7.11	8.08	9.07	7.45	7.82	7.18	5.90
Skew	0.33	0.05	-0.19	-0.07	0.26	0.06	0.07	Skew	-0.24	-0.23	-1.02	-0.47	-0.40	-0.54	-0.05
Kurt	2.38	2.91	2.57	3.67	3.08	2.33	3.87	Kurt	3.69	4.41	6.12	3.35	3.66	3.46	5.14

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.



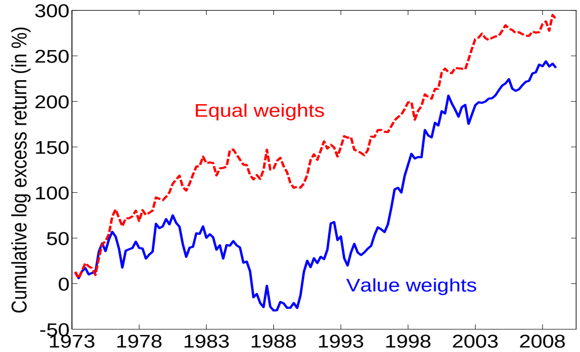
(a) Australia (b) Germany (c) Hong Kong

(d) Italy (e) Japan (f) Singapore

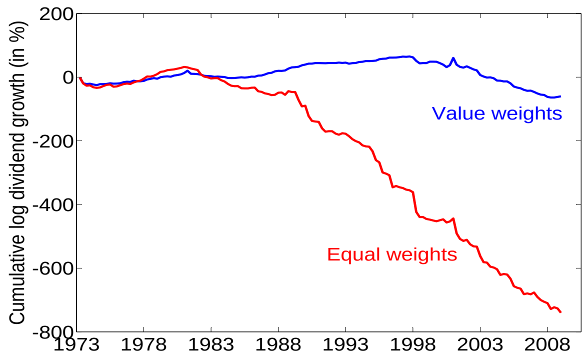
(g) Switzerland (h) U.K. (i) U.S.

Figure A.2: Cumulative returns, dividend growth, and spot rate changes of long-short portfolios

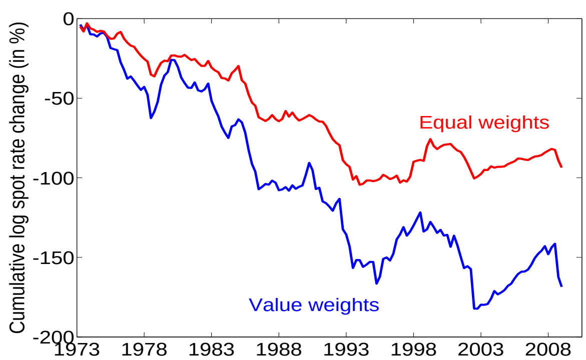
Cumulative returns, dividend growth, and spot rate changes of the long-short portfolio (portfolio 5 minus portfolio 1). Solid, blue lines show results for the full sample (all countries), whereas dashed, red lines show results for the sample of larger markets.



(a) Returns



(b) Dividend growth



(c) Spot rate changes