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Dividend Risk Premia

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Abstract

This article studies time variation in the expected excess returns of traded claims on dividends, bonds, and stock indices for international markets. We introduce a novel dividend risk factor that complements the bond risk factor of Cochrane and Piazzesi (2005). By aggregating over 4 regions (United States, United Kingdom, Eurozone, and Japan), we create global dividend and bond factors. Our global 2-factor model captures the excess returns of most Morgan Stanley Capital International (MSCI) country indices, as well as a variety of other test assets. Our findings highlight the value of the information contained in dividend and bond forward curves and suggest substantial comovement in international risk premia.

I. Introduction

The introduction of traded claims on index dividends (i.e., dividend derivatives) with several maturities allows investors to observe maturity-specific equity returns. Correspondingly, a recent strand of research has emerged that establishes important empirical findings on the term structure of equity risk premia: Van Binsbergen, Brandt, and Koijen (2012) impute short-term dividend strip returns from Standard & Poor's (S&P) 500 index options and show that these claims have higher Sharpe ratios than equity index returns and are more volatile than subsequent dividend realizations, thus revealing excess volatility for dividend strips. Relatedly, using the ratio of log price to dividends, they find that the predictability of dividend strip returns is higher than that for the equity index itself. Van Binsbergen, Hueskes, Koijen, and Vrugt (2013) use dividend derivatives to construct equity yields analogous to bond yields for the United States, Japan, and the Eurozone. Equity yields consist of maturity-specific risk premia and dividend

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growth expectations. Hence, by definition, equity yields have to predict future returns on dividend derivatives, future dividend growth, or both. Using equity yields of two specific maturities, the authors find strong predictability of future dividend growth as well as consumption growth. Furthermore, they reject the hypothesis of constant risk premia on dividend derivatives, which are found to be highly variable and procyclical and comove internationally. Moreover, the term structure of equity yields contains additional information over the term structure of bonds, and the principal components of equity and bond yield curves are negatively correlated. Van Binsbergen and Koijen (2017) extend the empirical evidence to the United Kingdom. More importantly, they show that the term structure of equity risk premia has common features with other asset classes, such as government bonds, corporate bonds, and volatility.

In the fixed-income literature, Cochrane and Piazzesi (2005) (CP) find that a single return-forecasting factor describes time variation in the expected excess returns of bonds of all maturities. Koijen, Lustig, and van Nieuwerburgh (2017) extend the evidence on the predictability of the bond term structure to the domain of stocks, showing that business-cycle risk is priced in the stock and bond markets. Building on these established facts, we apply the rationale of CP to the term structure of equity yields. Our results confirm that the dynamics of dividend risk premia of various maturities are captured by a common return-forecasting factor, just as the CP factor does for government bonds.

We provide further international evidence for the joint dynamics of dividend risk premia with maturities from 1 to 5 years by analyzing 4 regions (the United States, Japan, Eurozone, and the United Kingdom). Moreover, guided by the idea of a common factor structure across asset classes, we estimate a 2-factor model to explain variations in the excess returns of stock indices, dividend derivatives, and bonds, using both the dividend factor and the bond factor. The results show that the dividend factor is significantly and positively related to the subsequent excess returns of dividend derivatives and stock indices, whereas the bond factor is significant but with a negative sign. The latter finding is consistent with the negative relation of stocks and bonds since 2000, a fact that can be attributed to output-focused monetary policy and elevated macroeconomic uncertainty (see, e.g., Campbell, Pflueger, and Viceira (2018)). Only the bond factor is important in explaining excess bond returns.

We then move on to construct global dividend and bond risk factors by aggregating the local risk factors of the 4 core regions. We find that the variation in local asset returns is well captured by these global risk factors, suggesting substantial comovements in international risk premia. Building on this finding, the global dividend and bond factors are used to explain the return dynamics of a broad set of test assets. This global 2-factor model works well for most developed market MSCI country indices and for other test assets, such as high-yield bonds or a volatility-selling strategy. Because the global risk factors are constructed using only 4 core regions, this result highlights the validity of our factors. In contrast to a market-specific approach, our global dividend factor helps to explain variations in excess returns, even in markets that do not have traded dividend claims. Similar to the local 2-factor model, the global dividend factor relates positively to international equity index returns and equity-like assets, whereas the global bond factor

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is positively associated with government bond returns but negatively associated with equity returns.

Our results are statistically robust because we follow recent empirical studies in basing inference on block-bootstrapped standard errors. Furthermore, we evaluate the empirical models in terms of unconditional and conditional measures for predictability (Clark and West (2007), Giacomini and White (2006)). To shed light on economic robustness, we challenge our approach by including well-known equity index return predictors, such as the cyclically adjusted price–earnings ratio (CAPE) and the term spread. Employing robust methods to compare various models, we find that the global dividend and bond factors are not subsumed by these predictors. Neither local nor global versions of the control variables cause our factors to become redundant. Relating the dividend factor to other explanatory variables, we find it to be significantly related to risk aversion, liquidity risk, and valuation levels. Although the bond factor has similar exposure to risk aversion and liquidity, it is positively related to the term spread and negatively related to inflation expectations. Known predictors from the literature explain a larger fraction of the variation in the bond factor as compared to the dividend factor. Thus, the innovation of our dividend factor over existing predictors seems to be substantial. We find a strong relation between the global dividend factor and real-time proxies for business activity. This is consistent with the interpretation that the dividend factor captures increased risk premia during bad economic times.

We discuss possible extensions of our empirical model. Inflation expectations can be accounted for consistently across asset classes, either by decomposing bond and equity yields into inflation expectations as well as maturity-specific interest rate and dividend cycles, or by extracting an inflation risk factor from the term structure of inflation swaps. Consensus analysts' dividend growth expectations can also be incorporated explicitly into our model.

The remainder of the article is organized as follows: In Section II we discuss the literature related to this article, and in Section III we present in detail the data and notation used throughout the article. We motivate a common factor structure for stocks, bonds, and traded dividends in Section IV, and we present our approach to modeling dividend risk premia in Section V and then describe the risk factors constructed to develop an empirical 2-factor asset pricing model in Section VI. In Section VII we elaborate on possible extensions, and Section VIII concludes. The Appendix delineates the criteria to assess model accuracy and the bootstrapping methodology. We provide additional results, including further applications of the model in an international setup, and robustness checks in the Supplementary Material.

II. Related Literature

One of the leading questions in the empirical asset pricing literature asks what the factor structure of expected returns is across a broad set of asset classes. As noted by Cochrane (2017), it is still an open issue how many state variables are really required to capture the time-series dynamics of expected returns. Although the CP (2005) factor has some explanatory power beyond bond returns, it seems obvious that at least one more factor is necessary to appropriately account

for equity-like risk. The present work provides such a dividend factor, which augments the CP factor to cover a wide range of asset classes.

Brennan (1998) claims that creating tradable dividend strips similar to Treasury strips would increase allocative efficiency by enabling investors to be exposed to realized cumulative dividends without bearing valuation risk at the time of divestment. Importantly, he also states that traded prices for future dividend payments should increase informational efficiency, a notion that is supported by the results of the present study. Shortly after the publication of his article, and underpinned by the hedging demands of banks arising from positions in index derivatives, over-the-counter (OTC) markets for index dividend swaps emerged. These derivatives allow investors to gain exposure to cumulative dividends paid over a specific maturity year. Manley and Mueller-Glissmann (2008) provide institutional details on traded dividend derivatives. The introduction of exchange-listed dividend futures with several (annual) maturities in mid-2008 substantially increased the attention paid to traded claims on index dividends. Van Binsbergen et al. (2012) extract short-term dividend strip returns from S&P 500 index options and show that these claims have capital asset pricing model (CAPM) betas below 1 and higher Sharpe ratios than equity index returns, thus indicating a downward-sloping term structure of equity risk premia. This finding is in contrast to most leading theoretical asset pricing models. Furthermore, dividend strip returns exhibit excess volatility and are predictable. Van Binsbergen et al. (2013) employ a data set on OTC dividend swaps to investigate the properties of equity yields constructed similarly to bond yields. Because equity yields consist of maturity-specific risk premia and dividend growth expectations, they have to predict future returns on dividend derivatives, future dividend growth, or both. Using the equity yields of two specific maturities as predictors, the authors find strong predictability of future dividend growth as well as consumption growth. Furthermore, they find the risk premia of dividend derivatives to be highly variable and procyclical and to comove internationally. Using principal-component analysis, they further relate the term structures of equity, nominal bonds, and real bonds. Cejnek and Randl (2016) extract the ex ante risk premia of constant-maturity dividend strategies using a carry model and relate these to ex post realized returns. Further, they analyze the performance of short-duration dividend strategies and show that it is related to downside risk. Using an updated international sample of dividend swaps, Van Binsbergen and Koijen (2017) confirm earlier empirical findings on the term structure of equity risk premia. They categorize recent asset pricing theories and relate the predictions of these models to the empirical evidence. They extend the observation of a downward-sloping term structure of risk premia beyond the domain of equity by highlighting common features across asset classes, such as dividend derivatives, government bonds, corporate bonds, volatility, and housing.

In a recent article, Kragt, de Jong, and Driessen (2019) model the term structure of dividends with a 2-factor affine model, in which the first factor mean reverts to the second factor over the short run, whereas the second factor reverts to a constant over the business-cycle horizon. Although both our article and Kragt et al. (2019) highlight the importance of the information that can be inferred from dividend forward curves, our article differs in both methodology and objectives.

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By extracting a return-forecasting factor from the dividend term structure, we focus on explaining the excess returns of dividend derivatives and other assets rather than modeling the dividend term structure. Moreover, we aim to provide a parsimonious factor structure for the time-series dynamics of expected returns across asset classes.

The literature on fixed-income securities provides extensive evidence on time-varying bond risk premia as well as the predictability of excess bond returns. Fama and Bliss (1987) show that, in contrast to the expectation hypothesis, n-year forward spreads predict excess returns on n-year bonds. CP (2005) show that a single return-forecasting factor constructed from five forward rates predicts excess returns on bonds of all maturities. Dahlquist and Hasseltoft (2013) and Kessler and Scherer (2009) provide international evidence on the robustness of the CP (2005) factor. Mylnikov (2014) develops a more parsimonious version of the CP factor, with favorable statistical properties, and focuses on the economic value added by forecasts. Cieslak and Povala (2015) decompose yields into inflation expectations and maturity-specific interest rate cycles. The increasing importance of credit risk in sovereign bond returns leads Dockner, Mayer, and Zechner (2013) to augment a default risk-free bond factor with a credit risk factor extracted from the term structure of credit default swap (CDS) spreads. Hammerschmid (2017) shows that a CP-style factor extracted from commodity futures predicts the excess returns of an aggregate commodity portfolio. This highlights the important role of information contained in forward curves. By relating the excess returns of value stocks to cash-flow risk and output risk proxied by the CP bond factor, Koijen et al. (2017) extend the evidence on the predictability of the bond term structure to the domain of stocks. The authors implement a 3-factor pricing model for stocks and bonds using the CP factor, as well as shocks to the level of the bond term structure and the market return as a proxy for the equity risk premium. Our article improves upon their proxy for cash-flow risk by utilizing information on the entire term structure of equity risk premia (the dividend factor) and provides additional test assets (returns on dividend derivatives). De Moor and Sercu (2013) claim that information related to dividend yields is valuable in identifying missing factors driving international stock returns (especially the size effect in their case). This provides further indication that extracting a global dividend risk factor might prove essential in capturing excess asset returns on a global scale.

Finally, the drivers of the correlation between bond and stock returns are of vital relevance to this work. Campbell et al. (2018) identify monetary policy regimes and macroeconomic uncertainty as the driving forces behind stock–bond correlations. Ilmanen (2003) finds low-inflation expectations and financial crises to be the drivers for negative stock–bond correlations. David and Veronesi (2013) explain the covariation of stocks and bonds using learning dynamics, in which stocks and bonds tend to move in opposite directions in a deflationary regime. Bansal, Connolly, and Stivers (2014) attribute the negative stock–bond return relation to risk movements because equity risk changes (measured by implied volatility from options) are highly related to stock and bond excess returns, but in opposite directions.

III. Data and Notation

Our main data source for dividend swaps is a sample of OTC mid-market prices obtained from Goldman Sachs.[1] The data range from Dec. 30, 2005, to Dec. 30, 2016, and cover dividend swaps for maturities up to 5 years for the underlying S&P 500, Financial Times Stock Exchange (FTSE) 100, Nikkei 225, and Euro Stoxx 50 indices.[2] We use a weekly data frequency. To obtain bond yields, we retrieve bootstrapped zero-coupon curves from Bloomberg. Various price index and total return time series, as well as data on term spreads, TED spreads, zero-coupon inflation swaps, consensus analysts' dividend forecasts, and core consumer price indices, are also retrieved from Bloomberg. Cyclically adjusted price–earnings ratios (CAPEs) are retrieved from Global Financial Data. We further use data on business conditions available to investors in real time: We download the Business Conditions Index as described by Aruoba, Diebold, and Scotti (2009) from the Web site of the Federal Reserve Bank of Philadelphia. Additionally, we obtain real-time predictions for current and next-quarter U.S. gross domestic product (GDP) from Now-Casting Economics Limited (see Giannone, Reichlin, and Small (2008) for a description of these time series).

A. Bonds

We denote zero-coupon bond yields by $Y_t^{\text{bonds},(n)}$, where numbers in parentheses indicate the maturity $n \in \{1,2,3,4,5\}$, measured in years, and the subscript t denotes time measured at a weekly frequency. We compute zero-coupon bond prices as follows:[3]

$$P_t^{\text{bonds},(n)} = \left(1 + Y_t^{\text{bonds},(n)}\right)^{-n}. \tag{1}$$

For $n \geq 2$, we calculate the n-year/1-year forward rate (1-year rate ending in n years) as

$$F_t^{\text{bonds},(n)} = \frac{P_t^{\text{bonds},(n-1)}}{P_t^{\text{bonds},(n)}} - 1 = \frac{\left(1 + Y_t^{\text{bonds},(n)}\right)^n}{\left(1 + Y_t^{\text{bonds},(n-1)}\right)^{n-1}} - 1. \tag{2}$$

Returns on zero-coupon bonds are given by

$$R_{t+52}^{\text{bonds},(n)} = \frac{P_{t+52}^{\text{bonds},(n-1)}}{P_t^{\text{bonds},(n)}} - 1, \tag{3}$$

and excess bond returns by

$$\text{RX}_{t+52}^{\text{bonds},(n)} = R_{t+52}^{\text{bonds},(n)} - Y_t^{\text{bonds},(1)}. \tag{4}$$

[1] Our sample of OTC dividend swaps is similar to the sample in Van Binsbergen et al. (2013), Cejnek and Randl (2016), and Kragt et al. (2019). We compare and augment OTC swap prices with dividend futures prices from exchange-listed contracts, where available, and do not find any issues of data quality.

[2] Given that dividend swaps mature in December, our data allow us to construct a term structure of up to 4 years for the period we analyze.

[3] We use capital letters to indicate that we use discrete returns and yields throughout the article. We prefer discrete returns because they are suggested to be appropriate for the analysis of trading rules in the appendix of CP (2005). However, the main results of the article remain qualitatively the same if log returns are used.

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We denote across-maturity average excess returns generally by $\overline{\mathrm{RX}}$ and calculate them for bonds as

$$\overline{\mathrm{RX}}^{\mathrm{bonds}}_{t+52} = \frac{1}{4}\sum_{n=2}^{5} \mathrm{RX}^{\mathrm{bonds},(n)}_{t+52}. \tag{5}$$

B. Dividends

To construct the corresponding variables for dividend markets, we first calculate dividend swap prices with $n \in \{1,2,3,4\}$ years maturity, $P_t^{\mathrm{dividends},(n)}$, by linearly interpolating the OTC prices of dividend swaps that mature in December. Note that dividend swaps are unfunded financial contracts with a fixed and a floating leg, where the latter is based on the dividends paid out on an index during a specific time period. Typically, the time period is 1 calendar year, with a single payment made at maturity. Thus, dividend swap prices are forward price levels. Consistent with the definition of bond market forward rates, we define n-year forward equity forward rates $F_t^{\mathrm{dividends},(n)}$ as follows:

$$F_t^{\mathrm{dividends},(n)} = \begin{cases} \dfrac{D_t}{P_t^{\mathrm{dividends},(1)}} - 1, & n = 1, \\ \dfrac{P_t^{\mathrm{dividends},(n-1)}}{P_t^{\mathrm{dividends},(n)}} - 1, & n \geq 2, \end{cases} \tag{6}$$

where D_t is the current value of aggregate index dividends (which is interpolated from the previous calendar year's realized dividends and the current year's dividend swap level), and $P_t^{\mathrm{dividends},(n)}$ is the price of the n-year dividend swap at time t. Note that dividend swap prices as used in the present article and dividend strip prices as discussed in Brennan (1998) are related via the appropriate risk-free bond yield: $P_t^{\mathrm{dividends},(n)} = S_t^{\mathrm{dividends},(n)}(1+Y_t^{\mathrm{bonds},(n)})^n$, where S denotes spot dividend strips. Thus, dividend swap prices do not contain the n-year risk-free bond yield as a component. This fact is used by Van Binsbergen et al. (2013) for their definition of n-year *forward equity yields* constructed from dividend swap (i.e., forward) prices, which can be written in a discrete-time version as $Y_t^{\mathrm{dividends},(n)} = \sqrt[n]{D_t / P_t^{\mathrm{dividends},(n)}} - 1$. Imputing a forward curve from the equity yield curve leads to our definition of *forward equity forward rates*.

In contrast to bond forward rates, which typically were positive in the past, there is no typical sign for forward equity forward rates. This is because forward equity forward rates as defined in equation (6) have two components: expected dividend growth from year $n-1$ to year n and a maturity-specific risk premium. A forward equity forward yield will be positive (negative) if the risk premium exceeds (is lower than) the expected growth rate of dividends. Whereas Van Binsbergen et al. (2013) and Cejnek and Randl (2016) model expected dividend growth to infer the maturity-specific dividend risk premia, we use the total forward equity forward rate to construct a dividend return-forecasting factor similar to the CP (2005) bond factor.

We calculate the excess returns of dividend investments as follows:

$$\mathrm{RX}^{\mathrm{dividends},(n)}_{t+52} = \frac{P^{\mathrm{dividends},(n-1)}_{t+52}}{P_t^{\mathrm{dividends},(n)}} - 1. \tag{7}$$

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Note that we do not need to subtract the risk-free bond yield here. One can enter a long position in a dividend swap maturing in n years' time, hold it for 52 weeks, and then sell it as an $(n-1)$-year swap. This does not require any cash outlay, and thus the resulting return can be interpreted directly as an excess return.[4] Across-maturity average excess returns on dividend investments are given by

$$\overline{\mathrm{RX}}^{\mathrm{dividends}}_{t+52} = \frac{1}{4}\sum_{n=1}^{4}\mathrm{RX}^{\mathrm{dividends},(n)}_{t+52}. \tag{8}$$

C. Stocks

We use total return stock indices to calculate equity returns. For the United States, we use the S&P 500 total return index; for the United Kingdom, we use the FTSE 100 total return index; for Japan, we use the Nikkei 225 total return index; and for the Eurozone, we use the Euro Stoxx 50 total return index. Additionally, we employ all MSCI country indices in developed markets. Levels of equity total return indices are denoted by P^{stocks}_t and are used to compute equity index returns as

$$R^{\mathrm{stocks}}_{t+52} = \frac{P^{\mathrm{stocks}}_{t+52}}{P^{\mathrm{stocks}}_{t}} - 1, \tag{9}$$

and corresponding excess returns as

$$\mathrm{RX}^{\mathrm{stocks}}_{t+52} = R^{\mathrm{stocks}}_{t+52} - Y^{\mathrm{bonds},(1)}_{t}. \tag{10}$$

Tables 1–3 provide summary statistics on excess returns. Table 1 contains excess returns on dividend swaps corresponding to equation (7), Table 2 shows excess bond returns (equation (4)), and Table 3 provides the excess returns of stock indices for the main markets (equation (10)). To compute excess returns, we subtract the 1-year bond yield of the appropriate country or currency zone and the 1-year U.S. bond yield for portfolios of countries (like the MSCI EM). Further summary statistics on zero-coupon bond yields, forward bond yields, and forward equity forward rates can be found in the Supplementary Material.

IV. Motivating a Common Factor Structure for Stocks, Bonds, and Traded Dividends

In order to motivate a simple 2-factor structure for excess returns on bonds, stocks, and traded dividends, we decompose return innovations into news components in the vein of Campbell and Shiller (1988), who state that changes in asset prices have to be associated with changes in the expectations of future cash flows, time-varying discount rates, or both. In like manner, the Campbell (1991) decomposition of equity returns consists of the components of dividends news, real interest rate news, and news on future excess returns. Similar decompositions have

[4]Market participants in dividend derivatives face margin requirements, and positions will be marked to market. The resulting cash balances are interest bearing; therefore, the interpretation as excess returns is still valid.

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TABLE 1

Summary Statistics: Excess Returns of Dividend Swaps

Table 1 provides summary statistics on the annual excess returns of dividend swap investments. The numbers are the excess returns of a dividend swap corresponding to equation (7) with n years to maturity, held for 1 year, and sold as an $n-1$-year dividend swap. The underlyings of the dividend swaps are aggregate index dividends on the Euro Stoxx 50, the Standard & Poor's (S&P) 500, the Financial Times Stock Exchange (FTSE) 100 and the Nikkei 225. All numbers are stated as percentages. The number of observations is equal to 520.

Contract	Minimum	Mean	Median	Maximum	Std. Dev.
US_1	−14.56	1.49	2.21	17.99	5.11
US_2	−32.98	2.36	3.33	53.64	12.87
US_3	−46.19	2.12	3.20	57.90	15.96
US_4	−45.90	1.98	2.73	60.72	16.82
$JAPAN_1$	−22.13	7.02	7.65	44.72	11.51
$JAPAN_2$	−49.99	9.43	11.66	120.34	26.56
$JAPAN_3$	−67.67	8.91	10.34	138.80	31.84
$JAPAN_4$	−69.52	9.30	9.44	128.21	33.72
$EURO_1$	−14.79	4.05	3.59	25.31	6.15
$EURO_2$	−43.22	6.14	4.71	104.22	22.32
$EURO_3$	−63.30	3.38	4.67	107.29	27.27
$EURO_4$	−64.65	1.57	2.60	106.34	27.65
UK_1	−8.27	2.21	0.88	27.24	5.98
UK_2	−39.18	5.51	2.05	101.59	20.70
UK_3	−58.57	3.78	2.10	108.55	26.03
UK_4	−61.27	2.95	1.14	106.55	26.94

TABLE 2

Summary Statistics: Excess Returns of Zero-Coupon Bonds

Table 2 provides summary statistics on the annual excess returns of zero-coupon bonds. The numbers are the excess returns of a zero-coupon bond corresponding to equation (4) with n years to maturity, held for 1 year, and sold as an $n-1$-year bond. We subtract the 1-year bond yield of the corresponding country to obtain the excess returns. In the Eurozone, we use EUR swap yields. All numbers are stated as percentages. The number of observations is equal to 520.

Contract	Minimum	Mean	Median	Maximum	Std. Dev.
US_2	−0.76	0.85	0.58	3.02	0.77
US_3	−1.35	1.79	1.41	5.94	1.45
US_4	−1.65	2.72	2.20	8.41	2.17
US_5	−2.34	3.48	3.10	10.66	2.89
$JAPAN_2$	−0.27	0.18	0.11	1.08	0.21
$JAPAN_3$	−0.37	0.45	0.34	2.16	0.43
$JAPAN_4$	−0.22	0.84	0.77	3.27	0.68
$JAPAN_5$	−0.29	1.18	1.12	4.09	0.83
$EURO_2$	−1.23	0.23	0.03	3.98	0.90
$EURO_3$	−1.97	1.11	0.69	7.07	1.71
$EURO_4$	−2.79	1.84	1.37	8.98	2.37
$EURO_5$	−3.57	2.54	2.26	10.20	2.98
UK_2	−1.43	0.87	0.66	5.02	1.17
UK_3	−2.95	1.90	1.77	8.31	2.17
UK_4	−3.94	2.77	2.93	9.19	2.75
UK_5	−5.00	3.41	3.75	10.97	3.57

been proposed for bond returns by Campbell and Ammer (1993), who consider the components of inflation news, real interest rate news, and news on future excess returns, as well as for dividend strip returns by Goncalves (2018), including news on dividends, real interest rates, and future excess returns of maturity-specific dividend strips. Traditionally, the empirical analysis of the return decomposition for any single asset class is implemented by a vector autoregression (VAR) estimation to disentangle returns into the news components. However, this approach has been challenged in the literature, the reason being, among other things, that at least one news term is just the residual of the others. Furthermore, Chen and Zhao (2009) note that utilizing a VAR to split returns into news innovations is very sensitive

TABLE 3
Summary Statistics: Excess Returns of Core Stock Indices

Table 3 provides summary statistics on the annual excess returns of stock indices. The numbers are the excess returns corresponding to equation (10). We subtract the 1-year bond yield of the corresponding country to obtain the excess returns. In the Eurozone, we subtract the 1-year EUR swap yield. The indices we use for the 4 regions are the Euro Stoxx 50, the Standard & Poor's (S&P) 500, the Financial Times Stock Exchange (FTSE) 100, and the Nikkei 225. All numbers are stated as percentages. The number of observations is equal to 520.

Market	Minimum	Mean	Median	Maximum	Std. Dev.
U.S.	−47.29	7.42	11.26	69.55	18.65
Japan	−53.58	5.05	2.71	79.25	25.82
Euro	−51.81	1.87	6.68	63.86	20.60
U.K.	−44.78	4.05	5.67	64.38	16.43

to the choice of the exogenous variables intended to identify these news innovations. By contrast, our approach is to identify news terms common to several asset classes, which allows us to propose a common factor structure, and estimate the related risk premia from forward curves. Forward curves contain information on both future spot prices and, more importantly, risk premia. To explain the returns of several asset classes in a common structure, it therefore appears promising to use forward curves related to the common components of the return decompositions.

We start by considering the Campbell (1991) log-linearization. The excess returns of stocks are denoted by $\mathrm{RX}^{\mathrm{stocks}}$, real dividends by d, and the real interest rate by i^*. The linearization constant is ρ. For all assets, the innovations in excess returns are denoted by $\tilde{\mathrm{RX}}^{[\cdot]}_{t+1} = \mathrm{RX}^{[\cdot]}_{t+1} - \mathbb{E}_t[\mathrm{RX}^{[\cdot]}_{t+1}]$. Campbell (1991) decomposes the innovations in excess stock returns into news on future dividend growth, future real interest rates, and future excess returns as follows:

$$\begin{aligned}(11)\quad \tilde{\mathrm{RX}}^{\mathrm{stocks}}_{t+1} &\approx (\mathbb{E}_{t+1} - \mathbb{E}_t)\left[\sum_{j=0}^{\infty}\rho^j \Delta d_{t+1+j} - \sum_{j=0}^{\infty}\rho^j i^*_{t+1+j} - \sum_{j=1}^{\infty}\rho^j \mathrm{RX}^{\mathrm{stocks}}_{t+1+j}\right] \\ &= N^{d}_{t+1} - N^{i^{*}\mathrm{stocks}}_{t+1} - N^{\mathrm{RX}^{\mathrm{stocks}}}_{t+1}.\end{aligned}$$

To be consistent, we use the following notation for bonds: Excess returns for n-year bonds are $\mathrm{RX}^{\mathrm{bonds},(n)}$, and inflation is π. Campbell and Ammer (1993) log-linearize bond returns to decompose their innovations into news on future inflation, future real interest rates, and future excess bond returns:

$$\begin{aligned}(12)\quad \tilde{\mathrm{RX}}^{\mathrm{bonds},(n)}_{t+1} &= (\mathbb{E}_{t+1} - \mathbb{E}_t)\left[-\sum_{j=1}^{n-1}\pi_{t+1+j} - \sum_{j=1}^{n-1} i^*_{t+1+j} - \sum_{j=1}^{n-1}\mathrm{RX}^{\mathrm{bonds},(n-1)}_{t+1+j}\right] \\ &= -N^{\mathrm{bonds},(n-1)\pi}_{t+1} - N^{\mathrm{bonds},(n-1)i^*}_{t+1} - N^{\mathrm{bonds},(n-1)\mathrm{RX}}_{t+1}.\end{aligned}$$

Finally, we decompose the excess returns of traded dividend claims. To this end, we slightly modify the approach suggested by Goncalves (2018), which is based on the original Campbell decomposition. To unify notation, $\mathrm{RX}^{\mathrm{dividends},(n)}$ denotes excess returns for n-year dividend strips. Return innovations are decomposed into news on future dividend growth, future real interest rates, and future

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excess returns. Ignoring constants, the decomposition can be written as follows:

$$\begin{aligned}(13)\quad \widetilde{\mathrm{RX}}_{t+1}^{\mathrm{dividends},(n)} &\approx \Delta d_{t+1} - \mathbb{E}_t \Delta d_{t+1} \\ &\quad + (\mathbb{E}_{t+1} - \mathbb{E}_t)\left[\sum_{j=1}^{n-1} \Delta d_{t+1+j} - \sum_{j=1}^{n-1} i^*_{t+1+j} - \sum_{j=1}^{n-1} \mathrm{RX}^{\mathrm{stocks}}_{t+1+j}\right] \\ &= \Delta d_{t+1} + N^{d^{\mathrm{dividends},(n-1)}}_{t+1} - N^{i^{*\mathrm{dividends},(n-1)}}_{t+1} - N^{\mathrm{RX}^{\mathrm{dividends},(n-1)}}_{t+1}.\end{aligned}$$

We can stack all news terms of the 3 decompositions stated in the previous equations into a single news vector $\mathbf{N}_{t+1}$. Note that although the components of $\mathbf{N}_{t+1}$ can be grouped and interpreted economically as news on dividends, inflation, real interest rates, and future equity and bond risk premia, the various entries of the vector do not strictly collapse into just a few identical news components. For example, the summation horizons are different for news terms relating to investments of different maturities. However, the seemingly high number of news terms can be reduced to a parsimonious factor structure. First, note that even for a 5-year horizon, setting ρ equal to 0.94 implies that approximately 25% of news content in the previous infinite sums can be attributed to the first 5 years.[5] Second, shocks can be assumed to be positively correlated across time (e.g., a shock on today's expectation of the equity premium in 5 years will generally be positively correlated with the shock on today's expectation of the equity premium in 6 years). Third, Goncalves (2018) shows that the shock on the stock market equity premium is a weighted average of the shocks on the dividend strips' equity premia (exponentially weighted by the Campbell–Shiller log-linearization constant). Fourth, the Campbell and Ammer (1993) decomposition for bonds shows that bonds of similar maturity share most of the components of the sum in the respective news terms. Given these insights into the correlation structure of news terms across horizons and asset classes, it can be expected that it is possible to reduce the dimensionality substantially. Consequently, we follow Section 5.3.1 of Campbell (2017) in assuming that empirical proxies for the news terms exist and that they follow a factor structure (i.e., $\mathbf{N}_{t+1} = \mathbf{B}\mathbf{F}_{t+1}$). If we are able to identify such factors $\mathbf{F}_{t+1}$, they should predict the future excess returns of the 3 asset classes we investigate as well as the original news vector $\mathbf{N}_{t+1}$.

For several asset classes, articles have shown that it is possible to construct affine asset pricing models consistent with a given factor structure (e.g., CP (2005) for bonds, Dahlquist and Hasseltoft (2013) for international bonds, and Yan (2015) for dividend strips and bonds). Atanasov, Cooper, Priestley, and Zhong (2017) show that cash-flow news as well as short- and long-term discount rate news can be imputed using the following 5 state variables: market return, dividend–price ratio, consumption-to-wealth ratio, short-term interest rate, and default yield spread. Lettau and Wachter (2011) jointly model the returns of the stock market, value and growth stocks, and the term structure of interest rates. In their model, shocks to dividend growth, the real interest rate, and expected inflation are priced. It follows from their model that a linear combination of forward rates predicts bond returns and that the regression coefficients for bonds of various maturities should be the same up to a constant of proportionality, as found

[5] That is, $(1-\rho)\sum_{t=1}^{5}\rho^t = 0.25$ for $\rho = 0.94$.

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by CP (2005). It is known that, in any factor model, factors and loadings are only identified up to an orthogonal transformation. Forward rates contain information on expected future spot prices and risk premia and are thus natural candidates to find a parsimonious factor structure for the news on dividends, inflation, real interest rates, and future equity and bond risk premia that we have identified as return drivers. Ultimately, it is an empirical question regarding which factor structure is suitable to explain the excess returns of stocks, bonds, and dividend strips. Cochrane and Piazzesi (2005) propose a single-factor model that is well able to explain the excess returns of bonds; we propose a 2-factor model for the excess returns of bonds and equity instruments.

V. An Empirical Model for Dividend Risk Premia

The extensive literature on fixed-income securities provides clear evidence on time variation in bond risk premia and the predictability of excess bond returns. Two seminal contributions in this respect are Fama and Bliss (1987) and CP (2005). Fama and Bliss (1987) show that, in contrast to the expectation hypothesis, forward spreads predict subsequent excess bond returns, whereas CP (2005) provide clear evidence that a linear combination of forward rates captures the risk premia of bonds of all maturities. However, bonds with different maturities differ in their exposure to the single return-forecasting factor. Recent evidence on the performance of dividend swaps (Cejnek and Randl (2016), Van Binsbergen and Koijen (2017)) shows substantial time variation in dividend risk premia as well as the predictability of dividend excess returns. Hence, we expect that extracting information from the whole term structure of forward equity forwards captures the dynamics of dividend risk premia and increases the predictability of excess returns on dividend swaps. We construct a return-forecasting factor from the term structure of forward equity forwards and show that this factor captures dividend risk premia. The method is inspired by standard methods from the fixed-income literature.

A. Dividend Regressions

We follow the 2-step procedure of CP (2005). In the first step, we explain the across-maturity average excess returns of dividends for each region using the term structure of forward equity forward yields in order to obtain a dividend factor. In the second step, we estimate factor loadings of the individual n-year contracts on the dividend factor. CP (2005) suggest that risk premia are slow-moving processes, which warrants a multiple-lag structure in the predictive regressions. We implement this by using 3 lags in addition to the contemporaneous independent variables for all unrestricted regressions and for the across-maturity average regressions. In all tables, we report the sum of the coefficients on all lags, and the reported p-values are calculated using a Wald test for the joint significance of all lags of a specific variable.[6] However, our results do not change qualitatively if we exclude the lags.

[6]For instance, the full regression equation for the across-maturity average regression reads as

$$\overline{\mathrm{RX}}^{\mathrm{dividends}}_{t+52} = \boldsymbol{\gamma}_0^T \mathbf{F}_{\mathbf{t}}^{\mathbf{dividends}} + \boldsymbol{\gamma}_1^T \mathbf{F}_{\mathbf{t-1}}^{\mathbf{dividends}} + \boldsymbol{\gamma}_2^T \mathbf{F}_{\mathbf{t-2}}^{\mathbf{dividends}} + \boldsymbol{\gamma}_3^T \mathbf{F}_{\mathbf{t-3}}^{\mathbf{dividends}} + \bar{\epsilon}_{t+52},$$

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For each market (the United States, the United Kingdom, Japan, and Eurozone), we regress the across-maturity average excess returns on all forward equity forward rates as follows:

$$\overline{\mathrm{RX}}_{t+52}^{\text{dividends}} = \boldsymbol{\gamma}^T \mathbf{F}_{\mathbf{t}}^{\mathbf{dividends}} + \bar{\epsilon}_{t+52}, \tag{14}$$

where $\mathbf{F}_{\mathbf{t}}^{\mathbf{dividends}} \equiv [1\ F_t^{\text{dividends},(1)}\ F_t^{\text{dividends},(2)}\ F_t^{\text{dividends},(3)}\ F_t^{\text{dividends},(4)}]^T$ and γ^T are vectors.

The results of Table 4 clearly indicate the predictability of dividend swap excess returns.[7] The results are weakest for the U.S. market. Especially important is the joint significance of the coefficients. The null hypothesis of $\boldsymbol{\gamma}^T = \mathbf{0}$ is rejected for all markets, including the United States. R^2 ranges between 0.15 (United States) and 0.64 (United Kingdom).

TABLE 4

Cochrane–Piazzesi Across-Maturity Average Regressions for Dividend Derivatives

Table 4 provides results for the following regression:

$$\frac{1}{4}\sum_{n=1}^{4} \mathrm{RX}_{t+52}^{\text{dividends},(n)} = \alpha + \gamma_1 F_t^{\text{dividends},(1)} + \gamma_2 F_t^{\text{dividends},(2)} + \gamma_3 F_t^{\text{dividends},(3)} + \gamma_4 F_t^{\text{dividends},(4)} + \bar{\epsilon}_{t+52};$$

that is, we regress across-maturity average excess returns on dividend derivatives on equity forward rates of all maturities n. Because Cochrane and Piazzesi (2005) argue that risk premia are slow-moving processes, the reported coefficients are the sum of 3 lags of equity forward rates. Standard errors are reported below the coefficients and are derived from a Wald test for the joint significance of all lags. This approach corresponds to a method developed by Dimson (1979). Standard errors are computed using a Newey–West (52 lags) covariance matrix to account for overlapping annual returns. The number of observations is equal to 517. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	U.S.	Japan	Euro	U.K.
Intercept	−0.0132	0.0792*	−0.0078	0.0222
	0.0904	0.0465	0.0439	0.0174
FEF_1	0.4706	0.0093	0.4289	0.3820
	0.4891	0.2887	0.3164	0.3448
FEF_2	0.2607	1.9033***	0.8337***	0.8815***
	1.0821	0.5168	0.3035	0.2230
FEF_3	0.1398	−4.2637*	−2.2710*	−0.3081
	0.3277	2.2420	1.1630	1.6523
FEF_4	−1.8402	4.9958*	2.5338	3.3603
	1.7159	2.7737	1.8212	3.0534
Adj. R^2	0.1519	0.4615	0.5139	0.6428
p-value ($\gamma = \mathbf{0}$)	0.0210	0.0000	0.0000	0.0000

As a second step, we use the estimated parameters $\hat{\gamma}$ to estimate the factor loadings of swap contracts of various maturities on the dividend factor. We therefore estimate constrained regressions of the following form, utilizing a single (market-specific) return-forecasting dividend risk factor ($\hat{\boldsymbol{\gamma}}^T \mathbf{F}_{\mathbf{t}}^{\mathbf{dividends}}$):

$$\mathrm{RX}_{t+52}^{\text{dividends},(n)} = b_n(\hat{\boldsymbol{\gamma}}^T \mathbf{F}_{\mathbf{t}}^{\mathbf{dividends}}) + \epsilon_{t+52}^{(n)}. \tag{15}$$

and we report $\sum_{k=0}^{3} \gamma_k^T$ as the coefficient and the p-value of a Wald test for the joint significance of $\boldsymbol{\gamma}_0$, $\boldsymbol{\gamma}_1$, $\boldsymbol{\gamma}_2$, and $\boldsymbol{\gamma}_3$. This method is based on Dimson (1979).

[7] The coefficients of the forward equity forward rates do not exhibit the tent-shaped pattern of CP (2005) for bonds. This is not surprising, however, because the tent-shaped relation of bond excess returns and forward rates also vanishes if one updates the bond sample to the present time. The tent shape is not required for the existence of return predictability, though.

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The results are displayed in Table 5 and provide even clearer evidence for return predictability. Given that we use overlapping returns in the regressions, we have to take care of possible autocorrelation in the residuals. We therefore report standard errors computed with the method proposed by Newey and West (1987). Given the structure of our data with overlapping 52-week returns, we select 52 lags. Moreover, to ensure the robustness of our results, we base statistical inference on standard errors from a block-bootstrap with a block structure of 52 periods. In the tables, we denote the 1% significance level with 3 asterisks, the 5% level with 2 asterisks, and the 10% level with 1 asterisk, based on block-bootstrapped standard errors. This is a conservative approach because the bootstrapped standard errors tend to be slightly larger than the Newey–West standard errors. We use the block-bootstrap method to complement the reported adjusted R^2 with a 90% confidence interval. We also provide the 95% quantile for adjusted R^2 under the null of no predictability. Furthermore, we calculate the test statistic proposed by Clark and West (2007) to compare the unconditional predictive precision of nested models, and we use the test statistic by Giacomini and White (2006) to test for conditional predictive performance. We follow Sarno, Schneider, and Wagner (2012) in their analysis of foreign exchange risk premiums and use in-sample predictions for model evaluation. In Sections 1 and 2 of the Appendix, we provide the details on the measures and the bootstrap.

In Table 5, 3 out of 4 markets have significant coefficients on the dividend factor, with adjusted R^2 in these regressions ranging from 0.30 to 0.72; bootstrapping confirms that these values are unlikely to be obtained under a no-predictability benchmark. Coefficients are not significant in the regressions for the United States, based on block-bootstrapped standard errors (although we find statistical significance using Newey–West standard errors with 52 lags). This result is not too surprising, given that Cejnek and Randl (2016) have documented that U.S. dividend claims perform worse relative to the underlying index than in the other 3 core markets. It is noteworthy that the United States was the last market in our core analysis that began trading listed dividend futures (the Chicago Mercantile Exchange (CME) started trading these products only in Nov. 2015). Thus, in terms of dividend markets, the Eurozone, the United Kingdom, and Japan are more liquid. Nonetheless, constructing the U.S. dividend risk factor is important because it is shown to be a useful predictor for U.S. equity returns (see, e.g., Table 8). For all other markets, the dividend excess returns of all maturities show significant exposure to the dividend risk factor. Thus, we arrive at the conclusion that a linear combination of forward equity forward rates predicts excess returns on dividend strategies just as has earlier been documented for bonds using a linear combination of bond forward rates. The loadings on the dividend factor increase with maturity, with the steepest increase taking place from the 1-year contract to the 2-year contract. This pattern is also evident in the corresponding fixed-income literature. The goodness of fit of the constrained regressions tends to drop marginally in maturity, except for the shortest-maturity claims, which exhibit the lowest values of R^2.

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TABLE 5

Cochrane–Piazzesi Constrained Regressions for Dividend Derivatives

Table 5 provides results for constrained Cochrane–Piazzesi (2005) regressions for dividend derivatives. The regression reads as

$$RX_{t+52}^{\text{dividends},(n)} = b_n(\boldsymbol{\gamma}^T \mathbf{F}_t^{\text{dividends}}) + \epsilon_{t+52}^{(n)},$$

where $\boldsymbol{\gamma}^T$ is derived from the results in Table 4. Newey–West (NW) (52 lags) and block-bootstrapped (BS) standard errors (SE) are reported below the coefficients. Below the adjusted R^2, a 90% confidence band under the model and the 95% quantile under no predictability are reported. We further provide p-values from the BS Clark and West (2007) (CW) and Giacomini and White (2006) (GW) measures. The number of observations is equal to 517. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	U.S.	Japan	Euro	U.K.
Panel A. Explaining Returns of 1-Year Dividend Swap				
Intercept	0.0087	0.0383	0.0306***	0.0119
SE (NW)	0.0133	0.0256	0.0113	0.0069
SE (BS)	0.0148	0.0247	0.0114	0.0074
Dividend risk factor (DRF)	0.3092	0.3584***	0.2562***	0.2843***
SE (NW)	0.1257	0.0741	0.0388	0.0228
SE (BS)	0.3316	0.0941	0.0593	0.0388
Adj. R^2	0.0986	0.2968	0.3833	0.5543
5% quantile	0.0009	0.1092	0.0936	0.3518
95% quantile	0.3139	0.5381	0.6514	0.6918
No predictability, 95% quantile	0.1959	0.0960	0.0863	0.0688
p-value (CW)	0.0844	0.0000	0.0000	0.0000
p-value (GW)	0.3390	0.0362	0.0060	0.0092
Panel B. Explaining Returns of 2-Year Dividend Swap				
Intercept	0.0007	−0.0012	0.0169	0.0147
SE (NW)	0.0341	0.0544	0.0394	0.0288
SE (BS)	0.0364	0.0554	0.0382	0.0284
DRF	1.1546	1.1038***	1.1809***	1.1199***
SE (NW)	0.3307	0.1668	0.1692	0.1543
SE (BS)	0.8561	0.2138	0.2457	0.1925
Adj. R^2	0.2190	0.5232	0.6163	0.7172
5% quantile	−0.0001	0.2276	0.1550	0.3487
95% quantile	0.5148	0.7270	0.8751	0.9010
No predictability, 95% quantile	0.2303	0.1242	0.1630	0.2366
p-value (CW)	0.0098	0.0000	0.0000	0.0000
p-value (GW)	0.3016	0.0374	0.0960	0.0842
Panel C. Explaining Returns of 3-Year Dividend Swap				
Intercept	−0.0036	−0.0205	−0.0153	−0.0088
SE (NW)	0.0434	0.0669	0.0546	0.0447
SE (BS)	0.0469	0.0715	0.0540	0.0443
DRF	1.2499	1.2693***	1.2993***	1.2909***
SE (NW)	0.4118	0.1862	0.2008	0.1629
SE (BS)	1.1250	0.2653	0.3251	0.1939
Adj. R^2	0.1665	0.4810	0.4992	0.6024
5% quantile	0.0001	0.2211	0.1411	0.2601
95% quantile	0.4635	0.6630	0.8087	0.8802
No predictability, 95% quantile	0.2134	0.1037	0.1156	0.1009
p-value (CW)	0.0358	0.0000	0.0000	0.0000
p-value (GW)	0.3594	0.0204	0.0514	0.0182
Panel D. Explaining Returns of 4-Year Dividend Swap				
Intercept	−0.0058	−0.0166	−0.0323	−0.0179
SE (NW)	0.0455	0.0727	0.0574	0.0481
SE (BS)	0.0491	0.0781	0.0558	0.0476
DRF	1.2864	1.2685***	1.2637***	1.3049***
SE (NW)	0.4776	0.2131	0.2117	0.1696
SE (BS)	1.3552	0.3412	0.3725	0.2026
Adj. R^2	0.1586	0.4279	0.4594	0.5754
5% quantile	0.0015	0.2324	0.1284	0.2765
95% quantile	0.4509	0.6104	0.7732	0.8546
No predictability, 95% quantile	0.2536	0.1221	0.1351	0.1015
p-value (CW)	0.0680	0.0000	0.0000	0.0000
p-value (GW)	0.3964	0.0248	0.0696	0.0146

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B. Bond Regressions

In addition to creating a dividend risk factor, we apply the CP (2005) method to zero-coupon bond yields in the corresponding 4 regions and for the same sample period. This allows us to spot similarities between our dividend risk factor and the CP bond risk factor. More importantly, we use both risk factors jointly to capture time variation in excess equity index returns later in the article. Again, we follow a 2-step procedure. Table 6 reports the results for the following across-maturity average regressions:

$$\overline{\mathrm{RX}}^{\mathrm{bonds}}_{t+52} \quad = \quad \boldsymbol{\gamma}^T \mathbf{F}^{\mathbf{bonds}}_{\mathbf{t}} + \bar{\epsilon}_{t+52}\,, \tag{16}$$

where $\mathbf{F}^{\mathbf{bonds}}_{\mathbf{t}} \equiv \left[1\ Y^{\mathrm{bonds},(1)}_t\ F^{\mathrm{bonds},(2)}_t\ F^{\mathrm{bonds},(3)}_t\ F^{\mathrm{bonds},(4)}_t\ F^{\mathrm{bonds},(5)}_t\right]^T$ and γ^T are vectors of coefficients.

TABLE 6

CP Across-Maturity Average Regressions for Zero-Coupon Bonds

Table 6 provides results for the following regression:

$$\frac{1}{4}\sum_{n=2}^{5} \mathrm{RX}^{\mathrm{bonds},(n)}_{t+52} \quad = \quad \alpha + \gamma_1 Y^{\mathrm{bonds},(1)}_t + \gamma_2 F^{\mathrm{bonds},(2)}_t + \gamma_3 F^{\mathrm{bonds},(3)}_t + \gamma_4 F^{\mathrm{bonds},(4)}_t + \gamma_5 F^{\mathrm{bonds},(5)}_t + \bar{\epsilon}_{t+52};$$

that is, we regress across-maturity average excess returns on zero-coupon bonds on forward bond yields of all maturities n. Because Cochrane and Piazzesi (2005) (CP) argue that risk premia are slow-moving processes, the reported coefficients are the sum of 3 lags of equity forward rates. Standard errors are reported below the coefficients and are derived from a Wald test for the joint significance of all lags. This approach corresponds to a method developed by Dimson (1979). Standard errors are computed using a Newey–West (52 lags) covariance matrix to account for overlapping annual returns. For the Eurozone, we use EUR swap rates. The number of observations is equal to 517. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	U.S.	Japan	Euro	U.K.
Intercept	−0.0218***	0.0055***	0.0044	−0.0189
	0.0032	0.0017	0.0067	0.0135
BY_1	−0.2049	−0.1193	0.9174*	0.7553
	1.1239	1.0079	0.4759	1.1151
FY_2	0.1980	−0.9759	−5.6549***	−3.0337
	2.2968	0.7738	1.5046	2.0714
FY_3	−0.8563	2.7313***	5.9740	1.7747*
	1.3411	0.8900	4.6748	1.0597
FY_4	1.0674	0.7401**	2.9330	0.8461
	0.7321	0.3614	5.5388	0.8834
FY_5	0.9591**	−1.5954***	−4.0486	0.5311
	0.3733	0.3447	2.7275	0.6920
Adj. R^2	0.4767	0.5705	0.3156	0.3077
p-value ($\gamma = 0$)	0.0000	0.0000	0.0000	0.0000

We find significant coefficients for all 4 markets. Although the dividend regressions for the U.K. market exhibit the highest value of R^2, the bond regression model fits best for Japan. Finally, we use the estimated CP (2005) bond risk factor ($\hat{\boldsymbol{\gamma}}^T \mathbf{F}^{\mathbf{bonds}}_{\mathbf{t}}$) in the following maturity-specific regressions:

$$\mathrm{RX}^{\mathrm{bonds},(n)}_{t+52} \quad = \quad b_n(\hat{\boldsymbol{\gamma}}^T \mathbf{F}^{\mathbf{bonds}}_{\mathbf{t}}) + \epsilon^{(n)}_{t+52}. \tag{17}$$

As is evident from Table 7, the variation in excess bond returns of all maturities and all 4 countries is significantly captured by the corresponding forward yields.

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TABLE 7
CP Constrained Regressions for Zero-Coupon Bonds

Table 7 provides results for constrained Cochrane–Piazzesi (2005) (CP) regressions for zero-coupon bonds. The regression reads as

$$RX_{t+52}^{bonds,(n)} = b_n(\boldsymbol{\gamma}^T \mathbf{F}_t^{bonds}) + \epsilon_{t+52}^{(n)},$$

where $\boldsymbol{\gamma}^T$ is derived from the results in Table 6. Newey–West (NW) (52 lags) and block-bootstrapped (BS) standard errors (SE) are reported below the coefficients. Below the adjusted R^2, a 90% confidence band under the model and the 95% quantile under no predictability are reported. We further provide p-values from the BS Clark and West (2007) (CW) and Giacomini and White (2006) (GW) measures. The number of observations is equal to 517. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	U.S.	Japan	Euro	U.K.
Panel A. Explaining Returns of 2-Year Bonds				
Intercept	0.0008	−0.0010***	−0.0035**	−0.0000
SE (NW)	0.0010	0.0004	0.0013	0.0024
SE (BS)	0.0013	0.0004	0.0015	0.0031
Bond risk factor (BRF)	0.3507***	0.4145***	0.4011***	0.3911***
SE (NW)	0.0893	0.0592	0.0786	0.0908
SE (BS)	0.0840	0.0667	0.0878	0.1068
Adj. R^2	0.3190	0.6175	0.2571	0.2016
5% quantile	0.2194	0.4938	0.1200	0.0625
95% quantile	0.5986	0.7834	0.3637	0.5183
No predictability, 95% quantile	0.1448	0.1669	0.1258	0.1175
p-value (CW)	0.0002	0.0000	0.0000	0.0020
p-value (GW)	0.0026	0.0142	0.0470	0.0586
Panel B. Explaining Returns of 3-Year Bonds				
Intercept	0.0012	−0.0010	−0.0015	−0.0021
SE (NW)	0.0014	0.0008	0.0032	0.0053
SE (BS)	0.0018	0.0007	0.0035	0.0058
BRF	0.7554***	0.8211***	0.8771***	0.9414***
SE (NW)	0.1365	0.1226	0.1042	0.1441
SE (BS)	0.1182	0.1239	0.1230	0.1613
Adj. R^2	0.4205	0.6046	0.3416	0.3433
5% quantile	0.2955	0.4987	0.2065	0.1731
95% quantile	0.7278	0.7864	0.4463	0.6667
No predictability, 95% quantile	0.0897	0.1549	0.0534	0.0652
p-value (CW)	0.0000	0.0000	0.0000	0.0000
p-value (GW)	0.0000	0.0038	0.0060	0.0028
Panel C. Explaining Returns of 4-Year Bonds				
Intercept	0.0002	−0.0004	0.0008	0.0007
SE (NW)	0.0026	0.0011	0.0052	0.0082
SE (BS)	0.0030	0.0010	0.0053	0.0081
BRF	1.2226***	1.3308***	1.2303***	1.2056***
SE (NW)	0.1889	0.1577	0.1679	0.2170
SE (BS)	0.1535	0.1594	0.1912	0.2337
Adj. R^2	0.4899	0.6270	0.3498	0.3521
5% quantile	0.3415	0.5074	0.2194	0.2078
95% quantile	0.7909	0.7851	0.4438	0.6488
No predictability, 95% quantile	0.0908	0.1010	0.0563	0.0931
p-value (CW)	0.0000	0.0000	0.0000	0.0000
p-value (GW)	0.0000	0.0002	0.0030	0.0042
Panel D. Explaining Returns of 5-Year Bonds				
Intercept	−0.0022	0.0024*	0.0041	0.0014
SE (NW)	0.0054	0.0014	0.0074	0.0124
SE (BS)	0.0058	0.0014	0.0075	0.0120
BRF	1.6713***	1.4336***	1.4915***	1.4619***
SE (NW)	0.2526	0.1995	0.2655	0.3651
SE (BS)	0.2116	0.2099	0.2946	0.3862
Adj. R^2	0.5144	0.4857	0.3259	0.3075
5% quantile	0.3720	0.3350	0.1937	0.1658
95% quantile	0.7822	0.6654	0.4308	0.6140
No predictability, 95% quantile	0.1201	0.0785	0.0737	0.1476
p-value (CW)	0.0000	0.0000	0.0000	0.0000
p-value (GW)	0.0000	0.0004	0.0048	0.0432

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The coefficients show the expected pattern, strictly increasing in maturity. Thus, longer-duration bonds are more exposed to the bond risk factor.

Based on the constrained regressions for dividends and bonds, it seems that the term structure of forward equity forwards contains equally important forward-looking information for dividend claims as does the forward yield curve for bonds. Levels of R^2 across maturities and regions are similar for both asset classes, as are the magnitudes of the coefficients. That factor loadings are increasing in maturity also applies to both asset classes; however, most of the increase is between the 1-year and the 2-year dividend claims, whereas the increase is more gradual for bonds.

C. Robustness Checks

We also estimate unconstrained 1-step regressions. This allows us to compare the shape of the return-forecasting factors for different maturities and to compare it to the results from the constrained regressions. The unconstrained regressions for bond excess returns of all maturities on all forward yields read as follows:

$$\begin{aligned} (18) \qquad \mathrm{RX}_{t+52}^{\mathrm{bonds},(n)} &= \alpha + \beta_1 Y_t^{\mathrm{bonds},(1)} + \beta_2 F_t^{\mathrm{bonds},(2)} + \beta_3 F_t^{\mathrm{bonds},(3)} \\ &\quad + \beta_4 F_t^{\mathrm{bonds},(4)} + \beta_5 F_t^{\mathrm{bonds},(5)} + \epsilon_{t+52}^{(n)}. \end{aligned}$$

The detailed results are presented in the Supplementary Material. We also regress the excess dividend swap returns of all maturities on all forward equity forward rates in the multivariate regression stated in equation (19):

$$\begin{aligned} (19) \qquad \mathrm{RX}_{t+52}^{\mathrm{dividends},(n)} &= \alpha + \beta_1 F_t^{\mathrm{dividends},(1)} + \beta_2 F_t^{\mathrm{dividends},(2)} \\ &\quad + \beta_3 F_t^{\mathrm{dividends},(3)} + \beta_4 F_t^{\mathrm{dividends},(4)} + \epsilon_{t+52}^{(n)}. \end{aligned}$$

Although there is heterogeneity across markets, the pattern across maturities for each market is remarkably similar. Detailed results for this exercise can be found in the Supplementary Material.

As a robustness check for our method of creating a dividend risk factor, we follow the line of thought of Mylnikov (2014), who argues that a more parsimonious return-forecasting model (which can essentially be viewed as a compromise between Fama and Bliss (1987) and CP (2005)) has favorable statistical properties and adds economic value in terms of implementing trading rules. We replicate the corresponding results for bonds and extend the model to the domain of dividend derivatives. All results can be found in the Supplementary Material.

After having elaborated on our method to construct a dividend risk factor, we move on to employ this factor jointly with a bond risk factor in order to predict excess equity index returns.

VI. Explaining Equity Index Returns

A. A 2-Factor Model

CP (2005) argue that stocks have certain characteristics in common with very long-term bonds, and thus the CP (2005) bond risk factor should also forecast excess equity index returns. Our dividend risk factor is even more directly related

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to equity risk. Hence, in this section, we tie together the dividend risk factor and the CP bond factor to capture time variation in excess equity index returns in the 4 core regions. Table 8 provides results on the following region-specific regressions, in which we relate stock index returns to both the bond risk factors and dividend risk factors as constructed before:

$$(20)\quad \mathrm{RX}_{t+52}^{\mathrm{stocks}} = a + b^{\mathrm{bonds}}(\hat{\boldsymbol{\gamma}}^{T,\mathrm{bonds}}\mathbf{F}_{\mathbf{t}}^{\mathrm{bonds}}) + b^{\mathrm{dividends}}(\hat{\boldsymbol{\gamma}}^{T,\mathrm{dividends}}\mathbf{F}_{\mathbf{t}}^{\mathrm{dividends}}) + \epsilon_{t+52}.$$

The dividend risk factor and the bond factor are significant in explaining stock index returns, with values of R^2 from 0.28 to 0.42. Whereas the dividend risk factor is positively associated with subsequent equity returns, the bond factor is negatively related to subsequent stock returns. As a robustness check, we verify that the bond factor also has a negative sign on a stand-alone basis (which is true with the exception of the United States, where the coefficient is statistically insignificant, as shown in the Supplementary Material). This is in contrast to the results reported by CP (2005). Their sample, however, ends in 2003. Campbell et al. (2018) claim that the relation between stocks and bonds shifts substantially over time due to different monetary policy regimes and time-varying macroeconomic uncertainty. They show that stocks and bonds were slightly positively related on average between 1960 and 2011 (with the highest positive relation in the 1980s), whereas the relation was negative in the 2000s, the period that most coincides with our sample period.[8] Our sample period contains the financial crisis and a period of very low-inflation expectations, both of which are drivers of

TABLE 8
2-Factor Model for Stock Indices

Table 8 presents results for the regression

$$\mathrm{RX}_{t+52}^{\mathrm{stocks}} = b_n^{\mathrm{bonds}}(\boldsymbol{\gamma}^{T,\mathrm{bonds}}\mathbf{F}_{\mathbf{t}}^{\mathbf{bonds}}) + b_n^{\mathrm{dividends}}(\boldsymbol{\gamma}^{T,\mathrm{dividends}}\mathbf{F}_{\mathbf{t}}^{\mathbf{dividends}}) + \epsilon_{t+52};$$

that is, we predict excess returns on stock indices using both the Cochrane–Piazzesi (2005) (CP) bond risk factor (BRF; $\boldsymbol{\gamma}^{T,\mathrm{bonds}}\mathbf{F}_{\mathbf{t}}^{\mathbf{bonds}}$) and the dividend risk factor (DRF; $\boldsymbol{\gamma}^{T,\mathrm{dividends}}\mathbf{F}_{\mathbf{t}}^{\mathbf{dividends}}$). Newey–West (NW) (52 lags) and block-bootstrapped (BS) standard errors (SE) are reported below the coefficients. Below the adjusted R^2, a 90% confidence band under the model and the 95% quantile under no predictability are reported. We further provide p-values from the BS Clark and West (2007) (CW) and Giacomini and White (2006) (GW) measures. The number of observations is equal to 517. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	U.S.	Japan	Euro	U.K.
Intercept	0.2199***	0.2182**	0.0633	0.0364
SE (NW)	0.0364	0.0943	0.0536	0.0334
SE (BS)	0.0470	0.0952	0.0566	0.0470
BRF	−7.8143**	−31.9390***	−5.1809**	−0.9076
SE (NW)	2.8994	9.4673	2.3326	1.4596
SE (BS)	3.1037	9.6441	2.4789	1.8247
DRF	1.4230**	0.5268**	0.7982*	0.6875***
SE (NW)	0.2905	0.1379	0.1994	0.1042
SE (BS)	0.6563	0.2298	0.4699	0.1359
Adj. R^2	0.3340	0.4181	0.2832	0.4191
5% quantile	0.1434	0.2342	0.2297	0.2458
95% quantile	0.5687	0.6384	0.5254	0.6894
No predictability, 95% quantile	0.2626	0.1789	0.2668	0.1610
p-value CW	0.0016	0.0000	0.0142	0.0000
p-value GW	0.0784	0.0046	0.0340	0.0110

[8]Using our method and code together with the original data set of CP (2005), which ends in 2003, we also find a positive coefficient on the bond factor, thus confirming the validity of our analyses.

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a negative stock–bond correlation as claimed by Ilmanen (2003) and David and Veronesi (2013).

Although the bond risk factor is significantly related to subsequent excess equity returns in 3 out of 4 markets (not in the United Kingdom), the dividend factor is significant in all 4 markets, including the United States. This result highlights the importance of forward curves in predicting excess equity returns. Moreover, it shows that augmenting the CP (2005) bond factor with a factor more directly related to equity risk results in substantially higher predictability, as measured in terms of R^2. Our regressions show that there is significant value in employing the 2 factors jointly.

Additionally, we test whether the dividend factor is still significant in predicting excess returns on dividend derivatives if we include the bond factor as well. For robustness, we also relate bond returns to both risk factors. However, we do not expect the dividend factor to have a substantial impact on bond prices. Results can be found in the Supplementary Material, where we provide further evidence that both factors are important drivers of excess returns on dividend swaps, whereas only the bond factor is useful in predicting excess bond returns.

B. A Global Factor Model

Having shown the vital relevance of the dividend risk factor taken together with the CP (2005) bond risk factor, we want to extend the analysis to a wider range of regions and even asset classes. Because reliable data on the term structure of forward equity forwards is only available for the 4 core regions, we construct a global dividend risk factor along with a global bond risk factor by aggregating the 4 local bond factors and 4 local dividend factors, respectively. We aggregate the local factors on an equal-weighted basis.[9] Figure 1 displays the global factors over time. Time variation is most pronounced for the dividend factor, which has the highest realizations in the recession period from late 2008 to mid-2009. Building on empirical evidence on the global comovements of risk premia as well as international tests of the CP factor for bonds in Kessler and Scherer (2009) and Dahlquist and Hasseltoft (2013), we expect the global versions of the factors to price assets that are not in the 4 regions used to construct the factors in the first place.

As a first step, we test if the 2-factor model presented before is still valid if we replace the local factors with the aggregated (global) bond factor $\mathrm{BF}_t^{\mathrm{global}}$ and dividend factor $\mathrm{DF}_t^{\mathrm{global}}$:

$$\mathrm{BF}_t^{\mathrm{global}} = \sum_{m=1}^{4} (\hat{\boldsymbol{\gamma}}^{T,\mathrm{bonds},m} \mathbf{F}_{\mathbf{t}}^{\mathbf{bonds,m}}), \tag{21}$$

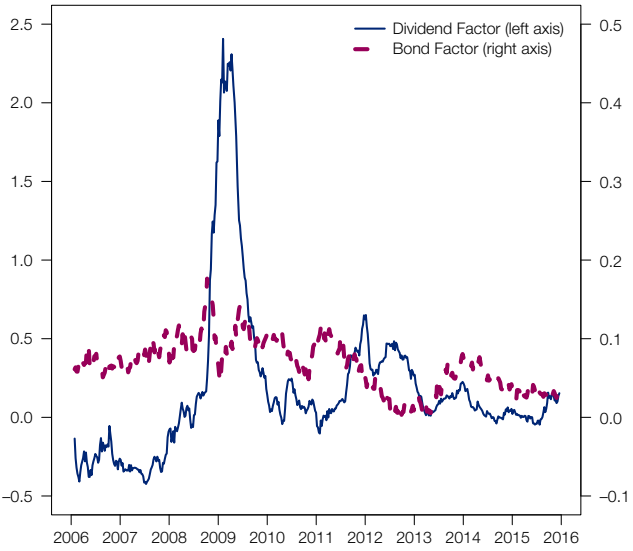
$$\mathrm{DF}_t^{\mathrm{global}} = \sum_{m=1}^{4} (\hat{\boldsymbol{\gamma}}^{T,\mathrm{dividends},m} \mathbf{F}_{\mathbf{t}}^{\mathbf{dividends,m}}), \tag{22}$$

[9]This implies equal weighting of the regional risk factors. Dahlquist and Hasseltoft (2013) use GDP-weighted international bond factors. They also report, however, that the results are largely unaffected by using equal-weighted international factors. Note that although the United States is the world's largest stock market, the numbers reported by Mixon and Onur (2017) show that Europe is the largest market for dividend derivatives.

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FIGURE 1
Global Factors

Figure 1 displays the global dividend factor $F_t^{\text{dividends,global}}$, constructed as the sum of the local dividend factors, and the global bond factor $F_t^{\text{bonds,global}}$, constructed as the sum of the local bond factors.



where $m \in \{\text{S\&P 500, FTSE 100, Nikkei 225, Euro Stoxx 50}\}$. Thus, we estimate the following regressions:

$$\text{RX}_{t+52}^{\text{stocks},i} = a + b^{\text{bonds,global}} BF_t^{\text{global}} + b^{\text{dividends,global}} \text{DF}_t^{\text{global}} + \epsilon_{t+52}^{\text{stocks},i}. \quad (23)$$

The results in Table 9 confirm that the global factors work even better than the local factors as R^2 increases. The magnitude of the coefficients is comparable to the local model. Note that we summed over the 4 local factors, and thus the magnitude of the coefficients in Table 9 should be multiplied by 4 to be comparable with those from Table 8. In the Supplementary Material we regress the excess equity returns of the 4 core regions on both the local dividend and bond factors as well as international dividend and bond factors (which are constructed by summing over all local factors except that of the region of the excess return on the left-hand side of the regression). It can be seen that the international factors are more important than the local factors; most of the local factors become insignificant after controlling for the international factors. Additionally, the levels of R^2 increase only marginally as compared to the global model. This provides reasonable justification in employing the global model for the analyses that follow.

The major advantage of employing global versions of the 2 risk factors is that we can use them to price any asset that we think should be driven by the variation in global equity and bond risk premia. This approach is especially interesting for assets and regions that we did not use to construct the global risk factors. Recall that we implicitly use dividend derivatives and bonds in the United States, United Kingdom, Japan, and the Eurozone to construct the risk factors.

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TABLE 9
A Global Model for the Core Markets: Stock Indices

Table 9 presents results for the regression

$$\begin{aligned} RX_{t+52}^{stocks,i} &= b_n^{bonds,global}(\boldsymbol{\gamma}^{T,bonds,global}\mathbf{F}_t^{bonds,global}) \\ &\quad + b_n^{dividends,global}(\boldsymbol{\gamma}^{T,dividends,global}\mathbf{F}_t^{dividends,global}) + \epsilon_{t+52}; \end{aligned}$$

that is, we predict excess returns on stock indices using both a global Cochrane–Piazzesi (2005) (CP) bond risk factor (BRF; $\boldsymbol{\gamma}^{T,bonds,global}\mathbf{F}_t^{bonds,global}$) and a global dividend risk factor (DRF; $\boldsymbol{\gamma}^{T,dividends,global}\mathbf{F}_t^{dividends,global}$). The global risk factors are constructed by summing over the local risk factors of all 4 markets in our core sample (Eurozone, United States, United Kingdom, Japan). Newey–West (NW) (52 lags) and block-bootstrapped (BS) standard errors (SE) are reported below the coefficients. Below the adjusted R^2, a 90% confidence band under the model and the 95% quantile under no predictability are reported. We further provide p-values from the BS Clark and West (2007) (CW) and Giacomini and White (2006) (GW) measures. The number of observations is equal to 517. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	U.S.	Japan	Euro	U.K.
Intercept	0.1676***	0.2938***	0.1486**	0.0744**
SE (NW)	0.0384	0.1133	0.0592	0.0304
SE (BS)	0.0466	0.1081	0.0625	0.0378
Global BRF	−2.0225**	−4.3514***	−2.5566***	−1.1259
SE (NW)	0.8628	1.3866	0.8727	0.6721
SE (BS)	0.8936	1.2734	0.8594	0.6869
Global DRF	0.2254**	0.2483*	0.2147**	0.2258***
SE (NW)	0.0460	0.0633	0.0502	0.0382
SE (BS)	0.0885	0.1383	0.0838	0.0674
Adj. R^2	0.4243	0.4495	0.3702	0.4746
5% quantile	0.3177	0.2979	0.2592	0.3499
95% quantile	0.6189	0.7220	0.6221	0.6752
No predictability, 95% quantile	0.2693	0.2741	0.1799	0.2170
p-value (CW)	0.0000	0.0000	0.0000	0.0000
p-value (GW)	0.0150	0.0290	0.0068	0.0092

By analyzing excess returns on a variety of assets not used to fit the models, we actually implement out-of-sample tests for our empirical strategy:

$$RX_{t+52}^{asset,i} = a + b^{bonds,global}BF_t^{global} + b^{dividends,global}DF_t^{global} + \epsilon_{t+52}^{asset,i}. \tag{24}$$

The assets we use for this purpose are as follows: MSCI world, MSCI emerging markets, and MSCI frontier markets indices and all individual country MSCI indices in developed markets; U.S.-style indices (value, growth, small value, small growth, momentum); an index rolling short positions in Volatility Index (VIX) futures contracts; U.S., euro, and emerging-market (high-yield) bond indices; and Deutsche Bank currency strategies (G10 carry, momentum, value, and global carry), as well as longer-term bonds and dividend derivatives. Tables 10 and 11 provide the detailed results, which reveal that innovations in the global dividend risk factor have a significant positive effect on the subsequent excess returns of most test assets, with the exception of a negative sign for currency momentum. Evidence is mixed but in line with expectations for the bond factor: negative and significant for most equity markets, positive for bonds, and insignificant for most currency strategies. The evidence for MSCI country indices, presented in Table 10, is clear, with nearly every single market having negative exposure to the global bond factor and highly significant positive exposure to the global dividend factor. Figure 5 provides a graphical overview of the fit of the 2-factor global model for MSCI country indices. The fact that the risk factors explain the excess returns of various asset classes, countries, and regions is a good indication of both

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TABLE 10
A Global Model for MSCI Equity Country Indices

Table 10 presents results for the regression

$$RX_{t+52}^{stocks,i} = b_n^{bonds,global}(\boldsymbol{\gamma}^{T,bonds,global}\mathbf{F}_t^{bonds,global}) + b_n^{dividends,global}(\boldsymbol{\gamma}^{T,dividends,global}\mathbf{F}_t^{dividends,global}) + \epsilon_{t+52};$$

that is, we predict excess returns on stock indices using both a global Cochrane–Piazzesi (2005) (CP) bond risk factor (BRF; $\boldsymbol{\gamma}^{T,bonds,global}\mathbf{F}_t^{bonds,global}$) and a global dividend risk factor (DRF; $\boldsymbol{\gamma}^{T,dividends,global}\mathbf{F}_t^{dividends,global}$). The global risk factors are constructed by summing over the local risk factors of all 4 markets in our core sample (Eurozone, United States, United Kingdom, and Japan). Newey–West (NW) (52 lags) and block-bootstrapped (BS) standard errors (SE) are provided below the coefficients. Below the adjusted R^2, a 90% confidence band under the model is reported. The 95% quantile for adjusted R^2 under no predictability is stated in the first row labeled "p(CW, GW)." This column further provides p-values from the BS Clark and West (2007) (CW) and Giacomini and White (2006) (GW) measures. The number of observations is 517, except for Israel (514 observations). *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	Intercept	Global BRF	Global DRF	Adj. R^2	p(CW, GW)
Australia	0.1255**	−2.1189***	0.2155***	0.4087	0.2192
SE (NW)	0.0468	0.7120	0.0517	0.2742	0.0000
SE (BS)	0.0576	0.7615	0.0817	0.7058	0.0038
Austria	0.1072*	−3.1895***	0.3238***	0.4088	0.1738
SE (NW)	0.0428	1.0611	0.0667	0.2642	0.0000
SE (BS)	0.0629	1.1643	0.1022	0.6695	0.0046
Belgium	0.2047***	−3.1620**	0.3522**	0.4085	0.2770
SE (NW)	0.0561	1.2117	0.0820	0.3192	0.0002
SE (BS)	0.0781	1.3052	0.1624	0.6114	0.0096
Canada	0.0836	−1.1071	0.1654**	0.2685	0.1774
SE (NW)	0.0471	0.7506	0.0420	0.0996	0.0018
SE (BS)	0.0607	0.8547	0.0690	0.5207	0.0398
Denmark	0.2081**	−1.8630	0.2231**	0.2288	0.1904
SE (NW)	0.0736	1.2977	0.0620	0.1287	0.0106
SE (BS)	0.0847	1.3514	0.1077	0.4686	0.0360
Finland	0.2903***	−4.2560***	0.1782	0.3233	0.1789
SE (NW)	0.0787	1.2033	0.0669	0.1834	0.0000
SE (BS)	0.0906	1.2657	0.1110	0.6044	0.0112
France	0.1559***	−2.5598***	0.2294***	0.4222	0.1952
SE (NW)	0.0469	0.8056	0.0492	0.3164	0.0000
SE (BS)	0.0491	0.7731	0.0807	0.6614	0.0056
Germany	0.1648**	−2.1493**	0.1941*	0.2558	0.2182
SE (NW)	0.0585	1.0655	0.0607	0.1388	0.0056
SE (BS)	0.0660	1.0859	0.1058	0.5513	0.0178
Hong Kong	0.0761	−0.4224	0.2432*	0.2459	0.2092
SE (NW)	0.0570	0.9930	0.0747	0.0590	0.0072
SE (BS)	0.0811	1.1562	0.1295	0.5482	0.0422
Ireland	0.2881***	−5.1092***	0.1964	0.3273	0.2658
SE (NW)	0.0778	1.5382	0.0880	0.1965	0.0018
SE (BS)	0.0940	1.6085	0.1680	0.5827	0.0534
Israel	0.0124	−0.3312	0.1671	0.1743	0.2237
SE (NW)	0.0812	0.8854	0.0516	0.0327	0.0508
SE (BS)	0.1041	1.1731	0.1141	0.5183	0.2188
Italy	0.1161	−2.8636***	0.2226***	0.3407	0.1712
SE (NW)	0.0835	1.0523	0.0485	0.2526	0.0006
SE (BS)	0.0851	1.0681	0.0775	0.6021	0.0090
Japan	0.2889***	−4.5443***	0.2109	0.4315	0.2834
SE (NW)	0.1151	1.3993	0.0636	0.2627	0.0002
SE (BS)	0.1087	1.2927	0.1426	0.7247	0.0410
Netherlands	0.1717***	−2.4335**	0.2762***	0.4088	0.1767
SE (NW)	0.0499	0.9346	0.0562	0.2842	0.0000
SE (BS)	0.0630	0.9663	0.0881	0.6459	0.0060
New Zealand	0.1815***	−2.6918***	0.1467	0.3611	0.3943
SE (NW)	0.0356	0.8070	0.0628	0.2253	0.0102
SE (BS)	0.0429	0.7794	0.1329	0.6262	0.0594
Norway	0.0770	−1.3371	0.2458**	0.2716	0.1950
SE (NW)	0.0571	1.0810	0.0691	0.1371	0.0036
SE (BS)	0.0706	1.1426	0.1017	0.5380	0.0120

(continued on next page)

TABLE 10 (continued)
A Global Model for MSCI Equity Country Indices

	Intercept	Global BRF	Global DRF	Adj. R^2	p(CW, GW)
Portugal	0.0689	−2.2185**	0.1906*	0.2523	0.2382
SE (NW)	0.0526	0.9167	0.0679	0.1320	0.0040
SE (BS)	0.0740	1.0985	0.1084	0.6242	0.0108
Singapore	0.0066	0.0384	0.2848**	0.3118	0.2357
SE (NW)	0.0606	0.9210	0.0879	0.0671	0.0006
SE (BS)	0.0769	0.9882	0.1243	0.7461	0.0336
Spain	0.1357	−2.3769**	0.2092**	0.2754	0.2046
SE (NW)	0.0949	1.1336	0.0574	0.1872	0.0008
SE (BS)	0.1016	1.1939	0.0893	0.5891	0.0200
Sweden	0.0878	−1.0294	0.2924***	0.3890	0.2553
SE (NW)	0.0540	0.9468	0.0680	0.2604	0.0000
SE (BS)	0.0649	0.9611	0.1115	0.6560	0.0202
Switzerland	0.1477***	−2.2960***	0.2254**	0.4624	0.3035
SE (NW)	0.0510	0.7333	0.0479	0.3849	0.0000
SE (BS)	0.0509	0.6874	0.0966	0.7210	0.0140
U.K. (MSCI)	0.0720*	−1.1116	0.2281***	0.4749	0.2244
SE (NW)	0.0312	0.6750	0.0391	0.3461	0.0000
SE (BS)	0.0397	0.7086	0.0704	0.6776	0.0102
U.S. (MSCI)	0.1666***	−1.9964**	0.2256***	0.4200	0.2629
SE (NW)	0.0399	0.8711	0.0460	0.3277	0.0000
SE (BS)	0.0474	0.8926	0.0858	0.6185	0.0124

the robustness of our empirical asset pricing model and the substantial global comovements in risk premia.

C. Robustness

As previously mentioned, we follow Sarno et al. (2012) and base the statistical inference of single coefficients on block-bootstrapped standard errors (and we additionally report Newey–West standard errors with 52 lags). The joint significance is evaluated using the Clark and West (2007) (CW) and Giacomini and White (2006) (GW) measures, as laid out in detail in the Appendix.

1. Known Predictors

In addition to technical robustness checks, we strive to evaluate if our global 2-factor model is superior to well-known predictive variables. The term spread, defined as the difference between the yield on a 10-year bond and a 1-year bond, as well as the CAPE, are 2 factors that have historically captured the time variation in excess equity index returns with decent accuracy. Thus, we estimate a version of the global model, where we add a global term spread and a global CAPE to the dividend and the bond factors:

$$\begin{aligned} (25)\quad \mathrm{RX}_{t+52}^{\mathrm{asset},i} &= a + b^{\mathrm{bonds,global}}\mathrm{BF}_t^{\mathrm{global}} + b^{\mathrm{dividends,global}}\mathrm{DF}_t^{\mathrm{global}} \\ &\quad + b^{\mathrm{term,global}}\mathrm{TERM}^{\mathrm{global}} + b^{\mathrm{CAPE,global}}\mathrm{CAPE}^{\mathrm{global}} + \epsilon_{t+52}^{\mathrm{asset},i}. \end{aligned}$$

To assess the value of our dividend and bond factors, we evaluate if this 4-factor model is superior to a 2-factor model that uses only the term spread and CAPE. The corresponding results are displayed in Table 12. The statistical measures we use to assess the predictive accuracy of a given model are the change in the hit ratio, ΔHR; the change in the predictive power, R^2, which is based on the ratio of the mean-squared errors of the model and the benchmark, respectively; and the p-values of a CW and a GW test. Note that in contrast to the tables so

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TABLE 11
A Global Model for Other Test Assets

Table 11 presents results for the regression

$$RX^{asset,i}_{t+52} = b_n^{bonds,global}(\boldsymbol{\gamma}^{T,bonds,global}\mathbf{F}_t^{bonds,global}) + b_n^{dividends,global}(\boldsymbol{\gamma}^{T,dividends,global}\mathbf{F}_t^{dividends,global}) + \epsilon^{(n)}_{t+52};$$

that is, we predict excess returns on various test assets (that were not used to construct the risk factors) using both a global Cochrane–Piazzesi (2005) (CP) bond risk factor (BRF) and a global dividend risk factor (DRF). The global risk factors are constructed by summing over the local risk factors of all 4 markets in our core sample (Eurozone, United States, United Kingdom, Japan). Newey–West (NW) and bootstrapped (BS) standard errors (SE) are provided below the coefficients. Below the adjusted R^2, a 90% confidence band under the model is reported. The 95% quantile for adjusted R^2 under no predictability is stated in the first row labeled "p(CW, GW)". This column further provides p-values from the block-bootstrapped Clark and West (2007) (CW) and Giacomini and White (2006) (GW) measures. The number of observations is 517, except for EM High Yield (312 observations). The test assets in this table are the following indices: Morgan Stanley Capital International (MSCI) World Local, MSCI Europe, MSCI European Economic and Monetary Union (EMU) Local, MSCI Emerging Markets Local, MSCI Frontier Markets, Standard & Poor's (S&P) 500 Value, S&P 500 Growth, S&P SC600 Growth, AQR Momentum, S&P 500 Volatility Index (VIX) Short-Term Futures Inverse, iBoxx USD Liquid High Yield, Markit iBoxx EUR Liquid High Yield, Bloomberg USD High-Yield Emerging Market Corporate Bond, JPMorgan Emerging Markets Bond, Deutsche Bank Currency Global Harvest, Deutsche Bank Currency Momentum, Deutsche Bank Currency Value, and Deutsche Bank G10 Diversified Rates Carry. We obtain excess returns on the test assets by subtracting the local 1-year U.S. bond yield for all indices but the Euro High Yield, where we subtract the 1-year EUR swap rate. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	Intercept	Global BRF	Global DRF	Adj. R^2	p(CW, GW)
AQR Momentum	0.1671***	−2.1079**	0.1804**	0.3150	0.2341
SE (NW)	0.0490	1.0219	0.0402	0.2055	0.0010
SE (BS)	0.0555	1.0605	0.0766	0.5212	0.0338
EM High Yield	−0.0045	0.7016	0.2379***	0.2691	0.2783
SE (NW)	0.0363	0.5028	0.0734	0.0549	0.0062
SE (BS)	0.0357	0.5662	0.0898	0.6625	0.3114
DB FX Global	−0.0273	0.1506	0.0603	0.1022	0.2594
SE (NW)	0.0298	0.3785	0.0358	0.0124	0.1640
SE (BS)	0.0403	0.4472	0.0651	0.5662	0.0794
DB FX Momentum	0.0202	0.0364	−0.0580*	0.1387	0.1945
SE (NW)	0.0190	0.3717	0.0218	0.0270	0.0522
SE (BS)	0.0271	0.4382	0.0343	0.4014	0.0658
DB FX Value	0.0118	0.2015	0.0184	0.0149	0.3336
SE (NW)	0.0255	0.6097	0.0173	0.0036	0.6930
SE (BS)	0.0335	0.6619	0.0359	0.2844	0.6668
DB FX Carry	−0.0255***	0.2325	0.0172	0.1999	0.4879
SE (NW)	0.0087	0.1800	0.0109	0.1189	0.1566
SE (BS)	0.0098	0.1833	0.0234	0.6433	0.2368
EM Bonds	−0.0100	0.7795	0.1306**	0.4603	0.2540
SE (NW)	0.0295	0.4888	0.0260	0.2811	0.0000
SE (BS)	0.0306	0.4850	0.0518	0.7029	0.0280
MSCI World Local	0.1571***	−2.1833***	0.2239***	0.4472	0.2410
SE (NW)	0.0430	0.8058	0.0462	0.3487	0.0000
SE (BS)	0.0492	0.8150	0.0857	0.6564	0.0072
MSCI EM Local	0.0277	−0.0227	0.2306*	0.2625	0.2114
SE (NW)	0.0522	0.8828	0.0761	0.0417	0.0054
SE (BS)	0.0757	1.0243	0.1258	0.6317	0.0588
U.S. High-Yield ETF	−0.0001	0.0599	0.2142***	0.5861	0.3618
SE (NW)	0.0203	0.5028	0.0358	0.4133	0.0000
SE (BS)	0.0274	0.5086	0.0725	0.7779	0.0524
U.S. High Yield	0.0066	0.1456	0.2115***	0.5958	0.2386
SE (NW)	0.0213	0.4901	0.0296	0.4033	0.0000
SE (BS)	0.0274	0.5163	0.0514	0.7896	0.0134
U.S. Small-Cap ETF	0.1770***	−2.3314**	0.2921***	0.5237	0.2389
SE (NW)	0.0529	0.9410	0.0434	0.3938	0.0000
SE (BS)	0.0641	1.0136	0.0873	0.7090	0.0134
U.S. Value ETF	0.1715***	−2.3614**	0.2496***	0.4515	0.2707
SE (NW)	0.0413	0.9177	0.0498	0.3484	0.0000
SE (BS)	0.0498	0.9444	0.0962	0.6711	0.0146
U.S. Growth ETF	0.1597***	−1.6777**	0.2025***	0.3843	0.2584
SE (NW)	0.0383	0.8176	0.0428	0.2724	0.0002
SE (BS)	0.0457	0.8398	0.0770	0.5665	0.0176

(continued on next page)

TABLE 11 (continued)
A Global Model for Other Test Assets

	Intercept	Global BRF	Global DRF	Adj. R^2	p(CW, GW)
MSCI Frontier Markets	0.1938**	−2.8673**	0.1727	0.2410	0.2059
SE (NW)	0.0790	1.2091	0.0659	0.0877	0.0080
SE (BS)	0.0982	1.3448	0.1193	0.5381	0.0796
MSCI Europe	0.0917*	−1.7139**	0.2051***	0.3835	0.1979
SE (NW)	0.0437	0.7424	0.0459	0.2689	0.0000
SE (BS)	0.0497	0.7532	0.0724	0.6404	0.0074
MSCI EMU	0.1299**	−2.3548***	0.2026**	0.3416	0.1863
SE (NW)	0.0557	0.8579	0.0518	0.2453	0.0000
SE (BS)	0.0586	0.8445	0.0798	0.6203	0.0050

TABLE 12
Robustness versus Global CAPE and Term-Spread Specification

Table 12 compares the predictability of the benchmark model that explains the subsequent 52-week excess returns of Morgan Stanley Capital International (MSCI) country indices using the global cyclically adjusted price–earnings ratio (CAPE) and term spread against an augmented model that additionally uses the global bond risk factor and the global dividend risk factor as explanatory variables. The columns provide the increase in the hit ratio ΔHR, the relative predictive ability R^2, and the p-value from the bootstrapped Clark and West (2007) (CW) and Giacomini and White (2006) (GW) measures. N is the number of observations.

Market	ΔHR	R^2	p(CW)	p(GW)	N
Australia	0.1393	0.3742	0.0006	0.0908	517
Austria	−0.0309	0.3754	0.0000	0.0818	517
Belgium	−0.0077	0.3017	0.0018	0.1842	517
Canada	0.1064	0.3358	0.0024	0.1026	517
Denmark	0.1122	0.2384	0.0038	0.1872	517
Finland	0.1528	0.3987	0.0000	0.0240	517
France	0.0348	0.3366	0.0002	0.0788	517
Germany	0.0851	0.2468	0.0042	0.2136	517
Hong Kong	0.1760	0.2591	0.0128	0.1606	517
Ireland	−0.1025	0.4145	0.0000	0.0094	517
Israel	0.0875	0.2235	0.0298	0.1740	514
Italy	0.0851	0.2928	0.0008	0.1686	517
Japan	0.0580	0.3379	0.0000	0.0380	517
Netherlands	0.0658	0.3453	0.0006	0.0680	517
New Zealand	0.0116	0.3115	0.0026	0.0406	517
Norway	0.0019	0.2725	0.0046	0.1714	517
Portugal	0.0580	0.2561	0.0148	0.2968	517
Singapore	0.1838	0.3848	0.0000	0.1228	517
Spain	0.1528	0.2646	0.0084	0.3106	517
Sweden	0.0174	0.2607	0.0068	0.2298	517
Switzerland	0.0580	0.3247	0.0000	0.0866	517
U.K. (MSCI)	0.0116	0.3380	0.0014	0.0690	517
U.S. (MSCI)	0.0464	0.3576	0.0004	0.0902	517

far in this article, the alternative model for the CW and GW test is not the no-predictability case but a 2-factor model with term spread and CAPE. We provide the full details of the measures in Section 1 of the Appendix, and we describe bootstrapping for the CW and GW tests in Section 2. Thus, p-values smaller than 0.10 indicate that the 4-factor model is superior to a model using the term spread and CAPE only, which implicitly confirms that our dividend and bond factor model adds significant value.

Most of the hit ratios increase, adjusted R^2 increases, and nearly all CW and GW p-values are substantially below 0.10. This is convincing evidence in favor of our factors. Nonetheless, to challenge our results even more, we repeat the same exercise but use local term spreads and CAPEs instead:

$$\text{RX}^{\text{asset},i}_{t+52} = a + b^{\text{bonds,global}}\text{BF}^{\text{global}}_{t} + b^{\text{dividends,global}}\text{DF}^{\text{global}}_{t} + b^{\text{term,local}}\text{TERM}^{\text{local}} + b^{\text{CAPE,local}}\text{CAPE}^{\text{local}} + \epsilon^{\text{asset},i}_{t+52}. \quad (26)$$

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TABLE 13

Robustness versus Local CAPE and Term-Spread Specification

Table 13 compares the predictability of the benchmark model that explains the subsequent 52-week excess returns of Morgan Stanley Capital International (MSCI) country indices using the local cyclically adjusted price–earnings ratio (CAPE) and term spread against an augmented model that additionally uses the global bond risk factor and the global dividend risk factor as explanatory variables. The columns provide the increase in the hit ratio ΔHR, the relative predictive ability R^2, and the p-value from the bootstrapped Clark and West (2007) (CW) and Giacomini and White (2006) (GW) measures. N is the number of observations.

Market	ΔHR	R^2	p(CW)	p(GW)	N
Australia	0.0754	0.3273	0.0014	0.0470	517
Austria	−0.0110	0.2878	0.0162	0.0018	364
Belgium	0.0043	0.3163	0.0112	0.0006	232
Canada	0.0271	0.1110	0.1006	0.3470	517
Denmark	0.0109	0.1320	0.0740	0.0604	457
France	−0.0058	0.3317	0.0000	0.0670	517
Germany	−0.0522	0.1452	0.0218	0.0808	517
Hong Kong	0.0244	0.4268	0.0000	0.0084	492
Ireland	−0.0237	0.3275	0.0000	0.0312	295
Italy	0.0503	0.2227	0.0030	0.1802	517
Japan	0.0251	0.4232	0.0000	0.0784	517
Netherlands	0.0000	0.2278	0.0946	0.0622	128
New Zealand	0.0593	0.2610	0.0040	0.0176	354
Norway	0.0457	0.1486	0.0482	0.3176	460
Portugal	0.1429	0.1499	0.0772	0.0930	483
Singapore	0.0433	0.5345	0.0000	0.0034	416
Spain	0.0716	0.2030	0.0168	0.1694	517
Sweden	0.0107	0.1815	0.0702	0.6688	467
Switzerland	0.0327	0.4280	0.0000	0.0048	459
U.K. (MSCI)	0.0039	0.2722	0.0006	0.0716	517
U.S. (MSCI)	0.0774	0.3378	0.0002	0.0106	517

Although the results, shown in Table 13, become somewhat weaker (e.g., the CW and GW p-values for the United States, Canada, and Norway are no longer significant), as could be expected, the overall picture still confirms the validity of using the global dividend and bond factors to capture risk premia.

2. Principal Components Analysis Specification

In order to verify our claim that the joint dynamic of forward interest rates and forward equity forwards has explanatory power for subsequent equity index returns, we implement a principal components analysis. We extract the first 7 principal components (PCs) because they explain 95% of the joint variance of the 36 forward rates (for each of the 4 regions, there are 5 bond and 4 dividend tenors). We then regress excess index returns on these PCs. We present the results in Table 14. Using this alternative method, we again find strong evidence for predictability.

3. Economic Drivers

Digging deeper into the drivers of the global dividend factor and the global bond factor, we regress these factors on a set of variables usually related to equity index performance: the level of implied volatility as a measure of risk aversion, the level of the TED spread, the level of inflation expectations (imputed from inflation swaps), and the level of CAPE and the term spread. To calculate global variables, all variables are aggregated over the 4 core markets. As shown in Table 15, more than half of the variation in the global dividend factor can be explained by the regression. The dividend factor seems to be related to risk aversion, CAPE, and liquidity, whereas it is not significantly related to the steepness of the yield curve. The same set of variables explains the global bond factor with an even higher R^2.

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TABLE 14
A PCA Model for Stock Indices

Table 14 provides regressions explaining the subsequent stock index returns with factors obtained from a principal-component analysis (PCA) of forward equity forwards and bond forward rates. The regression reads as

$$RX_{t+52}^{stocks,i} = \sum_{n=1}^{7} b_n PC_n + \epsilon_{t+52},$$

where PC_n is the nth principal component, and the number of principal components is chosen such that 95% of the variance is explained. Newey–West (NW) (52 lags) and block-bootstrapped (BS) standard errors (SE) are reported below the coefficients. Below the adjusted R^2, a 90% confidence band under the model and the 95% quantile under no predictability are reported. We further provide p-values from the BS Clark and West (2007) (CW) and Giacomini and White (2006) (GW) measures. The number of observations is equal to 517. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	U.S.	Japan	Euro	U.K.
Intercept	0.0742*	0.0505	0.0187	0.0405
SE (NW)	0.0135	0.0266	0.0176	0.0122
SE (BS)	0.0413	0.1132	0.0551	0.0316
PC_1	0.0221*	0.0327	0.0184	0.0155*
SE (NW)	0.0031	0.0050	0.0038	0.0029
SE (BS)	0.0113	0.0329	0.0146	0.0088
PC_2	−0.0177	−0.0106	−0.0148	−0.0260**
SE (NW)	0.0029	0.0065	0.0043	0.0025
SE (BS)	0.0145	0.0251	0.0201	0.0107
PC_3	−0.0188	0.0012	−0.0250	−0.0158
SE (NW)	0.0062	0.0207	0.0107	0.0059
SE (BS)	0.0152	0.0319	0.0223	0.0115
PC_4	0.0782***	0.0569	0.0677**	0.0560***
SE (NW)	0.0110	0.0207	0.0166	0.0112
SE (BS)	0.0238	0.0501	0.0327	0.0194
PC_5	−0.0425	−0.1056*	−0.0842**	−0.0336
SE (NW)	0.0146	0.0184	0.0167	0.0124
SE (BS)	0.0312	0.0566	0.0339	0.0259
PC_6	−0.0534*	−0.0441	−0.0566*	−0.0443*
SE (NW)	0.0122	0.0117	0.0114	0.0106
SE (BS)	0.0324	0.0293	0.0303	0.0263
PC_7	−0.0538*	−0.0943	−0.0861**	−0.0686***
SE (NW)	0.0242	0.0376	0.0285	0.0209
SE (BS)	0.0318	0.0606	0.0384	0.0256
Adj. R^2	0.7478	0.6451	0.6687	0.7218
5% quantile	0.5782	0.5133	0.5221	0.6561
95% quantile	0.8744	0.8545	0.8442	0.8550
No predictability, 95% quantile	0.4351	0.4251	0.3931	0.4026
p-value (CW)	0.0000	0.0000	0.0000	0.0000
p-value (GW)	0.0048	0.0088	0.0060	0.0014

Thus, the innovation of the dividend factor over known predictors appears to be greater than the innovation of the bond factor. This is consistent with our earlier finding that the dividend factor improves the prediction of equity excess returns substantially as compared to the bond factor. Although the bond factor has similar exposure to volatility risk and liquidity, it is also related to inflation expectations and the term spread.

Moreover, we analyze if the dividend risk factor proxies for bad economic times, consistent with a standard risk-based explanation for return predictability. We use 3 variables that track U.S. business conditions at a high frequency and are available to investors in real time. The Aruoba–Diebold–Scotti Business Conditions Index is a composite consisting of various economic indicators, such as weekly initial jobless claims, monthly payroll employment, industrial production, and so forth. Furthermore, we use a *nowcast* and a *forecast* designed to track the current and the next-quarter U.S. GDP, calculated by Now-Casting Economics

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TABLE 15

Drivers of Dividend and Bond Factors

Table 15 provides results from regressions of the dividend risk factor (DRF) and bond risk factor (BRF) on a set of explanatory variables. All variables are global, constructed by summation over the 4 core regions (United States, Japan, Eurozone, United Kingdom). Newey–West (NW) (52 lags) and block-bootstrapped (BS) standard errors are reported below the coefficients. We further provide *p*-values from the BS Clark–West (CW) (2007) and Giacomini–White (GW) (2006) measures. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	Global DRF	Global BRF
Intercept	0.8961***	−0.2265***
SE (NW)	0.6246	0.0365
SE (BS)	0.2293	0.0117
Implied volatility	0.9072**	0.0424**
SE (NW)	0.9336	0.0313
SE (BS)	0.4464	0.0211
TED spread	1.5997***	0.1177***
SE (NW)	0.3399	0.0242
SE (BS)	0.1882	0.0134
Inflation expectation	10.6080	−1.2072**
SE (NW)	33.7453	1.6863
SE (BS)	12.2126	0.5722
CAPE	−0.0846***	0.0091***
SE (NW)	0.0256	0.0010
SE (BS)	0.0074	0.0003
Term spread	0.0433	0.0652***
SE (NW)	0.1113	0.0043
SE (BS)	0.0415	0.0019
Adj. R^2	0.7089	0.8378
p-value (CW)	0.0000	0.0000
p-value (GW)	0.0000	0.0000

Limited. As can be seen from Table 16, there is a significant negative relation between the global dividend factor and real-time proxies for business activity. Thus, in periods with adverse business conditions, prices and realized returns are low, whereas expected future returns are high. This leads to the interpretation that the dividend factor captures increased risk premia during bad economic times.

TABLE 16

Global Dividend Risk Factor and Business Conditions

Table 16 reports the results of a set of regressions of the global dividend risk factor (DRF) on 3 variables that proxy for business conditions in the United States. In model 1 we regress on the Aruoba–Diebold–Scotti (ADS) Business Conditions Index, which is designed to track real business conditions at high frequency. Model 2 regresses on the high-frequency forecast for current-quarter U.S. gross domestic product (GDP) (*nowcast*), and model 3 regresses on the forecast for the subsequent-quarter U.S. GDP (*forecast*). The *nowcast* and *forecast* time series are provided by Now-Casting Economics Limited. Newey–West (NW) standard errors (SE) are provided below the coefficients. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	Global DRF	Global DRF	Global DRF
	1	2	3
Intercept	0.0305	0.7199***	1.0184***
SE (NW)	0.0810	0.1544	0.2233
ADS Business Conditions Index	−0.3627***		
SE (NW)	0.1143		
U.S. GDP nowcast		−0.8929***	
SE (NW)		0.1808	
U.S. GDP forecast			−1.2299***
SE (NW)			0.2836
Adj. R^2	0.3960	0.5499	0.5929
No. of obs.	517	517	517

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VII. Possible Extensions

As mentioned in Section IV, the Campbell and Ammer (1993) return decomposition reveals that inflation is a major driver of bond excess returns. Cieslak and Povala (2015) augment bond return forecasts obtained from a linear combination of forward rates by incorporating expected inflation. We apply their insights to explore whether using inflation improves bond return predictability in our sample period and whether the predictability of dividend swap returns can also be improved by including inflation forecasts. Furthermore, the Goncalves (2018) return decomposition reveals news on dividend growth as a return driver. Consequently, we use consensus analysts' dividend forecasts to augment our models for dividend swap returns.

A. Trend Inflation

Specifically, Cieslak and Povala (2015) decompose yields into inflation expectations and maturity-specific interest rate cycles. Similar to their analysis, we start by regressing the forward rates of various maturities on trend inflation, which is defined as a 120-month exponentially weighted moving average of annual changes in core CPI:

$$\tau_t^{\text{CPI}} = \frac{1-\nu}{1-\nu^N}\sum_{i=0}^{N-1}\nu^i\pi_{t-1}. \tag{27}$$

Note that instead of truncating an infinite sum of core inflation as Cieslak and Povala (2015) do, we use the formula for a finite geometric sum in equation (27). The parameter values match those of Cieslak and Povala (2015), with $N=120$ and $\nu=0.987$. We convert the time series from a monthly frequency into a weekly time series by updating the most recent summand π_t by a time-weighted average of the current and lagged monthly core inflation observations on a weekly basis. We run regressions of the form

$$F_t^{\text{bonds},(n)} = a_n + b_n\tau_t^{\text{CPI}} + \epsilon_t, \tag{28}$$

and we use the estimated residuals from these regressions as the maturity-specific inflation cycles $c_t^{\text{bonds},(n)}$. Subsequently, we regress the across-maturity average excess bond returns $\overline{\text{RX}}_{t+52}^{\text{bonds}}$ on the short-term cycle $c_t^{\text{bonds},(1)}$ and the average cycle $\bar{c}_t^{\text{bonds}}$, which is defined as the mean of $c_t^{\text{bonds},(n)}$ across all maturities except $n=1$.

$$\overline{\text{RX}}_{t+52}^{\text{bonds}} = \gamma_0 + \gamma_1 c_t^{\text{bonds},(1)} + \gamma_2\bar{c}_t^{\text{bonds}} + \epsilon_t. \tag{29}$$

Analogous to CP (2005) and Cieslak and Povala (2015), the fitted values $\widehat{\text{RX}}_{t+52}^{\text{bonds}}$ from regression (28) serve as a bond risk factor that enters second-stage regressions of the form

$$\text{RX}_{t+52}^{\text{bonds},(n)} = b_0 + b_1\widehat{\overline{\text{RX}}}_{t+52}^{\text{bonds}} + \epsilon_t. \tag{30}$$

In order to assess the additional explanatory power gained from trend inflation, we estimate a reduced-form version of the original CP (2005) setup as a basis for comparison. To do so, we regress across-maturity average bond excess

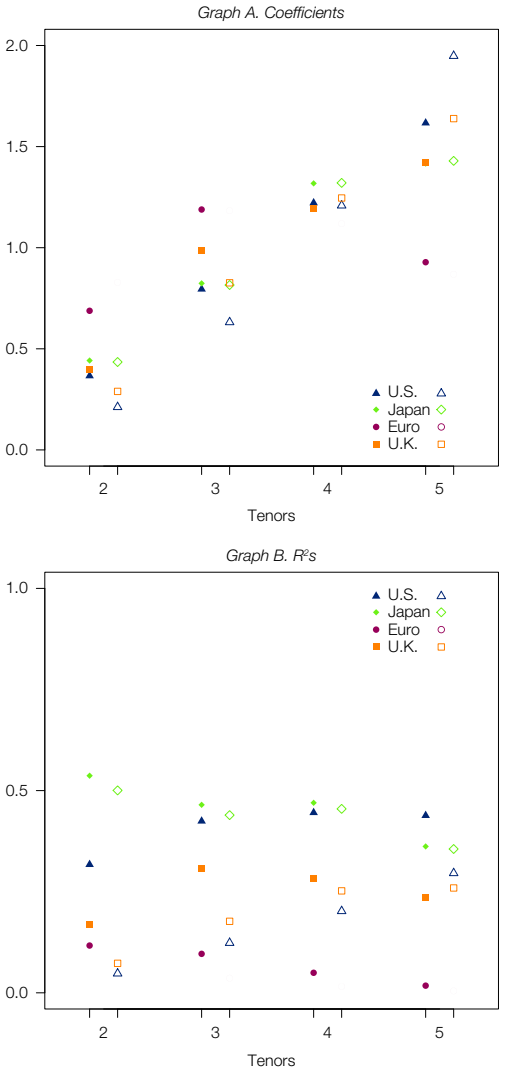
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returns on 1-year yields and an across-maturity average of the remaining forward rates in the first stage. In Figure 2, we illustrate the coefficients and R^2s of the corresponding second-stage regressions, both for this base case and the model

FIGURE 2

Accounting for Inflation in Bond Models: Second-Stage Coefficients and R^2 Comparison

Figure 2 compares the second-stage results of reduced-form Cochrane–Piazzesi (2005) (CP) bond regressions to second-stage Cieslak–Povala (2015) regressions. (In the first stage of reduced-form CP, we regress across-maturity average excess bond returns on the 1-year yield and an average of the remaining forward rates.) In the Cieslak–Povala regressions, we regress excess bond returns on a 1-year interest rate cycle and an average of the interest rate cycles of the remaining maturities (the interest rate cycles are obtained as residuals from maturity-specific regressions of bond forward rates on a measure of trend inflation). Graph A displays regression coefficients, and Graph B displays R^2s. For each maturity on the *x*-axis, there are 2 columns of markers. Filled markers present results for the CP base case for all 4 regions, and empty markers correspond to the Cieslak–Povala-style analysis for all 4 regions.



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including inflation. Although the coefficients are in the same range for both versions, the values of R^2 are consistently lower for the inflation-cycle model. This finding might be due to the low magnitude of bond yields in our sample period.[10]

To assess the importance of trend inflation for dividend swap returns, we extend the previous analysis to suit dividend swap data. More precisely, we use forward equity forward rates $F_t^{\text{dividends},(n)}$ in equation (27) to obtain maturity-specific inflation cycles $c_t^{\text{dividends},(n)}$ and dividend excess returns $\overline{\text{RX}}_{t+52}^{\text{dividends}}$ in equation (28), and finally, we run second-stage regressions of the form

$$\text{RX}_{t+52}^{\text{dividends},(n)} = b_0 + b_1 \hat{\text{RX}}_{t+52}^{\text{dividends}} + \epsilon_t \,. \tag{31}$$

Figure 3 displays the corresponding coefficients and R^2s. The values of R^2 are considerably higher for U.S. dividend swap returns after accounting for inflation. This finding is consistent for all maturities. For the other regions, the results remain qualitatively the same.

B. Inflation Swaps

Because we stress the importance of information extracted from forward curves throughout our article, there is an alternative avenue to include inflation in our models. We use data on traded inflation swaps for annual maturities up to 5 years to construct an inflation risk factor equivalent to the CP (2005) bond risk factor and our dividend risk factor. Specifically, we compute the excess returns of inflation swaps, $\overline{\text{RX}}_{t+52}^{\text{infl}}$, and forward inflation rates for all maturities, $\mathbf{F_t^{infl}}$, from the zero-coupon inflation swap data. We estimate the regression

$$\overline{\text{RX}}_{t+52}^{\text{infl}} = \boldsymbol{\gamma}^T \mathbf{F_t^{infl}} + \bar{\epsilon}_{t+52} \,, \tag{32}$$

and we obtain an inflation factor $\hat{\text{RX}}^{\text{infl}}$ from the fitted values. This enables us to augment the single-local-factor bond model and dividend model, respectively, by the inflation factor to obtain 2-factor models (one combining the inflation factor and the bond risk factor (BRF) to explain bond returns, and another one combining the inflation factor and the dividend risk factor (DRF) to explain dividend swap returns). Because the 1-factor models are nested in the corresponding 2-factor models, we test formally for both asset classes if the larger model is superior, based on the change in hit ratio, relative R^2, and the p-values of the CW and GW tests described in the Appendix. Tables 17 and 18 report the main results. Consistent with our earlier analysis of inflation cycles, the larger models do not add explanatory power for bond returns. However, the 2-factor model including inflation risk is superior for U.S. dividend swap returns. Again, this is consistent with previous results, as shown in Figure 3.

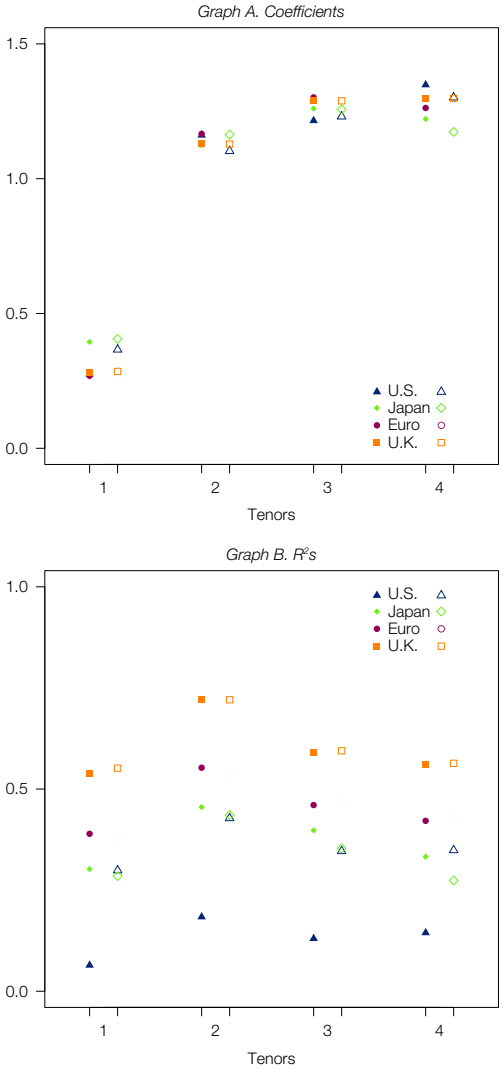
[10] Cieslak and Povala (2015) use bond maturities up to 20 years in their article, whereas we follow CP (2005) in using maturities up to 5 years. This has the advantage that our bond results are consistent with the analysis of dividend swaps, where longer maturities are not available for our sample period. To cross-check this finding, we replicate the Cieslak and Povala (2015) analysis using monthly U.S. data and log returns and then restrict the sample period to match our sample. Using only bond data up to 5 years' maturity, we find that R^2s are lower than for the reduced-form CP (2005) model. The replication results are available from the authors.

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FIGURE 3

Accounting for Inflation in Dividend Models: Second-Stage Coefficients and R^2 Comparison

Figure 3 compares the second-stage results of reduced-form Cochrane–Piazzesi (2005) (CP) dividend regressions to second-stage Cieslak–Povala (2015) regressions. (In the first stage of reduced-form CP, we regress across-maturity average excess dividend swap returns on the 1-year forward equity forward and an average of the remaining forward equity forward rates.) In the Cieslak–Povala regressions, we regress excess dividend swap returns on a 1-year dividend cycle and an average of the dividend cycles of the remaining maturities (the dividend cycles are obtained as residuals from maturity-specific regressions of forward equity forward rates on a measure of trend inflation). Graph A displays regression coefficients, and Graph B displays R^2s. For each maturity on the x-axis, there are 2 columns of markers. Filled markers present results for the CP base case for all 4 regions, and empty markers correspond to the Cieslak–Povala-style analysis for all 4 regions.



C. Expected Dividend Growth

Finally, we obtain consensus analysts' estimates for index dividends 1 and 2 years ahead, which allows us to compute a time series of expected dividend

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TABLE 17

Robustness of BRF Model versus Including an Inflation Risk Factor

In Table 17, we present the results of a model comparison. The base case is the second stage of a reduced-form Cochrane–Piazzesi (2005) (CP) regression (meaning that in the first-stage regressions, across-maturity average excess bond returns are regressed on the 1-year yield and an average of the remaining forward rates only instead of regressing on the forward rates of all available maturities). We compare this 1-factor model to a 2-factor model where excess bond returns of various maturities are regressed on the bond risk factor (BRF) and an inflation risk factor. The inflation risk factor is extracted from a term structure of zero-coupon inflation swaps using a method that is equivalent to the CP method for bonds. Because the second-stage CP (1-factor) regression is nested in the 2-factor model including the inflation risk factor, we can formally test for the difference in predictive power. The columns provide the increase in the hit ratio ΔHR, the relative predictive ability R^2, and the p-value from the bootstrapped Clark and West (2007) (CW) and Giacomini and White (2006) (GW) measures. N is the number of observations.

Contract	ΔHR	R^2	p(CW)	p(GW)	N
US_2	0.0079	0.0141	0.6322	0.0248	509
US_3	0.0098	0.0093	0.6976	0.0252	509
US_4	−0.0098	0.0083	0.7454	0.0990	509
US_5	0.0000	0.0008	0.9238	0.3220	509
$JAPAN_2$	−0.0022	0.0041	0.7472	0.7060	448
$JAPAN_3$	0.0022	0.0134	0.4756	0.1936	448
$JAPAN_4$	−0.0067	0.0469	0.1702	0.0772	448
$JAPAN_5$	0.0000	0.0494	0.1666	0.0598	448
$EURO_2$	−0.0412	0.0094	0.6794	0.4764	510
$EURO_3$	−0.0275	0.0147	0.6206	0.2840	510
$EURO_4$	−0.0020	0.0054	0.7666	0.3468	510
$EURO_5$	−0.0020	0.0006	0.9182	0.4386	510
UK_2	0.0019	0.0006	0.8226	0.5488	517
UK_3	0.0000	0.0001	0.9128	0.4408	517
UK_4	0.0097	0.0337	0.0302	0.1006	517
UK_5	0.0155	0.0670	0.0012	0.0556	517

TABLE 18

Robustness of DRF Model versus Including an Inflation Risk Factor

In Table 18, we present the results of a model comparison. The base case is the second stage of a reduced-form Cochrane–Piazzesi (2005) (CP) regression for dividend swap excess returns (meaning that in the first-stage regressions, across-maturity average excess dividend swap returns are regressed on the 1-year forward equity forward and an average of the remaining forward equity forward rates only instead of regressing on the forward equity forward rates of all available maturities). We compare this 1-factor model to a 2-factor model where excess dividend swap returns of various maturities are regressed on the dividend risk factor (DRF) and an inflation risk factor. The inflation risk factor is extracted from a term structure of zero-coupon inflation swaps using a method that is equivalent to the CP method for bonds. Because the second-stage CP (1-factor) regression is nested in the 2-factor model including the inflation risk factor, we can formally test for the difference in predictive power. The columns provide the increase in the hit ratio ΔHR, the relative predictive ability R^2, and the p-value from the bootstrapped Clark–West (CW) (2007) and Giacomini–White (GW) (2006) measures. N is the number of observations.

Contract	ΔHR	R^2	p(CW)	p(GW)	N
US_2	0.0570	0.2383	0.0028	0.0388	509
US_3	0.1827	0.2773	0.0070	0.0312	509
US_4	0.2102	0.2474	0.0152	0.0546	509
US_5	0.2377	0.2647	0.0096	0.0772	509
$JAPAN_2$	−0.0402	0.1145	0.1386	0.3222	448
$JAPAN_3$	−0.0134	0.0269	0.3344	0.5330	448
$JAPAN_4$	−0.0156	0.0048	0.6236	0.4516	448
$JAPAN_5$	0.0022	0.0001	0.9396	0.3828	448
$EURO_2$	−0.0216	0.0356	0.3278	0.2218	510
$EURO_3$	0.0275	0.0176	0.5698	0.1214	510
$EURO_4$	0.0098	0.0272	0.4582	0.1272	510
$EURO_5$	−0.0059	0.0195	0.5296	0.1522	510
UK_2	0.0019	0.0578	0.2374	0.6148	517
UK_3	−0.0213	0.0761	0.1396	0.7910	517
UK_4	−0.0077	0.0448	0.1526	0.9928	517
UK_5	0.0019	0.0469	0.1188	0.9840	517

growth rates. We proceed similarly to the Cieslak and Povala (2015) analysis, but we replace expected inflation with expected dividend growth. This analysis is implemented for dividend swap returns only. The results are depicted in

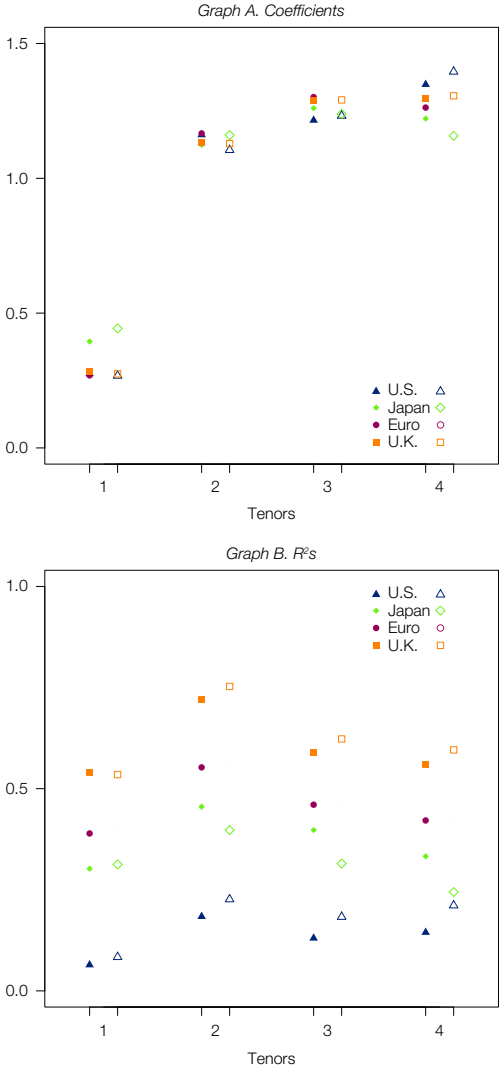
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Figure 4. Note that the base case is the same as in Figure 3 (reduced-form CP (2005)). Again, there is an improvement in R^2 for U.S. dividend swap returns,

FIGURE 4

Accounting for Analysts' Dividend Growth Expectations in Dividend Models: Second-Stage Coefficients and R^2 Comparison

Figure 4 compares the second-stage results of reduced-form Cochrane–Piazzesi (2005) (CP) dividend regressions to second-stage Cieslak–Povala (2015) regressions. (In the first stage of reduced-form CP, we regress across-maturity average excess dividend swap returns on the 1-year forward equity forward and an average of the remaining forward equity forward rates.) In the Cieslak–Povala regressions, we regress excess dividend swap returns on a 1-year dividend cycle and an average of the dividend cycles of the remaining maturities (the dividend cycles are obtained as residuals from maturity-specific regressions of forward equity forward rates on a time series of consensus analysts' expectations of dividend growth). Graph A displays regression coefficients, and Graph B displays R^2s. For each maturity on the x-axis, there are 2 columns of markers. Filled markers present results for the CP base case for all 4 regions, and empty markers correspond to the Cieslak–Povala-style analysis for all 4 regions.



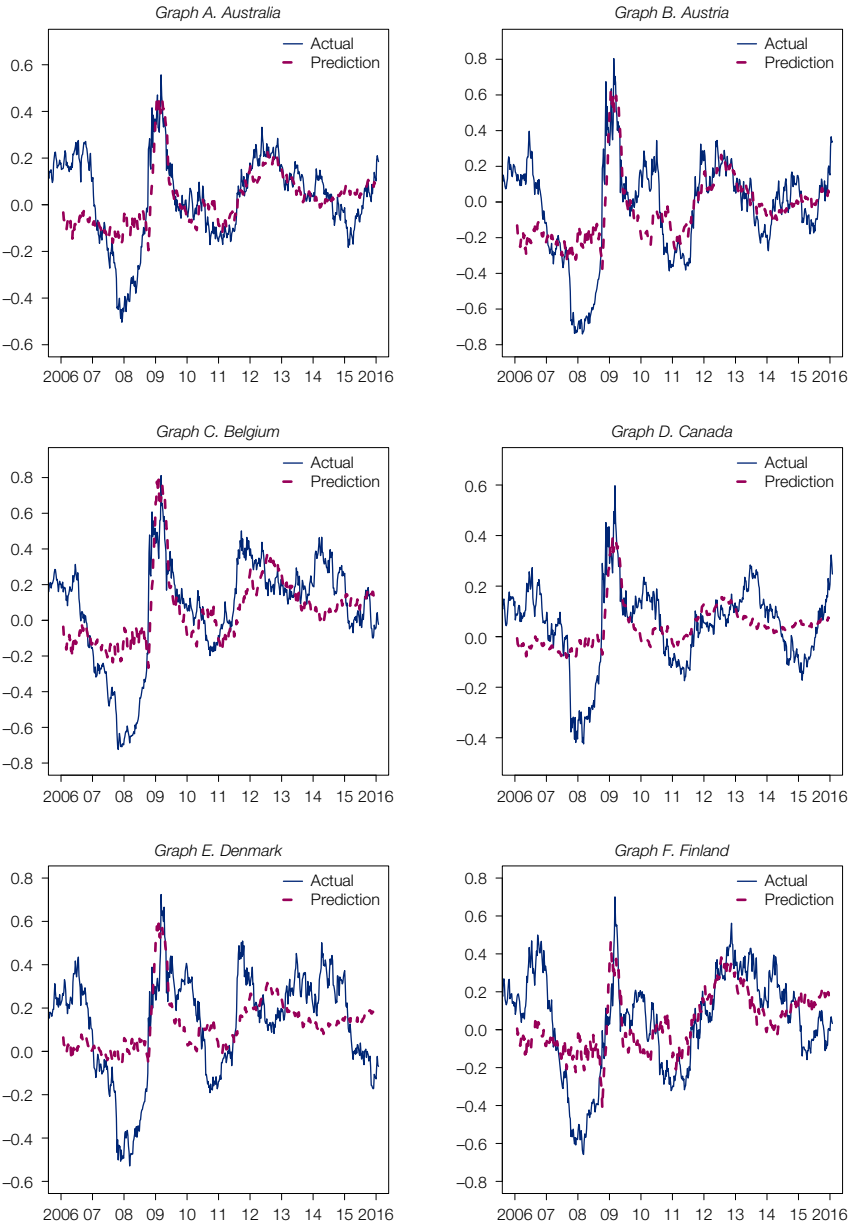
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FIGURE 5

Actual versus Predicted Index Excess Returns

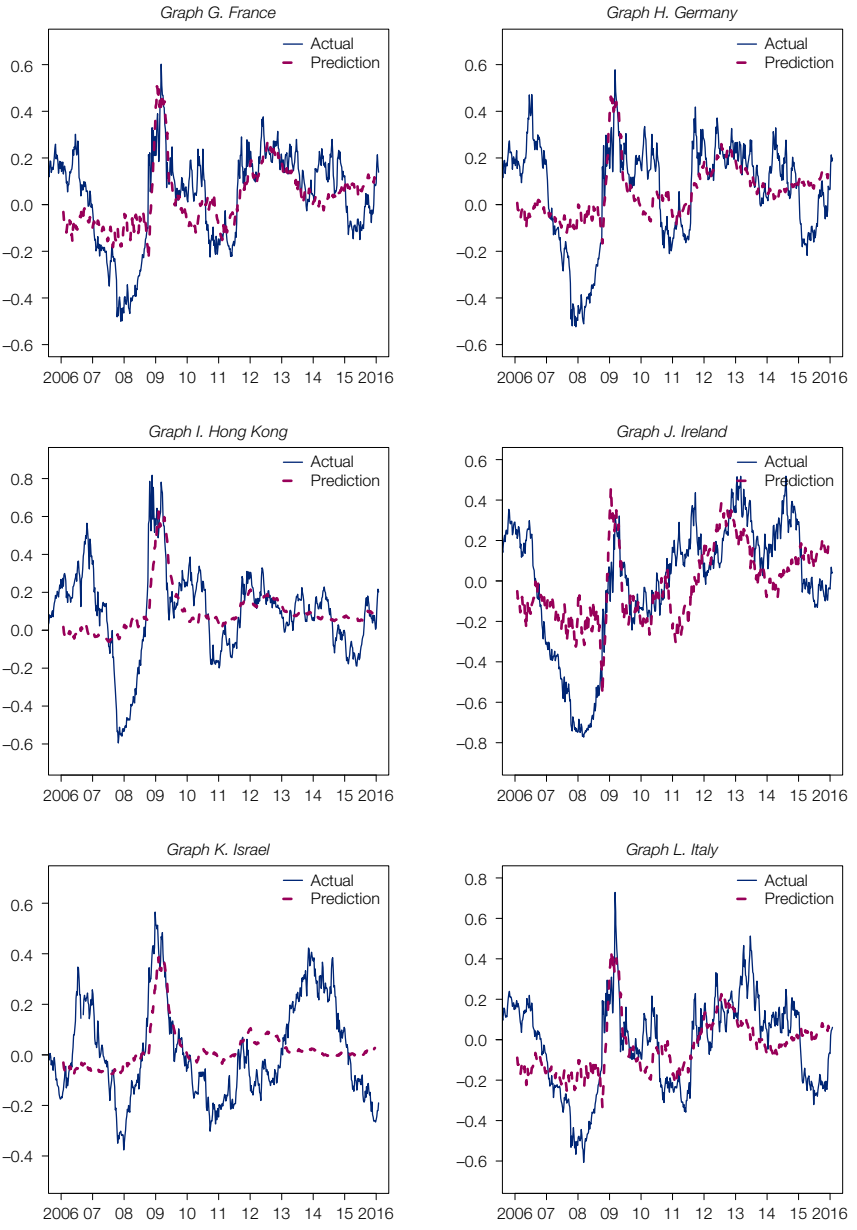
Figure 5 displays the actual versus predicted rolling 52-week excess returns of Morgan Stanley Capital International (MSCI) country indices. Predicted values are obtained from the global 2-factor model of equation (24): $RX_{t+52}^{stocks,i} = a + b^{bonds,global} BF_t^{global} + b^{dividends,global} DF_t^{global} + \epsilon_{t+52}^{stocks,i}$.



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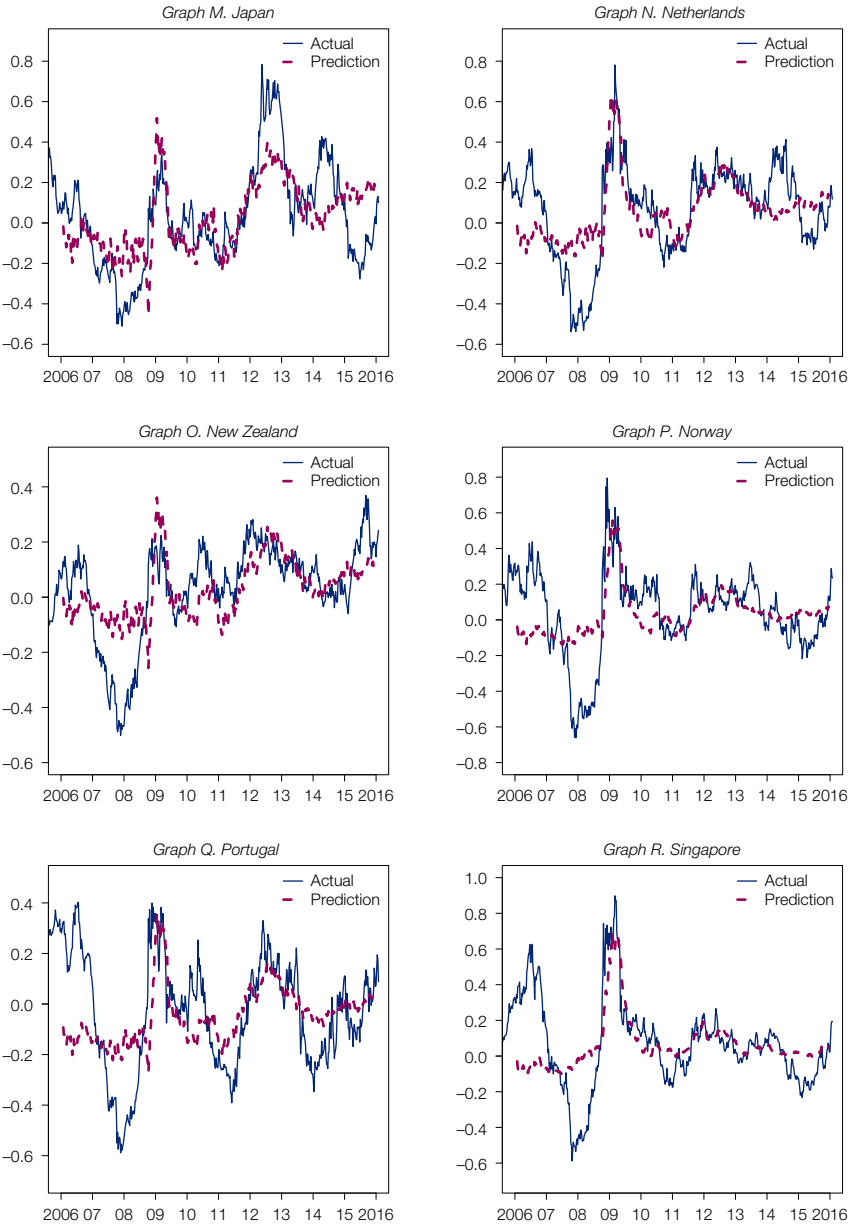
FIGURE 5 (continued)
Actual versus Predicted Index Excess Returns



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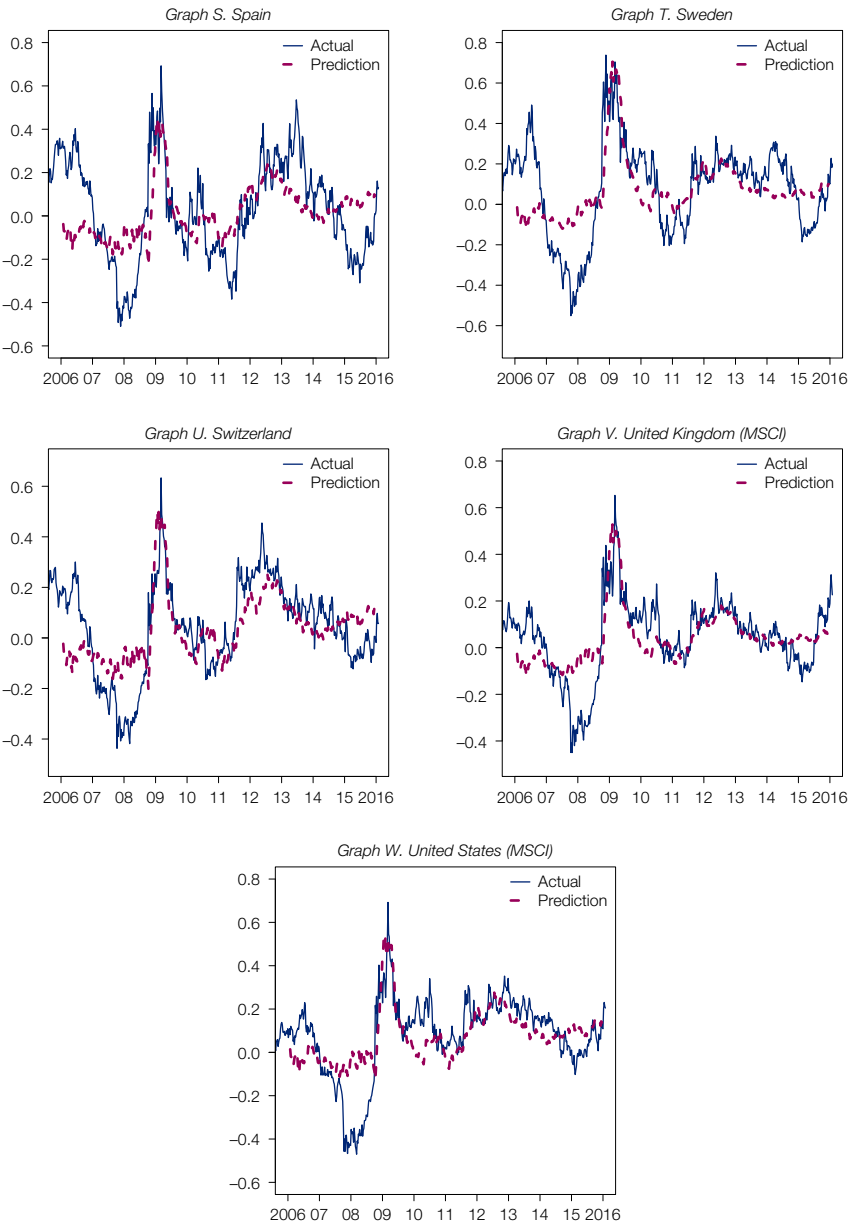
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FIGURE 5 (continued)
Actual versus Predicted Index Excess Returns



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FIGURE 5 (continued)
Actual versus Predicted Index Excess Returns



albeit smaller in magnitude than in the inflation-cycle analysis. There are only minor changes in coefficients or R^2s for the other regions.

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VIII. Conclusion

This article investigates risk premia in the market for traded claims on dividends (i.e., dividend derivatives), stocks, and bonds. Dividend derivatives of several maturities allow us to construct a term structure of equity forward rates in a way analogous to bond yields. We extend the well-known bond model of CP (2005) to suit the market for dividends and utilize the method to create a novel dividend risk factor. Although we confirm earlier evidence that excess returns on dividend derivatives investments are time-varying, we additionally shed light on a number of related research questions that have not been explored to the present date:

1. We find strong international evidence for predictability in the excess returns of dividend derivatives, with R^2s comparable to predictive regressions for fixed-income securities.

2. We show that a common return-forecasting factor drives the variation in excess returns on dividend derivatives of all maturities. Similar to the fixed-income literature, very short-maturity claims are least exposed to this dividend risk factor, whereas longer maturities have higher exposures to the same factor. However, the increase in exposure with increasing maturity is somewhat less pronounced than for bonds.

3. We tie together our findings on a unique dividend risk factor and the existing evidence for a corresponding bond risk factor to price dividend derivatives, bonds, and stocks using both factors jointly. The dividend risk factor is positively and significantly related to subsequent excess returns on dividend derivatives and stocks, whereas it has only marginal importance for pricing bonds. The bond factor is positively related to subsequent excess bond returns, whereas it is significantly negatively related to dividend derivatives and excess stock returns. This is consistent with the output-focused monetary policy, elevated macroeconomic uncertainty, and low-inflation expectations that persist throughout our sample period, all facts that the prior literature documents as giving rise to a negative stock–bond correlation. Using both the dividend factor and the bond factor in the predictive regressions increases the values of R^2 substantially. In predicting the excess returns of stock indices, for example, over the 4 core regions, the 2-factor model increases the R^2 by 0.24 on average as compared to a model that uses the bond factor only, and by 0.14 as compared to a single-factor model that only uses the dividend factor.

4. We further extend the local 2-factor model to a global 2-factor model by aggregating the factors over the 4 core regions. We interpret the excellent fit of the global model as evidence for substantial comovements in international risk premia.

5. Moreover, we employ the global 2-factor model to predict the excess returns of a variety of test assets, including all MSCI developed market country stock indices (excluding the 4 core markets that we use to construct the risk factors); regional stock indices; emerging market (EM) bonds; corporate high-yield bonds in the United States, the Eurozone, and emerging markets; and a volatility-selling strategy. Most test assets have significant positive exposure to the global dividend risk factor, whereas the global bond factor is positively related to

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fixed-income assets and negatively related to equity-like assets. The finding that 2 global factors capture the return dynamics of a vast set of assets still holds after using rigorous block-bootstrap methods for statistical inference and including well-known control variables.

6. There is a strong relation between the global dividend factor and real-time proxies for business activity. This is consistent with the interpretation that the dividend factor captures increased risk premia during bad economic times.

Our results confirm that the structure of expected returns in the time-series domain across a wide range of assets is well captured by 2 factors. Although we expect future research to show that additional factors are required to cover the expected return dynamics of alternative assets such as commodities, we document that the commonality in risk premia across assets is large enough so that only a few return-forecasting factors are necessary for multiple-asset portfolios.

Appendix. Statistical Inference

1. Model Evaluation

In assessing the predictive accuracy of our model, we follow Sarno et al. (2012) and compute the tests proposed by Clark and West (2007) and Giacomini and White (2006), which we denote as the CW and GW tests. Our focus is on analyzing time variations in dividend risk premia, not on the out-of-sample predictions of returns. Therefore, we follow Sarno et al. (2012) in their analysis of foreign exchange risk premiums and use in-sample predictions for model evaluation. The CW test statistic given in equation (A-1) is based on the comparison of the mean-squared prediction errors MSE^M and MSE^B of a model and its nested benchmark, respectively, adjusted for the upward bias in MSE^M due to the introduction of noise from estimating a larger model M under the null of B. The null hypothesis of the CW test is that the nested models have equal mean-squared errors; a large CW test statistic means that model M has a lower mean-squared prediction error. CW is defined as

$$\text{(A-1)} \qquad \text{CW} = \text{MSE}^B - \text{MSE}^M + N^{-1}\sum_{t=1}^{T}\left(\hat{r}_{t,T}^{B} - \hat{r}_{t,T}^{M}\right)^2,$$

where N is the number of observations in the sample. For stand-alone model evaluation, we use the constant model (no predictability) as a benchmark B, whereas for model comparison, the nested model serves as benchmark B, and the model with additional variables serves as the model M to be evaluated. We apply the block-bootstrap procedure described in Section 2 of the Appendix to obtain p-values.

To assess conditional predictive ability, either for testing a model against no predictability or for model comparison, we calculate the GW test statistic given in equation (A-2):

$$\text{(A-2)} \qquad \text{GW} = N\left(N^{-1}\sum_{t=m}^{T} h_t \Delta L_t\right)\hat{\Omega}_N^{-1}\left(N^{-1}\sum_{t=m}^{T} h_t \Delta L_t\right),$$

where $\Delta L_t = SE_t^B - SE_t^M$, $h_t = (1, \Delta L_{t-m})$, $m = 52$, and $\hat{\Omega}_N^{-1}$ is an estimate of the variance of $h_t \Delta L_t$. As proposed by Giacomini and White (2006), we obtain the test statistic as $N R^2$, where R^2 is the uncentered squared multiple-correlation coefficient for the regression of the constant unity on $(h_t \Delta L_t)$. This implementation tests the null hypothesis that the model and the benchmark have equal conditional predictive ability, using the m-period lagged

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squared prediction error as loss functions of the two competing predictions. We obtain p-values from bootstrapping, where we simulate the proportion of times we would obtain an observed value as large as the test statistic GW computed from the sample, even if the conditional predictability of models M and B are equal. The block-bootstrap procedure is described in detail in Section 2 of the Appendix.

For model comparison, we further calculate ΔHR as the difference between the proportion of times the sign of the excess return is correctly predicted by the model M (hit ratio of M) and the hit ratio of the benchmark B. Again following Sarno et al. (2012), the relative predictive ability is further assessed by the R^2 statistics given in equation (A-3):

$$R^2 = 1 - \frac{\text{MSE}^M}{\text{MSE}^B}. \tag{A-3}$$

2. Block-Bootstrap Procedure

Our analysis uses overlapping returns, and thus unadjusted standard errors would likely lead to overstating statistical significance. Although we mitigate potential problems arising from heteroscedasticity and autocorrelation through the use of Newey and West (1987) standard errors, we additionally employ a block-bootstrap procedure for both the calculation of standard errors and to obtain p-values for the CW and GW test statistics. In our bootstrap methodology for assessing the predictive ability of a model, we impose a data-generating process of no predictability. For model comparison, we impose the benchmark model as the data-generating process. An overlapping block-resampling scheme can handle serial correlation and heteroscedasticity, as described by Sarno et al. (2012) and the references cited in their Appendix F (e.g., Künsch (1989) and Politis and White (2004)). Specifically, we proceed as follows:

1. Run both the model regression of the form $y_t = \alpha^M + \boldsymbol{\beta}^M \boldsymbol{x}_t^M + \epsilon^M$ and the benchmark regression $y_t = \alpha^B + \boldsymbol{\beta}^B \boldsymbol{x}_t^B + \epsilon^B$. Note that $\boldsymbol{x}^B$ is a subset of $\boldsymbol{x}^M$, and if the benchmark model is no predictability, there are no $\boldsymbol{x}^B$ (i.e., the benchmark regression reduces to the computation of the mean). Save $\boldsymbol{\beta}^M$, ϵ^M, $\hat{\boldsymbol{y}}^{\boldsymbol{B}}$, and compute the CW and GW test statistics. Set $\tilde{y}_t = \hat{y}_t^B + \epsilon_t^M$.
2. Form an artificial sample $S_t^* = (y_t^*, \boldsymbol{x}_t^M)$ by randomly sampling, with replacement, b overlapping blocks of length l from the sample $(\tilde{y}, \boldsymbol{x}^M)$.
3. Run the regressions $y_t^* = \alpha^{*M} + \boldsymbol{\beta}^{*M} \boldsymbol{x}_t^{*M} + \epsilon^{*M}$ and $y_t^* = \alpha^{*B} + \boldsymbol{\beta}^{*B} \boldsymbol{x}_t^{*B} + \epsilon^{*B}$. Save $\boldsymbol{\beta}^{*M}$ and compute adjusted R^2 and the CW* and GW* test statistics.
4. Repeat steps 2 and 3 5,000 times.
5. Obtain the covariance matrix $\Sigma_{\boldsymbol{\beta}^M}$ from the 5,000 vectors of $\boldsymbol{\beta}^{*M}$. Determine the 1-sided p-values of the test statistics by computing the proportional number of times that CW* > CW and GW* > GW. Compute confidence intervals for adjusted R^2 for the model and benchmark cases.

Supplementary Material

Supplementary Material for this article is available at https://doi.org/10.1017/S0022109019000309.

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