Global Equity Yields

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Abstract

We use the model of Giglio, Kelly, and Kozak (2021) to construct a panel of global equity yields. We revisit stylized facts about equity yields, primarily based on US data, and provide several new results. On old facts, we study the dynamics of global equity yields, their slopes, and the relative contribution of risk premium and growth expectations in explaining variation in yields. On new facts, we study comovements in risk premia and growth expectations across markets and Fama French portfolios, estimate the term-structure of the global equity risk premium, and link yields to changes in exchange rates and future macroeconomic outcomes.

JEL Codes: G11, G12, G15

Keywords: International Finance, Equity Yields, Term-Structure, Equity Risk Premium, Dividend Growth Expectations, Exchange Rate Predictability

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I. Introduction

The forward equity yield—the sum of a dividend growth expectation and a risk premium—is pivotal for understanding various economic outcomes. Measurement of equity yields usually comes from dividend futures on indices of large companies (Van Binsbergen et al., 2013; Van Binsbergen and Koijen, 2017). While these futures contracts provide direct measurements of equity yields, limited available maturities, short time-series, and small cross-sections raise concerns regarding statistical power and the generalizability of the results.

While this literature made substantial progress in extending the data on equity yields (see Giglio et al. (2021) for extending the US time-series, and see Gormsen (2021) for cross-sectional extensions), a panel dataset with a long time-series is missing. Filling this gap is important for several reasons. First, panel data makes it possible to study equity yields with market and calendar time-fixed effects, which control for market-specific characteristics and aggregate shocks. Second, it allows for more precise inference of model output (e.g., the term-structure of risk premia). Third, inference based on a global panel is not liable to the concern by Karolyi (2016) regarding a US bias in academic research in finance.

In this paper, we make the affine model of equity prices, dividends, and returns developed by Giglio et al. (2021) suitable for an international context. The model makes it possible to calculate equity yields for the market index and diversified equity portfolios, without data on dividend futures. We use the model to extend the data on equity yields across markets and anomalies, starting in the early 1990s, covering local and global recessions in 12 equity markets.[1] In total, this gives about 3,000 market-months of "new data" on equity yields.

We start by verifying the model's usefulness outside the US. We do so by showing that the model-implied forward equity yield closely matches the forward equity yield based on the FTSE 100 Dividend Index Futures, the most liquid non-US contract. Having verified that the model matches the dynamics of forward equity yields observed in the futures market

[1] These markets are: Austria (AT), Australia (AU), Switzerland (CH), Germany (DE), France (FR), United Kingdom (GB), Hong Kong (HK), India (IN), Malaysia (MY), Sweden (SE), United States (US), and South-Africa (ZA).

outside the US, we use it to compute long time-series of forward equity yields for various markets. We use this output in multiple contexts.

We first analyze the dynamics of global forward equity yields over time, crisis periods, and portfolios. Second, we study the dynamics of the slope of forward equity yields (long-term minus short-term yields). Third, we use a variance decomposition to calculate the relative importance of risk premium and dividend growth expectations in explaining time-series variation in forward equity yields. Fourth, we study comovements in risk premia and expected dividend growth across markets and Fama and French (1993) portfolios. Fifth, we provide estimates of global equity risk premia for different investment horizons. Sixth, we link forward equity yields to exchange rates. Seventh, we test whether the risk premia and dividend growth expectations are useful in forecasting macroeconomic outcomes.

Across all markets and periods, the average forward equity yield is negative in regular periods and positive or flat in crisis periods. The average slope of equity yields is procyclical; in good (bad) times it is 8.2% (-3.7%). Restricting the analysis to within-country variation in economic conditions, we find that the slope shifts down from its unconditional mean by 8.4% in crisis periods. Our estimates are precise, with standard errors of less than 0.4%. We repeat the analysis for portfolios formed on market capitalization and book-to-market in the spirit of Fama and French (1993). We find that the slope of the short legs of the Fama and French 3-factor model (i.e., big companies and growth stocks) drops substantially more in crisis periods than the long legs (i.e., small companies and value stocks).

Our conclusions regarding the dynamics of forward equity yields at the market level are similar to Bansal et al. (2021); despite they are using futures prices, other measures of the state of the economy, and US data. We show that their results are unlikely driven by confounding slow-moving events in the time-series, or are specific to the US.

By the definition of forward equity yield, we decompose its slope into two terms. The first term is the risk premium on the longest maturity strip above the 1-year maturity strip. The second term is long-term expected dividend growth in excess of short-term growth. The slope is the first term minus the second term. We find that the main reason for the flatting of the slope in crisis periods is a large drop in short-term expected dividend growth. We come to similar conclusions for the Fama and French portfolios. Overall, our findings are in line with Van Binsbergen et al. (2013) in their study of dividend futures for the US (S&P500), JP (Nikkei 225), and the Euro-area (Eurostoxx 50).

We then use the global panel to understand variation in forward equity yields. We have two main findings. First, most of the time-series variation in forward equity yields, both in the US and outside the US, reflect changes in dividend growth expectations, especially at short maturities. Although the picture is more balanced for long-maturity yields, the high volatility of dividend growth expectations contradicts the view that most of the time-series variations in stock prices are due to changes in discount rates (Campbell, 1991; Cochrane, 2017). Second, we decompose the variance of risk premia and dividend growth expectations into a within-market component and a between-market component. A market refers to five portfolios, the four long and short portfolios in the Fama and French 3-factor model, and the region-specific market portfolio. We find that markets are highly integrated concerning risk premia and dividend growth expectations in the short run, while country-specific effects matter more in the long run, echoing the findings of Asness et al. (2011).

We use Fama MacBeth cross-sectional (Fama and MacBeth, 1973) regressions to estimate the evolution of maturity-specific global equity risk premia since 1995. The 1-year maturity risk premium reflects the discount rate in excess of the one-year risk-free rate on a dividend payment from an equally weighted global equity index. The n-period risk premium is defined analogously. Our main finding is that the risk premium increases with the horizon; consistent with the predictions of the habit model (Campbell and Cochrane, 1999) and the long-run risk model (Bansal and Yaron, 2004).

Several theories have recently been developed to understand the dynamics of exchange rates (see Verdelhan, 2020, for an excellent overview). Gabaix and Maggiori (2015) develop a theory of exchange rate determination based on capital flows in imperfect financial markets.

Their idea is that shifts in the demand and supply of assets result in large-scale capital flows fed through the global financial system, which affects exchange rates. Following this logic, we hypothesize that when expected dividend growth in market i exceeds that of the US, capital will flow into market i, which results in currency appreciation.

We test our hypothesis by regressing changes in exchange rates on two lagged spreads. The first is the wedge in expected dividend growth between country i and the US. The second is the corresponding wedge in the risk premium. In line with the capital flow mechanism in Gabaix and Maggiori (2015), we find that high expected growth in non-US countries with respect to the US predicts currency appreciation relative to the US dollar. In regard to risk premia, we find that when the risk premium in a non-US country exceeds the risk premium in the US, the currency depreciates relative to the US dollar. To the best of our knowledge, we are the first to link forward equity yields and exchange rates.

In our final application, we test whether the risk premia and dividend growth expectations are useful in forecasting macroeconomic outcomes. Given that we have data on markets whose macroeconomic conditions and equity yields differ, we gain substantial power in decoupling the role of risk premia from growth expectations as leading indicators of the macroeconomy; measurable by consumption growth, unemployment changes, and industrial production growth. These variables have homogenous definitions across markets and have either a long tradition in macro-finance (see, e.g., Hansen and Singleton, 1982; Chen et al., 1986), or have recently been linked to the theoretical literature on the term-structure of the equity premium (Hall, 2017). The forecasting regression is a dynamic model with a market-specific intercept. Our central finding is that dividend growth expectations have significant predictive power on all macro outcomes, while risk premia are less important.

Our paper is related to several strands of literature. First, we build on the literature that applies affine models to understand the risk-return properties of financial assets (Lemke and Werner, 2009; Cochrane and Piazzesi, 2005; Giglio et al., 2021). We closely follow the setup in Giglio et al. (2021) and focus on equities. The central idea is to use both the time-series and cross-sectional variation in equity portfolios to identify a set of model parameters that makes it possible to value any equity portfolio "dividend-by-dividend" in the spirit of Brennan (1998). Previous literature has also attempted to measure the term-structure of equity from the cross-section of equities (Bansal et al., 2005; Hansen et al., 2008; Lettau and Wachter, 2007).[2] Importantly, Giglio et al. (2021) differ from these efforts by specifying their model dynamics in accordance with recent empirical US evidence brought forward by Kozak et al. (2020) and Haddad et al. (2020). The key insights are that the returns of a few principal components of anomaly portfolios price the cross-section of stock returns, and that their valuation ratios predict future returns. We replicate these analyses in the additional markets we study and find that these results generalize to many countries outside of the US.

Second, we contribute to the literature aiming to understand forward equity yield and their components following the seminal work by Van Binsbergen et al. (2012).[3] The somewhat "irregular" sample of mostly US data, covering the last 20 years, with frequent economic crises, has led to a dispute about the dynamics of forward equity yields. Critics of the "new facts", which are inconsistent with a host of asset pricing models, argue that the sample is unrepresentative and inference from derivative contracts is unreliable due to low market liquidity (Mixon and Onur, 2017; Bansal et al., 2021; Kirshon, 2020). In addition, the prices of these contracts may be influenced by the views and preferences of financial intermediaries, rather than the preferences of the aggregate household sector; the decision-making unit in most asset pricing models . Our panel dataset and the focus on listed equities—possible due to Giglio et al. (2021)—solve these concerns.

Finally, we add to the literature that links global capital allocation to country-specific risk premia and growth expectations. Lucas (1990) noted that, from a macroeconomic point of view, returns on assets correlate negatively with GDP per capita. David et al. (2014) suggest that the differences in levels of invested capital are due to differences in risk premia and

[2]The idea is to exploit information in portfolios of stocks with different cash-flow growth and discount rates properties. Related work studying the term-structure of the equity risk premium using firm-level measures of duration includes: Weber (2018); Jankauskas et al. (2021); Gormsen and Lazarus (2021).

[3]For a literature review, see Van Binsbergen and Koijen (2017).

required rate of return, which again can be accounted for by differences in exposure to long-run risk across countries. We find that differences in risk premia and growth expectations affect exchange rates, possibly due to the reallocation of capital.

The paper is organized as follows. Section II contains the empirical model. We present our data sources, variable definitions, and the estimation procedure in section III. The main results are in Section IV. Sections V and VI contain additional analysis and conclusions.

II. The Empirical Model

We make the model developed by Giglio et al. (2021) (henceforth GKK) work internationally. The model makes it possible to price dividend strips—claims on realized dividends of an equity portfolio n periods ahead—without data on dividend strips. We aim to recover the discount rate and dividend growth expectations for different equity portfolios at different horizons around the world. To do so, we use a slight modification of GKK. In the following, we define discount rate and dividend growth expectations in terms of model output and provide a minimum of details about the model necessary to understand the output.

A. *Equity Yields*

We denote the price of the dividend strip at time t that pays D_{t+n} at time $t+n$ by $P_t^{(n)}$. Its current dividend is denoted by D_t. The realized gross return on the dividend strip is $R_{t:t+n}^{(n)} = D_{t+n}/P_t^{(n)} = (D_t/P_t^{(n)})(D_{t+n}/D_t)$. The (annualized) equity yield is defined as:

$$e_t^{(n)} := \frac{1}{n} \ln \left(\frac{D_t}{P_t^{(n)}}. \right) \tag{1}$$

It is the annualized log expected hold-to-maturity return minus the annualized log expected dividend growth on the strip. To see this, start with the realized gross return on the dividend strip, then condition on information available at time t, take logs, and rearrange:

$$\begin{aligned}
R^{(n)}_{t:t+n} &= \frac{D_{t+n}}{P^{(n)}_t}\frac{D_t}{D_t} \\
E_t\left[R^{(n)}_{t:t+n}\right] &= \frac{D_t}{P^{(n)}_t}E_t\left[\frac{D_{t+n}}{D_t}\right] \\
\frac{1}{n}\ln\left(E_t\left[R^{(n)}_{t:t+n}\right]\right) &= \frac{1}{n}\ln\left(\frac{D_t}{P^{(n)}_t}\right)+\frac{1}{n}\ln\left(E_t\left[\frac{D_{t+n}}{D_t}\right]\right) \\
e^{(n)}_t &= \frac{1}{n}\ln\left(E_t\left[R^{(n)}_{t:t+n}\right]\right)-\underbrace{\frac{1}{n}\ln\left(E_t\left[\frac{D_{t+n}}{D_t}\right]\right)}_{:=\, g^{(n)}_t}
\end{aligned} \tag{2}$$

We use $g^{(n)}_t$ to denote expected dividend growth from time t to $t+n$. The forward equity yield is defined as the equity yield in excess of the annualized log risk-free rate: $ef^{(n)}_t := e^{(n)}_t - r^f_{t:t+n}$. Subtracting the log risk-free rate from Eq. 2 gives the forward equity yield:

$$\begin{aligned}
ef^{(n)}_t &= \frac{1}{n}\ln\left(E_t\left[R^{(n)}_{t:t+n}\right]\right)-r^f_{t:t+n}-g^{(n)}_t \\
&= \underbrace{\frac{1}{n}\ln\left(E_t\left[\frac{R^{(n)}_{t:t+n}}{R^f_{t:t+n}}\right]\right)}_{:=\, \theta^{(n)}_t} - g^{(n)}_t.
\end{aligned} \tag{3}$$

We use $\theta^{(n)}_t$ to denote the risk premium associated with the expected dividend n periods from time t. Therefore, the forward equity yield is the difference between the log expected hold-to-maturity excess return of the strip $\theta^{(n)}_t$ (henceforth risk premia) and the log expected dividend growth on the strip $g^{(n)}_t$ (henceforth expected dividend growth).[4]

The model gives equity yields $e^{(n)}_t$, risk premia $\theta^{(n)}_t$, and dividend growth expectations $g^{(n)}_t$ as a function a state vector F_t. The state vector F_t summarizes all future investment

[4] Van Binsbergen et al. (2013) and Bansal et al. (2021) define the risk premia as: $\theta_{t,n} := E_t\left[\ln\left(\frac{R_{t:t+n}}{R^f_{t:t+n}}\right)\right]$. We deviate slightly from them as our definition follows from the closed-form solution of GKK.

opportunities. Starting with the equity yields:

$$e_t^{(n)} = \frac{1}{n} \ln \left(\frac{D_t}{P_t^{(n)}} \right) = \frac{1}{n} \left[\ln(\exp(y_t) - 1) - \ln \left(\frac{P_t^{(n)}}{P_t} \right) \right],$$

where $y_t \equiv \ln(1 + \frac{D_t}{P_t})$. The price of the dividend strip $P_t^{(n)}$ as a fraction of the price of the portfolio P_t all strips $n = 1, 2, ..., \infty$ is given by:

$$\begin{aligned}
\frac{P_t^{(n)}}{P_t} &= E_t^Q \left(\frac{D_{t+n}}{P_t} \exp(-\sum_{i=1}^{n} r_{f,t+i-1}) \right) \\
&= E_t^Q \left([\exp(y_{t+n}) - 1] \exp(\sum_{i=1}^{n} \Delta p_{t+i}) \exp(-\sum_{i=1}^{n} r_{f,t+i-1}) \right) \\
&= E_t^Q \left(\exp \left(y_{t+n} + \sum_{i=1}^{n} (\Delta p_{t+i} - r_{f,t+i-1} \right) \right) - E_t^Q \left(\exp \left(\sum_{i=1}^{n} (\Delta p_{t+i} - r_{f,t+i-1} \right) \right) \\
&= \exp(a_{n,1} + d_{n,1} F_t) - \exp(a_{n,2} + d_{n,2} F_t), \qquad (4)
\end{aligned}$$

where $\Delta p_{t+1} := \ln(P_{t+1}/P_t)$ is the capital gain from t to $t+1$, E_t^Q denotes the conditional expectation under the risk-neutral measure, and $a_{n,1}, a_{n,2}$, $d_{n,1}, d_{n,2}$ are parameters defined in Appendix C.C. The log expected hold-to-maturity excess return of the strip $\theta_t^{(n)}$ is:

$$\begin{aligned}
\ln \left(E_t \left[R_{t:t+n}^{(n)} \right] \right) - r_t^f &= \ln E_t \left[\frac{D_{t+n}}{P_t} R_{f,t}^{-1} \right] - \ln \left[\frac{P_t^{(n)}}{P_t} \right] \\
&= \ln \left[\exp(\widehat{a}_{n,1} + \widehat{d}_{n,1} F_t) - \exp(\widehat{a}_{n,2} + \widehat{d}_{n,2} F_t) \right] - \\
&\qquad \ln \left[\exp(a_{n,1} + d_{n,1} F_t) - \exp(a_{n,2} + d_{n,2} F_t) \right], \qquad (5)
\end{aligned}$$

where the notation $\widehat{x}$ refers the physical counterpart to the risk-neutral parameters.

We interpolate local risk-free bond yields ($r_{t:t+n}^f$) to get a complete term-structure with maturities ranging from 1 month to 15 years. Specifically, we fit a Nelson-Siegel-Svensson model month-by-month and use the following maturities: 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 15, 20, 30 years; given data on at least four maturities.[5] The one-year local government bond

[5] Columns 2 to 14 in Table VIII show the starting dates for our sample of local bond yields per maturity

yield is the risk-free rate with the shortest maturity. If unavailable, we use the one-year interpolated yield. For a few cases, interpolated yields are also unavailable. In these cases, we estimate the local one-year risk-free via a regression that includes US yields and exchange rate changes as predictors. The average R^2 of these regressions is 61% for all markets and 70% for developed mar. Additional details are available in Appendix A.B.

B. A Linear Factor Model

The state vector F_t that determines the dynamics of equity yields follows a linear model

$$F_{t+1} = c + \rho F_t + u_{t+1}, \tag{6}$$

with log-normally distributed shocks and $var_t(u_{t+1}) = \Sigma$. Let m_{t+1} be the log-linear SDF with time-varying risk prices λ_t:

$$m_{t+1} = -r_f - \frac{1}{2}\lambda_t' \Sigma \lambda_t - \lambda_t u_{t+1}, \tag{7}$$

where u_{t+1} represent a vector of priced shocks. The price of risk follows:

$$\lambda_t = \lambda + \Lambda F_t. \tag{8}$$

The Euler equation contains provides restrictions to the factor model, which we now describe. Any asset satisfies the Euler equation:

$$\begin{aligned} 1 &= E_t \left[\exp(m_{t+1}) \left(\frac{P_{t+1} + D_{t+1}}{P_t} \right) \right] \\ &= E_t \left[\exp(m_{t+1} + \Delta p_{t+1} + y_{t+1}) \right]. \end{aligned} \tag{9}$$

per market. The last column shows the initial date from which we have a complete local bond yield term-structure.

Under log-normality we have:

$$0 = E_t m_{t+1} + E_t \Delta p_{t+1} + E_t y_{t+1} + \frac{1}{2} V_t[m_{t+1} + \Delta p_{t+1} + y_{t+1}]. \tag{10}$$

We now specify the dynamics of log price changes Δp_{t+1} for any assets that satisfy the Euler equation. This gives functional forms for the dividend process y_{t+1} and the total returns ($r_{t+1} = \Delta p_{t+1} + y_{t+1}$). We start by specifying p assets that are fully diversified and exposed to the priced shocks u_{t+1}. For these assets, log price changes Δp_{t+1} follow:

$$\Delta p_{t+1} - r_f = \gamma_0 + \gamma_1 F_t + \gamma_2 u_{t+1}. \tag{11}$$

It then follows that the yield $y_t := \ln(1 + D_t/P_t)$ will be linear in the factors F_t:

$$y_t = b_0 + b_1 F_t. \tag{12}$$

Thus:[6]

$$r_{t+1} - r^f_{t+1} = \beta_0 + \beta_1 F_t + \beta_2 u_{t+1}. \tag{13}$$

As in the bond literature (see e.g., Cochrane and Piazzesi, 2005), we will have portfolios spanning the same risks as the fully diversified portfolios but measured with error. For these portfolios, log price changes and yields follow:

$$\Delta p_{t+1} - r_f = \gamma_0 + \gamma_1 F_t + \gamma_2 u_{t+1} + \nu_{t+1}, \tag{14}$$

$$y_t = b_0 + b_1 F_t + \epsilon_t. \tag{15}$$

Thus:[7]

$$r_{t+1} - r^f_{t:t+1} = \beta_0 + \beta_1 F_t + \beta_2 u_{t+1} + \varepsilon_{t+1} \tag{16}$$

[6] $\beta_0 = \gamma_0 + b_0 + b_1 c$, $\beta_1 = \gamma_1 + b_1 \rho$, and $\beta_2 = \gamma_2 + b_1$.
[7] $\varepsilon_{t+1} = \epsilon_{t+1} + \nu_{t+1}$

The state vector F_t contains the returns and yields of p fully diversified portfolios: the market and $p-1$ principal component constructed from long-short equity anomalies. As a result, the state vector F_t contains $k = p + p$ variables; half from returns of the fully diversified portfolios (F_r, t), and the remaining are yields (F_y, t):

$$F_t \equiv \begin{bmatrix} F_{r,t} \\ F_{y,t} \end{bmatrix}. \tag{17}$$

GKK impose three restrictions. First, there are p priced risks, and the p fully diversified portfolios span them. This implies that only the first p elements of λ_t are non-zero, which implies that λ_y, $\Lambda_{y,r}$ and $\Lambda_{y,y}$ are zero. Second, time-variation in investment opportunities is driven solely by the dividend yields of the fully diversified portfolios ($\Lambda_{rr} = \mathbf{0}_{p\times p}$). Restrictions 1 and 2 imply that conditional expected excess returns are a function of lagged yields but not lagged realized returns ($\rho_{r,r} = \mathbf{0}_{p\times p}$). We implement these two assumptions as follows:

$$\begin{pmatrix} \lambda_{r,t} \\ \mathbf{0}_{p\times 1} \end{pmatrix} = \begin{pmatrix} \lambda_r \\ \mathbf{0}_{p\times 1} \end{pmatrix} + \begin{pmatrix} \mathbf{0}_{p\times p} & \Lambda_{ry} \\ \mathbf{0}_{p\times p} & \mathbf{0}_{p\times p} \end{pmatrix} \begin{pmatrix} F_{r,t} \\ F_{y,t} \end{pmatrix}. \tag{18}$$

Third, the conditional mean of yields is only a function of lagged yields, not lagged returns ($\rho_{y,r} = \mathbf{0}_{p\times p}$), which implies the following restrictions:

$$\rho = \begin{pmatrix} \mathbf{0}_{p\times p} & \rho_{r,y} \\ \mathbf{0}_{p\times p} & \rho_{y,y} \end{pmatrix}. \tag{19}$$

III. Data and Estimation

We first explain where the data come from, define variables, and explain how we construct the data we use in the estimation. Details about variable definitions are in Appendix A and details on how we construct the state-vector F_t are in Appendix B. We then explain in brief how we estimate the model. Details about the estimation are in Appendix C.

A. Data Sources

We use data from multiple sources. Data on US equities come from Serhiy Kozak's website.[8] The data source for the international sample is Compustat Global (CG). Exchange rates and dividend futures (for the UK) come from the same source. FX comes from Refinitiv DataStream (DS).[9] For local bond yields, we use DS whenever available; otherwise, Global Financial Data (GFD). Dividend futures for the UK are also obtained from this source.

B. Equities

We download the US market portfolio from CRSP and its dividend yield from Robert Shiller's dwebsite.[10] Anomaly returns and dividend yields are from Serhiy Kozak's. For all other markets, we get market returns and dividend yields from DS and stock-specific information necessary to construct characteristic sorted portfolios from CG. For the market portfolios, we use the market indices from DS instead of a value-weighted portfolio of the stocks in CG because—as we explain below— we need to impose a few restrictions on the sample we use to form characteristic sorted portfolios.

We construct 35 of the 50 characteristic-sorted portfolios in GKK.[11] These 35 characteristics cover five types of anomalies defined by Hou et al. (2020) and works well internationally.[12] We construct anomaly portfolios in local currency and use the same filters in all markets but adjust them to local conditions. We proceed as follows. We first download daily stock prices (PRC), daily adjustment factors (AJEXDI), volume (Code: CSHTRD), daily return factors (Code: TRFD), shares outstanding (Code: CSHOC), share codes (Code: TPCI), standard industry classification codes (Code: SICCD), delisting reason (Code: DLRSN),

[8] `https://www.serhiykozak.com/data`

[9] Data on dividend futures starts in July 2011. Mnemonics: LYZ1211, LYZ1212, LYZ1213, LYZ1214, LYZ1215, LYZ1216, LYZ1217, LYZ1218, LYZ1219, LYZ1220, LYZ1221, LYZ1222, LYZ1223, LYZ1224, LYZ1225, LYZ1226, LYZ1227.

[10] `http://www.econ.yale.edu/~shiller/data.htm`

[11] We use as many anomalies as possible (usually 35). The exact number depends on the availability of data in the specific market. Appendix A.A contains a list of the anomalies.

[12] Namely: trading frictions, value-versus-growth, momentum, profitability, and investment.

delisting date (Code: DLDTE), currency codes for prices (CURCD) and dividends CURCDV), and dividends (DIVD). For the international sample. dividends, D, refers to DIVD. We exclude firms in public administration and unclassified companies by removing all firms whose sic codes begin with 9. We also remove firms in the miscellaneous investment sector (Sic: 679) and telecom (Sic: 4812 and 4813). We remove telecoms because the largest firms in this sector can make up a substantial part of the total market value in certain periods for some markets. This is problematic for estimation because these large companies often pay high dividends, making the dividend yields of anomaly portfolios very volatile. CG does not contain information on delisting returns. Therefore, we follow Jensen et al. (2021) and assign a return of -30% in the month a stock is delisted for delisting reasons 2 or 3.

The data coverage in CG is lower than in the US. To ensure that we have sufficient stocks in all portfolios, we impute missing accounting data as follows. First, we download all relevant accounting characteristics in GBP. We then apply Random Forest imputation recursively. Specifically, we use the so-called miceforest algorithm by Wilson (2022) over a rolling window, which uses a random forest estimated and tuned based on data available at the time of the prediction to predict missing data. In total, we impute ca. 1,4 million data points out of a total of 1,85 million missing data points.

To select which equity markets to include in the analysis, we first calculate the top 20 markets by market capitalization using the market capitalization indices from GFD. From 1990 to 2020, the top 20 countries always account for more than 85% of global market capitalization. For each market, we construct characteristic sorted portfolios. Of the 20 markets, 11 had a sufficient cross-section to create well-diversified anomaly portfolios.[13]

We form three portfolios for each characteristic using 70/30 breakpoints. For the international sample, we restrict anomaly portfolios to stocks that have paid dividends over the last 12 months (Dimson et al., 2003, use a similar assumption in their analysis of the UK equity market). At the beginning of the sample, a few anomalies are missing data (for example,

[13]Excluding the US.

shvol, llrev, ivol. All anomalies are defined in Appendix A.A). This happens at most 2% of the time. In these cases, we fill in with the time series median.

C. Interest Rates

We need local government bond yields to calculate forward equity yields. For the US, we use data from Gürkaynak et al. (2007).[14] Outside the US, we use yields from DS and GFD, which complement each other. For instance, DS does not provide yields for maturities shorter than one year, whereas Global Financial Data does. In addition, the starting point of the bond yields generally differs between the two databases (for example, 1-year local bond yields for the UK start in 1970 in DS, whereas only in 1979 in GFD). For every market, we download all available maturities that may be available after June 1972 (monthly data). When bond yields from DS are unavailable, we use GFD.[15] Appendix A.B lists starting and ending dates for bonds with and without interpolation.

D. Currency Adjustments

We use the first two digits of the isin code to assign stocks to markets (for example, we assign all stocks whose isin starts with "GB" to Great Britain). We download exchange rates from CG. We use the exchange rates to ensure that all market and accounting data for firms belonging to a given market are reported in the same currency throughout our sample period. With the purpose of estimating market-specific risk forward equity yields, we estimate the model from the point of view of a local investor (e.g., for the UK, a British investor). For that reason, returns and interest rates are always in local currency.

[14] Available at https://www.federalreserve.gov/pubs/feds/2006/200628/200628abs.html

[15] Tickers are available upon request.

E. A Global State Vector

The state-vector F_t contains returns and yields of the market portfolio and principal component portfolios from long-short anomalies. GKK motivate the use of principal component portfolios by leveraging two empirical results from the US equity market. First, Kozak et al. (2020) show that a small number of principal components from a large set of anomaly portfolios can explain the cross-section of returns. Second, Haddad et al. (2020) show that the returns of the first principal components are predictable by valuation ratios. In Appendix B.A, we present results showing that the second finding holds internationally.[16]

To construct our state-vector F_t, we combine local equities with US equities, as the long history featured by the US data is crucial for the estimation. Concretely, the market portfolio included in F_t is an equally weighted portfolio between the US market portfolio and the relevant local market portfolio (i.e., the UK market portfolio).[17] Similarly, the principal component portfolios are constructed from a set of anomalies that includes both US anomalies and anomalies for the relevant local market (i.e., the UK anomalies). Due to the latter implementation choice, the state vector F_t will contain 10 elements (i.e., $p = 5$) and not 8 as in GKK. This is due to the fact that in a larger set of anomalies, an additional principal component is required to achieve an explained variance level of about ca. 50% (54.7% in GKK).

The construction of the combined set of anomalies is as follows. The first year is 1973, for which we only have data for the US. Consequently, we need to impute local anomalies—usually starting in 1990—back to 1973 using the complete set of US anomalies. This is a common preliminary step before performing principal components when a dataset has a small number of missing variables. We use the function "imputePCA" from the R library "missMDA". This function imputes the missing values of a dataset using an iterative PCA al-

[16]In unreported results, we have verified that the first finding also holds internationally.

[17]As not every market has available data for the market portfolio since 1973, the weight of the US portfolio in the first years of some equally weighted market portfolios will be 100%.

gorithm. This procedure ensures a balanced panel of anomalies. Definitions of the anomalies that enter the state-vector F_t are in Appendix B.B.

Jointly using US and local equities raises the concern of whether US data subsume information in the local market. To alleviate this potential concern, we show in Appendix B.C that the elements of a state vector constructed uniquely with US data can explain at most two (the first two) elements of the state vector constructed following our empirical choices.

F. Estimation

We relegate details about the estimation to Appendix C and explain the procedure in brief in the following. The model is estimated using GMM. The moment conditions for the fully diversified portfolios come from Eq. 6, 12, and 13. The moment conditions for other portfolios (with returns and yields measured with error) come from Eq. 15 and 16. Our estimated parameters are then the ones that jointly minimize these moment conditions and comply with the parameter restrictions implied by the Euler Equation. The system is overidentified.

GKK also price portfolios "measured with error".[18] In practice, this means that the system will fit the returns r and yields y of 50 long anomalies and 50 short anomalies (i.e., size, value, etc.). Proceeding exactly as in their setting would require us to price 35 long and 35 short anomalies per market, an endeavour that would suppose a tremendous computational cost. Thus, we deviate from their implementation and price a smaller number of portfolios: A local market portfolio (as the state vector F_t does contains an equally weighted portfolio, and we want to ensure that the local market is priced), and both the long and short legs of a size, value, profitability, investment, momentum and "principal component" portfolio. The principal component portfolio is the first principal component of the set of anomalies of a given market. Using a principal component portfolio works well because anomaly portfolios have a strong factor structure.[19]

[18] More formally, they estimate their model so that the moment conditions for equations 16 and 15 hold.

[19] For example, the first principal component of anomalies explains on average ca. 80%. of the cross-

IV. Main Results

A. *Validity Checks*

We first examine the internal and external validity of the model. We stick to the setup we use for international markets in both validity checks. For internal validity, we use the US market and compare our results with GKK. We use the UK, the most liquid non-US contract, for external validity. For the US, the original data come from Serhiy Kozak's website. For the UK, we use our data.

For internal validity, we compare our 1-year forward equity yields (ef_t^1) and their slope ($ef_t^7 - ef_t^1$) to the similar quantities in GKK. Figure 1 shows the results.

[Insert Figure 1 here]

The model-implied yields closely track the movements in the data over the entire sample. Comparing the results for 1-year and 7-year, we match both yields and the difference between them, the slope (the correlation coefficient is 88%).

The model generates a secular decline in equity yields since the late 1980s, followed by an upward trend post-2000, and replicates the forward equity yield spikes during the recession periods in the 1990s and around 2008. In Appendix D, we show that conclusion also holds for both large and small companies and value and growth companies. As a result, using a lower-dimensional set of portfolios has little impact on the results. This is important for smaller equity markets, where we often must choose between how diversified the typical anomaly portfolio is and how many portfolios we can construct.

Regarding external validity, we compare the model-implied forward equity yields for the UK with the yields on the corresponding futures in Figure 3. We present maturities of 2 and 7 to ease the comparison with Figure 3 in Gormsen (2021). The plot shows that the model-implied yields closely track the equity yields based on futures prices in the UK.

sectional return variation of anomalies.

[Insert Figure 3 here]

B. *The stylized facts about model implied forward equity yields*

Table I provides the summary statistics of the forward equity yields from 12 markets. The upper panel reports the results using all stocks. The lower panel is restricted to companies with high market capitalization, mimicking the universes of stocks included in the divided futures. The first seven columns present the forward equity yields covering maturities from 1 to 7 years. The eighth column shows the unconditional slope, which is the difference between the 7 and 1-year forward equity yield.

[Insert Table I here]

The slope is positive across markets and periods. Rows two and three highlight the behavior of equity yields conditional on the economy's state. Following Gormsen (2021), we define "Bad-times" as months in which the dividend price ratio is above its time series median. These periods are market specific.

We find a positive (negative) slope in good (bad) times. These results are similar to Bansal et al. (2021); despite their inference relies on futures prices and other measures of the state of the economy. The last two rows show that our conclusions are unaffected by excluding the US. Therefore, our findings are not liable to the concern by Karolyi (2016) regarding a US bias in academic research in finance. Overall, the results highlight the pivotal role of the state of the economy in understanding time-series variation in forward equity yields. Going forward, we present the results based on all stocks (the market portfolio) and relegate the portfolio analysis to the Appendix.

In Table II, we regress the slope on the "Bad-times" dummy variable with various controls. To set a benchmark, we report the unconditional average, as in Table I, but now with standard errors. The average slope in good (bad) times is 8.2% (-3.7%). These estimates are precise, with standard errors between 0.3-0.4%. In the second column, we control for market-and time-fixed effects, thus focussing exclusively on within-market variation in the slope. The resultant coefficient on the "Bad-times" dummy is -11.4%. The third column shows a similar pattern for the US; albeit with a more modest decline in the slope in bad times. The last two columns show that our general conclusions are unaffected by excluding the countries where dividend futures were available at some point in our sample. In conclusion, the slope is much flatter in crisis periods than in regular periods.

[Insert Table II here]

We repeat the above analysis for portfolios formed on market capitalization and book-to-market in the spirit of Fama and French (1993). All results are in Appendix D.B. To summarize, we find that the slope of the short legs of the Fama and French 3-factor model (i.e., big companies and growth stocks) drops substantially more in bad-times than the long legs (i.e., small companies and value stocks). For example, with the specification with country and time fixed effects, we find a slope coefficient of -8.3% for growth stocks but only -3.6% for value stocks. The difference is statistically significant.[20]

We can decompose the slope into two terms by using Eq. 3. The first term is the risk premium on the longest maturity strip in excess of the 1 year maturity strip, $\theta_t^{(7)} - \theta_t^{(1)}$. The second term is long-term expected dividend growth in excess of short-term dividend growth, $g_t^{(7)} - g_t^{(1)}$. The slope is the first term minus the second term. The decomposition tells whether the flat slope in crisis periods reflects changes in the term-structure of risk premia ($\theta_t^{(n)}$) or growth expectations ($g_t^{(n)}$). Table III presents the results from regressing the slope on these two components.

[Insert Table III here]

The slope flattens in crisis periods because of the differences between expected dividend

[20]The slope coefficient on the "Bad-times" dummy exceeds that of all Fama French portfolios. This is because we get the market series from DataStream while we construct the Fama French portfolios from data available through Comustat Global.

growth in the short and long-term spikes. The wedge between short and long-term expectations mainly reflects a large drop in short-term dividend growth expectations. These results are consistent with the findings of Van Binsbergen et al. (2013) in their analysis of dividend futures for the US (S&P500), JP (Nikkei 225), and the Euro-area (Eurostoxx 50). In Appendix D.B, we show that the dynamics of dividend growth expectations also is the main reason for the flat slope in crisis periods for the Fama and French portfolios.

C. Variation in forward equity yields

In this section, we explain the variation in forward equity yields. We start with the definition of the forward equity yield: $ef_t^{(n)} = \theta_t^{(n)} - g_t^{(n)}$ and decompose its time-series variation into two components: $Var(ef_t^{(n)}) = Cov(ef_t^{(n)}, \theta_t^{(n)}) - Cov(ef_t^{(n)}, g_t^{(n)})$. By normalizing the two components by total variance, we get the fraction of time-series variation in yields due to movement in risk premia ($\theta_t^{(n)}$) and growth expectations ($g_t^{(n)}$). We report the results for the US and all non-US markets together. For the latter, we report the equally-weighted average across markets. The results are in Table IV. Each row represents a maturity-specific variance decomposition.

[Insert Table IV here]

Variation in expected dividend growth explains most of the time-series variation in forward equity yields, both in the US and outside of the US. In both regions, the relative importance of time-series variation in risk premia increase with the maturity of the forward equity yield. The high volatility of dividend growth expectations calls into question the dominant view that most time-series in stock prices are due to changes in discount rates (Campbell, 1991; Cochrane, 2017).

In Table V, we study the comovement in risk premia and dividend growth expectations. In the variance decomposition, a market contains five portfolios, the four long and short portfolios in the Fama and French factor model, and the market portfolio. We then decompose the variance of risk premia and dividend growth expectations into a within-market component and a between-market component.

In the short-run, almost all of the variation in both components comes from variation within a region. This finding provides multiple insights. First, the five portfolios in the Fama-French 3-factor model exhibit substantial variation in risk premia and expected dividend growth. Second, investing in Fama and French portfolios across regions provides limited diversification benefits. In the medium to long-term, the relative importance of variation within- and between regions becomes more balanced. This suggests that short term risk premia and growth expectations are almost perfectly correlated across markets in the short run, and that country-specific effects matter only in the long-run.

D. Term-structure of Global Equity Risk Premium

The term-structure of equity risk premia plays a pivotal role in capital budgeting and as a diagnostic tool for asset pricing theory (Van Binsbergen and Koijen, 2017). We now use Fama MacBeth cross-sectional (Fama and MacBeth, 1973) regressions to estimate the global risk premium for different horizons. Starting in 1995, we run the following regression for each month t:

$$\theta^{(n)}_{j,t} = \gamma^{(n)}_{\theta} 1_M + \epsilon^{(n)}_{\theta,j,t}, \tag{20}$$

where $j = 1, 2, ...M$ index geographical region and 1_M is a vector on ones with length M. For example, when the independent variable is a 1-year risk premium, $\theta^{(1)}_{j,t}$, we can interpret the coefficient $\gamma^{(1)}_{\theta}$ as the discount rate in excess of the one-year risk-free rate on a dividend payment from an equally weighted global equity index. In Figure 4, we plot the risk premia for investment horizons n of 1,7, 15, 25, and the term premium 7-1 years.

[Insert Figure 4 here]

Plot a) of Figure 4 shows that the 1-year risk premium fluctuates around 2.2%, with a 95% confidence level of roughly -5 to 5%. Plot b) shows the corresponding results for the 7-year risk premium. The mean is 5%, almost 3% above the short-term risk premium. The 95% confidence bounds are tighter than for the short-term risk premium; now ranging from roughly +/- 2.5%. We see a gradual decline in the risk premium leading up to the dot-com bubble reaching its lowest point in the sample in 2000. The risk premium quickly reverted to its unconditional mean after the burst of the dot-com bubble. Although we see a somewhat similar pattern for the 2008 financial crisis, it is much less pronounced. Using a VAR, Campbell et al. (2013) come to a similar conclusion after decomposing US stock market returns into a discount rate and a cash flow component.[21]

The lower panels of Figure 4 focus on the term-structure of risk premia. Plot c) shows the 15 and 25-year risk premia. The risk premium on the longest maturity claim is almost always the highest; consistent with the predictions of the habit model (Campbell and Cochrane, 1999) and the long-run risk model (Bansal and Yaron, 2004). In panel d) of Figure 4, we estimate the term-premium, here the 7-year risk premium in excess of the 1-year risk premium. The unconditional mean is 2.7%, and it is almost always positive. Toward the end of the sample, we mostly reject the null hypothesis that the term premium is zero.

V. Additional Analysis

In this section, we first examine the relationship between forward equity yields and exchange rates. Second, we test whether the risk premia and dividend growth expectations are useful in forecasting macroeconomic outcomes.

A. *Exchange Rates, Risk Premia, and Growth Expectations*

Recent theoretical and empirical work motivates the analysis. On the theory side, Gabaix and Maggiori (2015) develop a theory of exchange rate determination based on capital flows in imperfect financial markets. The central idea is that shifts in the demand and supply of

[21] They find that the stock market collapse in the early 2000s mainly reflected increases in discount rates, while in the drop in the late 2000s was also driven by a revision in investors' expectations of future cash-flows.

assets result in large-scale capital flows fed through the global financial system, which affects exchange rates. On the empirical side, Hau et al. (2009) show that countries experiencing plausibly exogenous capital flows, due to changes in the weights of the MSCI World Equity Index, saw their currencies appreciate.

To establish the hypothesis, let $S_{i,t}$ denote the exchange rate, that is, the number of units of local currency i per US dollar at time t. Let $q \in \{1, 3, 6, 12\}$ denote frequency. For example, with monthly data, we have $q = 1$ with the previous month denoted by q_{-1}. The outcome variable of interest is $\Delta S_{i,t,q} = S_{i,t}/S_{i,t,q_{-1}} - 1$. A positive value indicates depreciation of the local currency i with respect to the US dollar. Define $g^{(n)}_{US,t,q_{-1}}$ as the expected dividend growth for the US equity market and let $g^{(n)}_{i,t,q_{-1}}$ be the corresponding expected dividend growth for market i. Similarly, let the risk premium for the US equity market and market i be $\theta^{(n)}_{US,t,q_{-1}}$ and $\theta^{(n)}_{i,t,q_{-1}}$. We use these variables to construct two variables potentially informative about capital flows and changes in exchange rates. The first is the wedge in expected dividend growth, $\left(g^{(n)}_{US,t,q_{-1}} - g^{(n)}_{i,t,q_{-1}}\right)$, and the second is the wedge in risk premium, $\left(\theta^{(n)}_{US,t,q_{-1}} - \theta^{(n)}_{i,t,q_{-1}}\right)$. Adding up, we run regressions of the following type:

$$\Delta S_{i,t,q} = a_i + \beta_t + b^{g(n)}_q \left(g^{(n)}_{US,t,q_{-1}} - g^{(n)}_{i,t,q_{-1}}\right) + b^{\theta(n)}_q \left(\theta^{(n)}_{US,t,q_{-1}} - \theta^{(n)}_{i,t,q_{-1}}\right) + \varepsilon_{i,t,q}, \tag{21}$$

where a_i is a country specific intercept and β_t is calendar time-fixed effects.

Motivated by the theory and empirics introduced above, we hypothesize that when expected dividend growth in market i exceeds that of the US, capital will flow into market i, which increases demand for the local currency i, which appreciates. As a result, we expect $b^{g(n)}_q$ to be negative. A similar mechanism could be at play for risk premia, but the sign of the relationship is less straightforward.

Table VI presents the results for monthly changes in exchange rates. Each column represents a maturity n, ranging from 1 year to 15 years.

[Insert Table VI here]

The coefficients in the first row show that when expected dividend growth in country i is higher than in the US, the country's currency appreciates. The coefficients are statistically insignificant for short to medium-term growth expectations, but statistically significant for 10 and 15 years growth expectations. In regard to risk premia, the coefficients are positive, and as with the growth expectations, increasing in significance with maturity. As opposed to growth expectations, when the risk premium in a country i is higher than in the US, the country's currency depreciates.

B. *Forward equity yields as Leading Indicators*

We now test whether the risk premia and dividend growth expectations are useful in forecasting macroeconomic outcomes. Given that we have data on markets whose macroeconomic conditions and equity yields differ, we gain substantial power in decoupling the role of risk premia from growth expectations as leading indicators of the macroeconomy. Our macroeconomic variables are consumption growth, unemployment changes, and industrial production growth. We choose these variables because they have homogenous definitions across markets and have either a long tradition in macro-finance (see, e.g., Hansen and Singleton, 1982; Chen et al., 1986), or have recently been linked to the theoretical literature on the term-structure of the equity premium (see Hall, 2017). The forecasting regression is a dynamic model with market-specific intercepts given by:

$$y_{i,t,q} = a_i + b_q^{g(n)} g_{t,q-1}^{(n)} + b_q^{\theta(n)} \theta_{t,q-1}^{(n)} + \rho_{i,q} y_{i,t,q-1} + \epsilon_{i,t,q}, \tag{22}$$

where t denotes calendar time, $q = \{3, 6, 12\}$ is the frequency, and $y_{i,q}$ the outcome variable. The outcome variables are defined as follows. First, consumption growth over q-months is: $g_{i,t,q}^C = C_{i,t,q}/C_{i,t,q-1} - 1$, where C_t is the level of consumption at time t. Second, changes in the unemployment rate is: $\Delta U_{i,t,q} = U_{i,t,q} - U_{i,t,q-1}$, where U_t is the unemployment rate at time t. Third, growth in industrial production is: $g_{i,t,q}^{IP} = IP_{i,t}/IP_{i,t,q-1} - 1$, where IP_t is industrial production at time t.

Table VII presents the results from the estimation based on long-term risk premia and dividend growth expectations.[22]

[Insert Table VII here]

Dividend growth expectations have significant predictive power on all macro outcomes. The role of risk premia is statistically weak. A few examples are helpful for understanding the economic magnitudes. The numbers refer to US data. First, higher expected growth $g_{i,q-1}^{(7)}$ predicts higher consumption growth $g_{i,q}^{C}$. A one standard deviation increase in expected dividend growth (2.9%) predicts an increase in consumption growth of roughly 10 basis points ($2.9\% \times 3.2\% \approx 0.1\%$). The coefficient in front of expected dividend growth increases with the forecast horizon. For example, at the 12 months horizon, the same shock predicts an increase in consumption growth of roughly twice the size of the 3 months horizon. Second, higher expected dividend growth predicts a lower unemployment rate. A one standard deviation increase in expected dividend growth predicts a drop in the unemployment rate over the next 12 months of 7 basis points. Third, higher expected growth predicts higher industrial production growth. A one standard deviation increase in expected dividend growth predicts roughly a 60 basis points increase in industrial production over the next 12 months.

An income effect can explain the positive association between expected dividend growth and consumption growth. When investors expect dividends to be high in the future, their demand today increases due to consumption smoothing. As a result, expected dividend growth predicts consumption growth. The positive association between expected dividend growth and future growth in industrial production can have a similar explanation, albeit more direct as the equity market is related to changes in industrial activity in the long run. If investors and managers have similar expectations, expected long-term dividend growth

[22] The corresponding results for short term risk premia and dividend growth expectations are in Appendix D.C. They are qualitatively similar but with smaller coefficients in absolute value and are generally less statistically significant.

should predict industrial production growth.

The association between expected dividend growth and fluctuations in employment is negative. This is intuitive—again, if investors and managers have a similar view on the future—as we expect companies to scale down on employment in periods with low expected long-term growth.

The association, or lack of it, between long-term risk premia and unemployment, is somewhat puzzling. The central idea in Hall (2017) is that unemployment is high when risk premia are high; as a higher cost of capital implies a lower present value of the benefit of a new hire to an employer. While the third column under unemployment in Table VII is in line with Hull's hypothesis, the standard errors of the coefficient are too large to reject the null of no relationship between current risk premia and changes in unemployment.

To sum up, we extend the analysis of Van Binsbergen et al. (2013). which are the first to show the usefulness of equity yields in macroeconomic forecasting, along several dimensions. First, we use model-implied yields rather than equity yields backed out from dividend futures. This is a step forward as model-implied yields can, in principle, be constructed for any equity market with a reasonably large cross-section of stocks. Second, we show the relevance of equity yields for predicting not only consumption growth but also changes in unemployment rates and growth in industrial production. Third, the size of our panel allows us to restrict the variation we use to identify the associations between the components of forward equity yields and future macroeconomic outcomes to within-country variation.

VI. Conclusion

We use a modified version of the model developed by Giglio et al. (2021) to construct a panel of global equity yields. We test the model outside the US by comparing the model-implied forward equity yield for the UK, the most liquid non-US contract, with the equity yield based on the FTSE 100 Dividend Index Futures. We closely match both the levels of yields and the slope (long-term minus short-term yields). We use our newly built panel of equity yields from 12 markets to revisit a set of stylized facts about equity yields, primarily based on US data, and to provide several new ones.

Across all markets and periods, the average forward equity yield is negative in regular periods and positive or flat in crisis periods. We decompose its slope into two terms by the definition of forward equity yield. The first term is the risk premium on the longest maturity strip above the 1-year maturity strip. The second term is the expected long-term dividend growth above short-term dividend growth. The slope is the first term minus the second term. We find that the main reason for the flatter slope in crisis periods is a large drop in short-term expected dividend growth. Our estimates are precise and robust to include country and calendar time fixed effects.

We decompose the variance of forward equity yields. Regarding time-series variation, most of the variation, both in the US and outside the US, comes from changes in dividend growth expectations, especially at short maturities, contradictory to the dominant view that most time-series in stock prices are due to changes in discount rates (Campbell, 1991; Cochrane, 2017). Regarding cross-sectional variation, markets appear highly connected in the short run. In the long run, country-specific effects matter more.

We use Fama MacBeth cross-sectional (Fama and MacBeth, 1973) regressions to estimate the global risk premium for different horizons. Our estimates are remarkably precise, with standard errors equal to 20-50% of the unconditional mean. For example, the mean 7-year risk premium estimate is 5% with a 95% confidence interval of roughly +/- 2.5%. We use the same method to estimate the term premium, defined as the 7-years risk premium in excess of the 1-year risk premium. Since 1995, the start of our sample, the term-premium is almost always positive. Since 2010, we mostly reject the null hypothesis that the global term premium is zero. Taken together, our findings regarding the global risk premium align well with leading asset pricing models (Campbell and Cochrane, 1999; Bansal and Yaron, 2004). Our estimates of the term-structure of risk premia have implications for investors and theorists. For investors, knowing the maturity-specific discount rate is useful for valuation. For theorists, these estimates work as diagnostic tools for assessing asset pricing theories.

We link forward equity yields to changes in exchange rates. Motivated by the theoretical work by Gabaix and Maggiori (2015), we predict changes in local currencies relative to the US dollar with risk premium and dividend growth expectations in the US in excess of non-US countries. The idea is that when expected dividend growth in market i exceeds that of the US, capital will flow into market i, which increases demand for the local currency i, which then appreciates. Our results line up with their prediction.

Given that we have data on markets whose macroeconomic conditions and equity yields differ, we gain substantial power in decoupling the role of risk premia from growth expectations as leading indicators of the macroeconomy. As a result, we test whether the risk premia and dividend growth expectations forecast macroeconomic outcomes. Our results suggest a pivotal role for dividend growth expectations in predicting consumption growth, unemployment changes, and industrial production growth.

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Tables

Table I
Global Forward Equity Yields ($ef_{t,n}$)

This table reports the average forward equity yields for 12 markets and the US, conditional on the state of the economy. "Bad times" is based on Gormsen (2021) and refers to periods in which the dividend price ratio is above the time series median. "Good Times" refers to the complement. The unconditional mean contains all periods.

	Market Portfolio								
Economic state	1	2	3	4	5	5-1	6	7	7-1
Unconditional	-6.03	-5.50	-4.95	-4.49	-4.10	1.93	-3.78	-3.54	2.49
Good Times	-14.35	-11.44	-9.69	-8.43	-7.47	6.89	-6.72	-6.14	8.21
Bad Times	3.01	0.96	0.18	-0.21	-0.44	-3.45	-0.59	-0.71	-3.71
Good Times ex-US	-12.65	-9.90	-8.29	-7.14	-6.26	6.39	-5.59	-5.08	7.57
Bad Times ex-US	4.24	1.65	0.77	0.35	0.12	-4.12	-0.02	-0.11	-4.35

	Large Stocks								
Economic state	1	2	3	4	5	5-1	6	7	7-1
Unconditional	-4.53	-4.22	-3.91	-3.62	-3.37	1.16	-3.16	-3.00	1.53
Good Times	-11.79	-9.30	-7.86	-6.87	-6.12	5.67	-5.56	-5.12	6.67
Bad Times	3.34	1.29	0.37	-0.10	-0.38	-3.73	-0.57	-0.69	-4.04
Good Times ex-US	-9.75	-7.70	-6.53	-5.69	-5.05	4.69	-4.57	-4.20	5.55
Bad Times ex-US	4.27	1.88	0.91	0.43	0.16	-4.11	-0.00	-0.11	-4.38

Table II
Panel Regression: Forward Equity Yields (Market)

This table reports the results from regressing the slope of the equity forward equity yields ($ef_t^7 - ef_t^1$) on the dummy variable "Bad times". It takes the value of one for the months the dividend price ratio is above the time series median and is market specific. Statistical significance is indicated by ***, **, and * for the 0.01, 0.05, and 0.10 levels. Standard errors are based on the Robust Covariance Matrix Estimator developed by Driscoll and Kraay (1998).

	Forward Equity Yield Slope: $ef_t^7 - ef_t^1$				
Bad Times	-0.119^{***}	-0.114^{***}	-0.050^{***}	-0.122^{***}	-0.122^{***}
	(0.004)	(0.005)	(0.004)	(0.005)	(0.007)
Constant	0.082^{***}		0.040^{***}		
	(0.003)		(0.003)		
Markets:	All	All	US	All ex-US	All
Excluded Markets:	Non	Non	Non-US	US	US, UK, FR
Market fixed effects:	No	Yes	No	Yes	Yes
Time fixed effects:	No	Yes	No	Yes	Yes
Observations	3,394	3,394	532	2,862	2,237
R^2	0.202	0.157	0.188	0.171	0.145

Table III
Decomposition of the equity forward equity yield (Market)

The table presents the results from regressing the slope of the equity forward equity yield ($ef_t^7 - ef_t^1$) as well as its two terms on the dummy variable "Bad times". The first term is the risk premium on the 7-years maturity strip in excess of the 1 year maturity strip, $\theta_t^{(7)} - \theta_t^{(1)}$. The second term is long-term expected dividend growth in excess of short-term dividend growth, $g_t^{(7)} - g_t^{(1)}$. The "Bad-times" dummy variable takes the value of one for the months the dividend price ratio is above the time series median and is market specific. Statistical significance is indicated by ***, **, and * for the 0.01, 0.05, and 0.10 levels. Standard errors are based on the Robust Covariance Matrix Estimator developed by Driscoll and Kraay (1998).

Dependent variable	$ef_t^7 - ef_t^1$	$\theta_t^7 - \theta_t^1$	$g_t^7 - g_t^1$
Bad-times	-0.114^{***}	-0.002	0.112^{***}
	(0.009)	(0.004)	(0.009)
Market fixed effects:	Yes	Yes	Yes
Calendar time fixed effects:	Yes	Yes	Yes
Observations	3,394	3,394	3,394
R^2	0.157	0.0002	0.154

Table IV
Time-series Variation in Forward Equity Yields

This table reports the average (across markets) variance decomposition of forward equity yields ($ef_t^{(n)}$). By definition, the forward equity yield equals the sum expected dividend growth rates ($g_t^{(n)}$) and a risk premium ($\theta_t^{(n)}$). As a result, $Var(ef_t^{(n)}) = Cov(ef_t^{(n)}, \theta_t^{(n)}) - Cov(ef_t^{(n)}, g_t^{(n)})$.

	US Market		Outside US	
Maturity (n)	$\frac{Cov(ef_t^{(n)},\theta_t^{(n)})}{Var(ef_t^{(n)})}$	$-\frac{Cov(ef_t^{(n)},g_t^{(n)})}{Var(ef_t^{(n)})}$	$\frac{Cov(ef_t^{(n)},\theta_t^{(n)})}{Var(ef_t^{(n)})}$	$-\frac{Cov(ef_t^{(n)},g_t^{(n)})}{Var(ef_t^{(n)})}$
1-Year	0.31	0.69	0.05	0.95
2-Years	0.39	0.61	0.08	0.92
3-Years	0.43	0.57	0.10	0.90
4-Years	0.43	0.57	0.12	0.88
5-Years	0.43	0.57	0.14	0.86
6-Years	0.42	0.58	0.15	0.85
7-Years	0.41	0.59	0.16	0.84

Table V
Variance Decomposition

This table presents the results from decomposing the variation in risk Premium ($\theta_t^{(n)}$) and dividend growth expectations ($g_t^{(n)}$) into a within-market component and a between-market component. A market consists of a market portfolio and four portfolios formed based on a firm's size (small and big) and book-to-market ratio (value and growth).

	Risk Premium ($\theta_t^{(n)}$)		Growth Expectations ($g_t^{(n)}$)	
Maturity (n)	Between Variation	Within Variation	Between Variation	Within Variation
1-Year	0.10	0.90	0.04	0.96
2-Years	0.12	0.88	0.05	0.95
3-Years	0.19	0.81	0.08	0.92
4-Years	0.23	0.77	0.10	0.90
5-Years	0.27	0.73	0.12	0.88
6-Years	0.30	0.70	0.14	0.86
7-Years	0.33	0.67	0.16	0.84

Table VI
Panel Regression: Predicting FX 1-months returns (Market)

This table presents the results from regressing changes in the exchange on lagged values of risk premia and expected dividend growth in the US in excess of the local market i. The dependent variable is $\Delta S_{i,t,q} = S_{i,t}/S_{i,t,q-1} - 1$, where $S_{i,t}$, denote the exchange rate (i.e., the number of units of local currency i per US dollar) and $q = 1$ stands for monthly frequency. A positive value ($\Delta S_{i,t,q} > 0$) implies a depreciation of the local currency i with respect to the US dollar. The independent variables are the wedge in expected dividend growth, $\left(g^{(n)}_{US,t,q-1} - g^{(n)}_{i,t,q-1}\right)$, and the wedge in risk premium, $\left(\theta^{(n)}_{US,t,q-1} - \theta^{(n)}_{i,t,q-1}\right)$. The components are: $g^{(n)}_{US,t,q-1}$, which is the expected dividend growth for the US equity market, $g^{(n)}_{i,t,q-1}$, which is the corresponding expected dividend growth for market i, $\theta^{(n)}_{US,t,q-1}$, which is the risk premium for the US equity market, and $\theta^{(n)}_{i,t,q-1}$. which is the risk premium for market i. All regressions include market- and calendar-time fixed effects. Statistical significance is indicated by ***, **, and * for the 0.01, 0.05, and 0.10 levels. Standard errors are based on the Robust Covariance Matrix Estimator developed by Driscoll and Kraay (1998).

	Dependent variable: $\Delta S_{i,t,q}$				
Maturity (n)	$n = 1$	$n = 5$	$n = 7$	$n = 10$	$n = 15$
$g^{(n)}_{US,t,q-1} - g^{(n)}_{i,t,q-1}$	-0.005	-0.017	-0.029	-0.051^{*}	-0.076^{**}
	(0.004)	(0.016)	(0.020)	(0.027)	(0.036)
$\theta^{(n)}_{US,t,q-1} - \theta^{(n)}_{i,t,q-1}$	0.018	0.067^{*}	0.085^{*}	0.122^{**}	0.157^{**}
	(0.013)	(0.040)	(0.045)	(0.055)	(0.064)
Market fixed effects:	Yes	Yes	Yes	Yes	Yes
Calendar time fixed effects:	Yes	Yes	Yes	Yes	Yes
Observations	2,851	2,851	2,851	2,851	2,851
R^2	0.002	0.002	0.003	0.003	0.004

Table VII
Predicting Macroeconomic Variables (Market)

The table presents the results from predicting macroeconomic outcomes observed at time q with short-term risk premia ($\theta^{(7)}_{q-1}$) and growth expectations ($g^{(7)}_{q-1}$). All specifications include the lagged value of the variable we predict. The macroeconomic outcomes include 1) consumption growth, $g^c_{i,q} := C_{i,t}/C_{i,t-q} - 1$, where C_t is consumption at time t, 2) changes in unemployment rate, $\Delta U_{i,q} = U_{i,t} - U_{i,t-q}$, where U_t is the unemployment rate at time t, and 3) growth in industrial production, $g^{IP}_{i,q} := IP_{i,t}/IP_{i,t-q} - 1$, where IP_t is industrial production at time t. All regressions include market-fixed effects. N denotes number of observations. Statistical significance is indicated by ***, **, and * for the 0.01, 0.05, and 0.10 levels. Standard errors are based on the Robust Covariance Matrix Estimator developed by Driscoll and Kraay (1998).

Horizon	Consumption ($g^c_{i,q}$)			Unemployment ($\Delta U_{i,q}$)			Industrial Production ($g^{IP}_{i,q}$)		
(months)	$q=3$	$q=6$	$q=12$	$q=3$	$q=6$	$q=12$	$q=3$	$q=6$	$q=12$
$g^{(7)}_{i,q-1}$	0.032***	0.046**	0.070*	−0.007**	−0.010**	−0.024**	0.100***	0.118***	0.201***
	(0.009)	(0.017)	(0.030)	(0.002)	(0.003)	(0.008)	(0.017)	(0.015)	(0.028)
$\theta^{(7)}_{i,q-1}$	−0.022	−0.029	−0.041	0.008	0.004	−0.014	−0.062	−0.046	−0.033
	(0.018)	(0.036)	(0.082)	(0.006)	(0.011)	(0.023)	(0.038)	(0.064)	(0.163)
$y_{i,q-1}$	−0.063	0.102	0.105	0.314*	0.423***	0.231**	0.052	0.115**	−0.095
	(0.111)	(0.129)	(0.098)	(0.146)	(0.067)	(0.068)	(0.086)	(0.048)	(0.054)
N	709	703	693	1,941	1,938	1,932	2,125	2,119	2,104
R^2	0.190	0.328	0.426	0.123	0.204	0.079	0.048	0.060	0.055

Figures

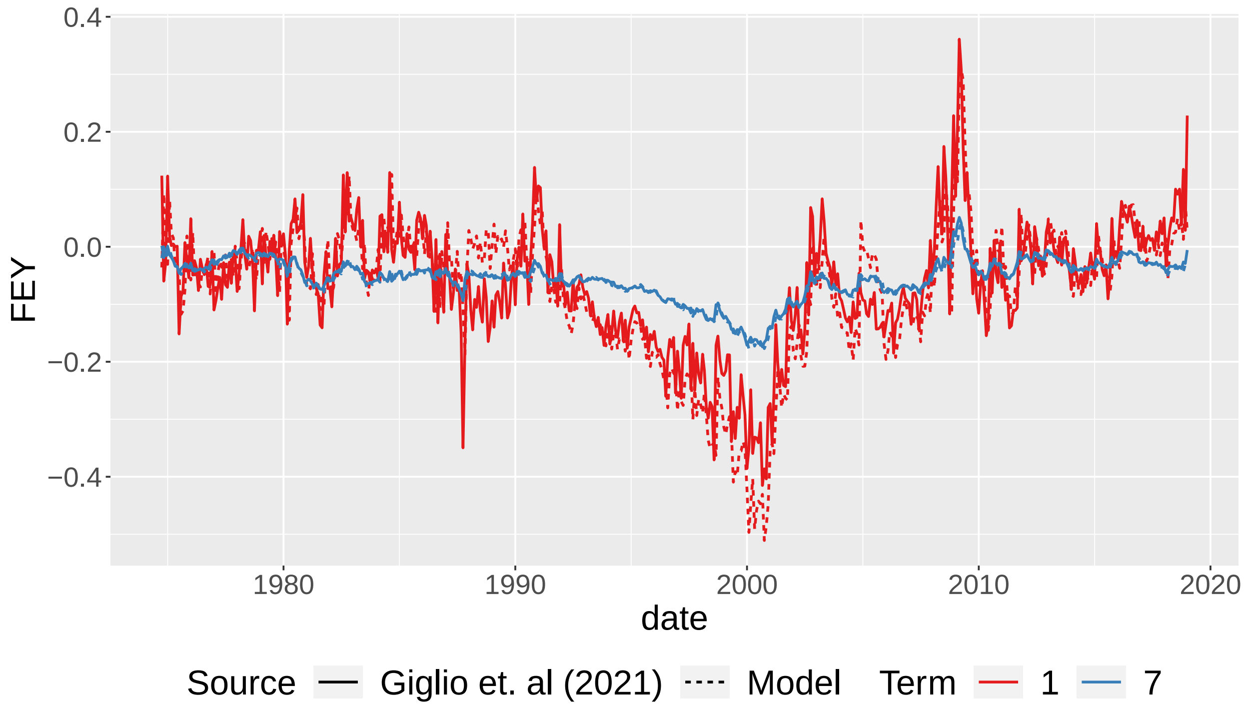


Figure 1 US Forward Equity Yield (ef_t^n). The figure compares forward equity yields from Giglio et al. (2021) against forward equity yields derived form our model specification - estimation (dotted line).

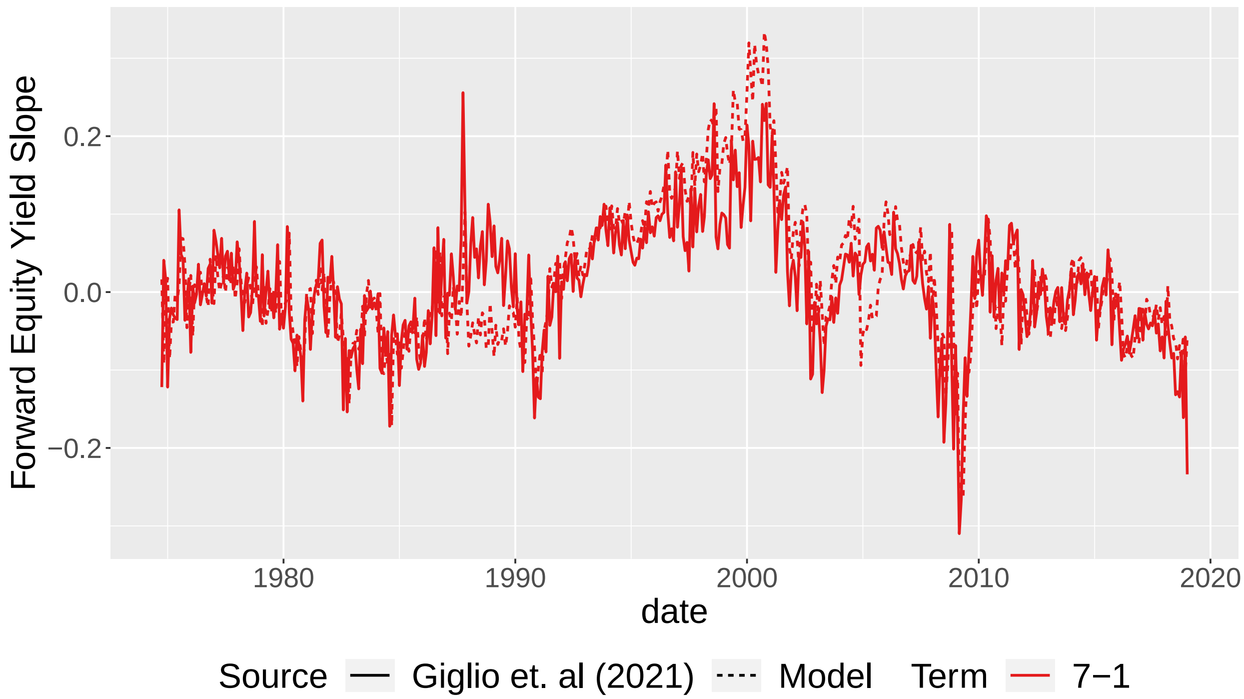


Figure 2 US Forward Equity Yield Slope ($ef_t^7 - ef_t^1$). The figure compares forward equity yields from Giglio et al. (2021) against forward equity yields derived from our model specification - estimation (dotted line).

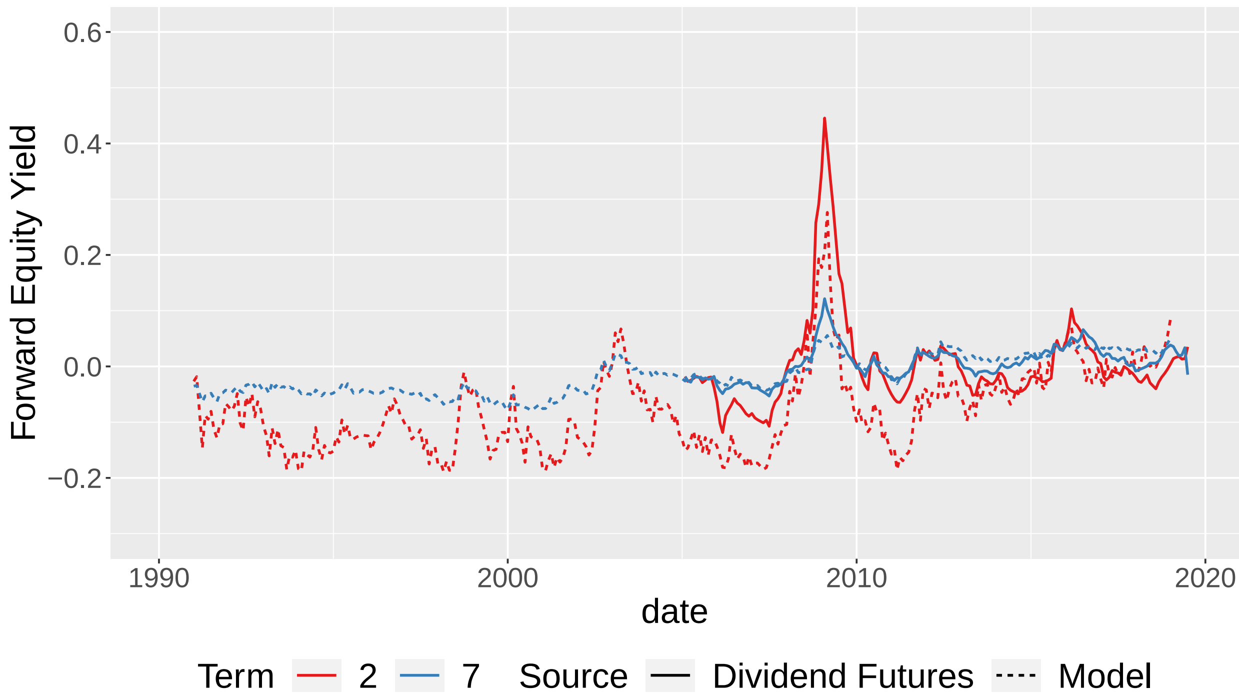
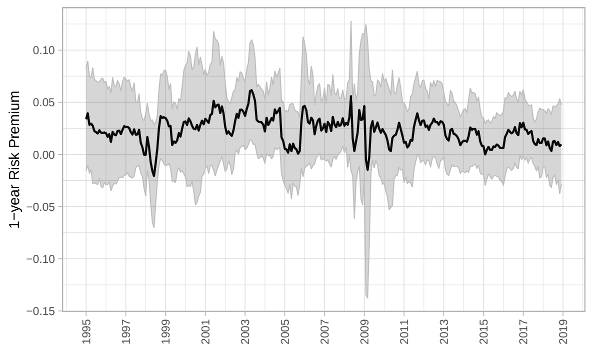
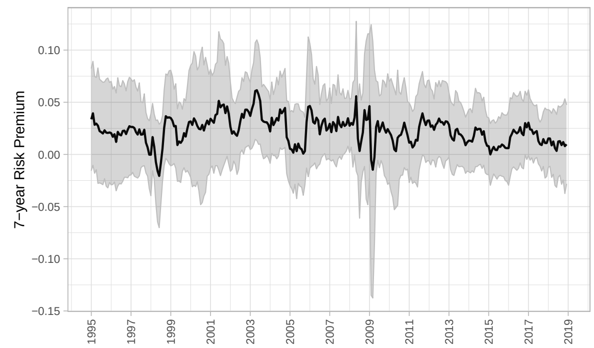


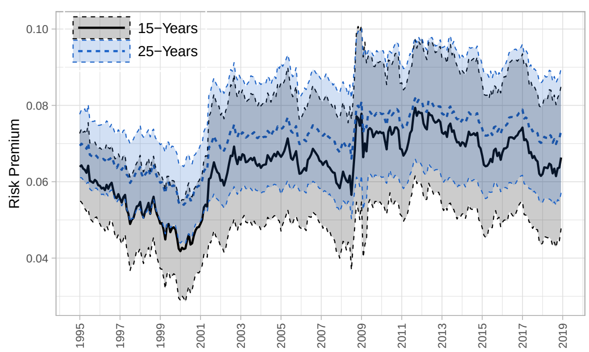
Figure 3 UK Forward Equity Yield (ef_t^n). The figure compares forward equity yields from the data (solid line) against forward equity yields derived from the model (dotted line).



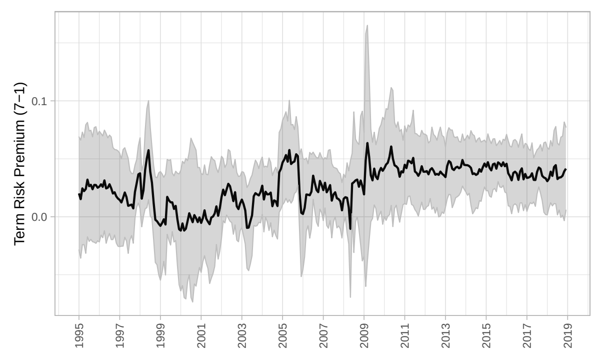
(a) 1-year Risk Premium ($\gamma_\theta^{(1)}$)



(b) 7-year Risk Premium ($\gamma_\theta^{(7)}$)



(c) Long-term Risk Premia ($\gamma_\theta^{(15)}, \gamma_\theta^{(25)}$)



(d) Term-premium ($\gamma_\theta^{(7)} - \gamma_\theta^{(1)}$)

Figure 4 Global Risk Premium. This figure plots the estimated equity risk premium for different investment horizons for a global market portfolio consisting of 12 Markets. The solid line shows the point estimate, and the shaded area shows the confidence interval based on +/- 2 standard deviations. Standard errors are based on 1000 bootstrap replications for each month.

Appendices

Appendix A. Data

Appendix A. Appendix to the section "Equities".

In the following, we define all the characteristics we use. We use the lag operator (L) to denote lagged values (e.g., $X_{t-1} = L(X_t)$) and Δ to denote first differences (e.g., $\Delta X_t = X_t - X_{t-1}$). We only use annual accounting data and rebalance all portfolios annually or monthly. We refer to the definitions in Kozak for additional details.[23]

Size (size). End-of-June price times shares outstanding. Rebalanced annually.

Value (value). Book equity from the previous year scaled by market equity from December of the previous year. Book equity is calculated following Fama and French (1993). Rebalanced annually.

Gross Profitability (prof). (REVT-COGS)/(AT), where REVT is the total revenue, and COGS is the cost of goods sold. Rebalanced annually.[24]

Accruals (accruals). accruals = (ΔACT -ΔCHE - ΔLCT + ΔDLC + ΔTXP - ΔDP)/($\frac{1}{2}$ (AT + L(AT)), where ΔACT is the annual change in total current assets, ΔCHE is the annual change in total cash and short-term investments, ΔLCT is the annual change in current liabilities, ΔDLC is the annual change in debt in current liabilities, ΔTXP is the annual change in income taxes payable, ΔDP is the annual change in depreciation and amortization, and ($\frac{1}{2}$ (AT + L(AT)) is average total assets over the last two years. Rebalanced annually.

Asset Turnover (aturnover). aturnover = SALE/AT. Sales to total assets. Rebalanced annually.

Earnings/Price (ep). ep = IB/MEDec. Net income scaled by market value of equity at the end of December. Rebalanced annually.

[23] https://sites.google.com/site/serhiykozak/data

[24] The standard definition based on US data is: prof = GP/AT, where GP is gross profit, and AT is total assets.

Net Operating Assets (noa). We do not adjust for non-controlling interest (MIB) as is common with US data because this variable is rarely available in the international dataset. Therefore, noa = ((AT - CHE) - (AT - DLC - DLTT PSTK - CEQ)) / L(AT), where AT is total assets, CHE is cash and short-term investments, DLC is debt in current liabilities, DLTT is long-term debt, PSTK is preferred capital stock, and CEQ is common equity. Updated annually.

Investment (inv). inv = (ΔPPEGT + ΔINVT)/L(AT) where ΔPPEGT is the annual change in gross total property, plant and equipment, Δ INVT is the annual change in total inventories, and L(AT) is lagged total assets. Rebalanced annually.

Investment-to-Capital (invcap). invcap = CAPX/PPENT is the ratio of capital expenditure to property, plant, and equipment. Rebalanced annually.

Investment Growth (igrowth). growth = CAPX/L(CAPX), where CAPX denotes capital expenditures. Rebalanced annually.

Sales Growth (sgrowth). sgrowth = SALE/L(SALE). Rebalanced annually.

Leverage (lev). lev = AT/MEDec. Market leverage is the ratio of total assets (AT) to the market value of equity at the end of December. Rebalanced annually.

Return on Assets (annual) (roaa). roaa = IB/AT, which is net income scaled by total assets. Rebalanced annually.

Return on Equity (annual) (roea). roea = IB/BE, which is the net income scaled by the book value of the equity. Rebalanced annually.

Growth in LTNOA (gltnoa). gltnoa = GRNOA - ACC, where ACC=((RECT - L(RECT)) + (INVT - L(INVT)) + (ACO - L(ACO)) - (AP - L(AP)) - (LCO - L(LCO)) - DP) / ((AT + L(AT)/2), where RECT = Receivables, INVT denotes total inventory, ACO stands for current assets, AP is accounts payable, LCO means current liabilities (Other), DP denotes depreciation and amortization, AT is total assets, PPENT is net property, plant and equipment, INTAN measures intangible assets, AO refers to assets (Other) and LO refers to liabilities (Other). GRNOA = ΔNOA, where NOA = (RECT + INVT + ACO + PPENT

+ INTAN + AO - AP - LCO - LO) / AT. Rebalanced annually.

Momentum (6m) (mom). mom = $\sum_{l=2}^{7}(1 + r_{t-l})$, which is the cumulative performance in the previous 6 months by missing the most recent month. Rebalanced monthly.

Industry Momentum (indmom). indmom = $rank(\sum_{l=1}^{6}(1 + r_{t-l}^{ind}))$ We deviate from the standard definition, which uses the Fama and French 49 industries, and use only the 12 Fama and French industries. The reason is to make sure that the industry portfolios are well diversified in all markets. Rebalanced monthly.

Value-Momentum. valmom = rank(value) + rank(mom). value and mom are defined earlier. Rebalanced monthly.

Value-Momentum-Profitability (valmomprof). valmomprof = rank(value) + rank(prof) + rank(mom). value, mom, and prof are defined earlier. Rebalanced monthly.

Momentum (mom12). mom12 = $\sum_{l=2}^{1} 2(1 + r_{t-l})$ Cumulative performance in the previous year by skipping the most recent month. Rebalanced monthly.

Momentum-Reversal (momrev). momrev =$\sum_{l=14}^{19}(1+r_{t-l})$ Buy and hold returns from $t - 19$ to $t - 14$. Rebalanced monthly.

Short-term Reversal (strev). strev = r_{t-1}, which is the return in the previous month. Rebalanced monthly.

Idiosyncratic Volatility (ivol). ivol = $std(r_{i,t} - \beta_i r_{m,t} - s_i SMB_t - h_i HML_t)$. It is the standard deviation of the residual from a stock-level regression of daily stock returns on the Fama and French three-factor model using an estimation window of three months. The factors are country-specific and constructed following Fama and French. Before running the regressions, we winsorize the daily returns at the 98% level. The ivol characteristic is lagged one month. Rebalanced monthly.

Beta Arbitrage (betaarb). beta = $\beta_{t-60:t-1}$ with respect to a country-specific equal-weighted return index. Estimated over the past 60 months (minimum 36 months) using daily data. Before running the regressions, we winsorize the daily returns at the 98% level. The beta characteristic is lagged one month. Rebalanced monthly.

Industry Relative Reversals (indrrev). indrrev = $r_{i,t} - r_t^{ind}$. It is the the return on a stock in excess of the return on its industry. We deviate from the standard definition, which uses the Fama and French 49 industries, and use only the 12 Fama and French industries. The reason is to ensure that the industry portfolios are well diversified in all markets. Rebalanced monthly.

Price (price). price = ln(ME/shrout), where ME is market equity and shrout is the number of outstanding shares. Rebalanced monthly.

Share Volume (shvol). Here, we deviate slightly from the standard definition. We use the average number of shares traded during the previous three months, scaled by outstanding shares. In calculating the average over the three months, we only include months with non-zero volume. If all months have zero volume, we assign a zero value to shvol. Rebalanced monthly.

Cash Flow-to-Price (cfp). cfp = (IB + DP) / MEDec, which is net income plus depreciation and amortization, scaled by the market value of equity measured at the same date. Rebalanced monthly.

Industry Momentum-Reversal (indmomrev). indmomrev = $rank$(industry momentum) + $rank$(industry relative-reversals low-vol). Sum of Fama and French 49 industries ranks on industry momentum and industry relative reversals (low vol). Rebalanced monthly.

Industry Relative Reversals (indrrevlv). indrrevlv = $r_1 - r_{-1}^{ind}$ if ivol of the firm is smaller than the median ivol in the cross-section. Thus, only stocks with idiosyncratic volatility lower than the median for the month are included in the sorts. $r_1 - r_{-1}^{ind}$ measures the difference between a stock's prior month's return and the prior month's return of its industry (based on the Fama and French 49 industries). Rebalanced monthly.

Value-Profitability (valprof). valprof = $rank$(value) + $rank$(prof). Sum of ranks in univariate sorts on book-to-market and profitability. Annual book-to-market and profitability values are used throughout the year. Rebalanced monthly.

Long-term Reversals (lrrev). $lrrev = \sum_{l=13}^{60} r_{t-l}$. Cumulative returns from $t60$ to $t13$.

Rebalanced monthly.

Seasonality (season). $season = \sum_{l=1}^{5} r_{t-l\times 12}$ Average monthly return in the same calendar month over the last 5 years.

Value (monthly) (valuem). valuem = BE/L(ME). Book-to-market ratio using the prices from the previous month. Rebalanced monthly.

Sales-to-Price (sp). sp = Sale/MEDec. Total revenues divided by market value of equity at the end of December. Rebalanced annually.

Appendix B. Appendix to the section "Interest Rates".

Table VIII shows the starting dates for our sample of local bond yields per maturity per market. The last column shows the initial date from which we have a complete local bond yield term-structure.

Table VIII
Bond Yields: Starting dates before and after interpolation

The table presents the sample of interest rates before and after interpolation.

	Before Interpolation													After
Market	12m	24m	36m	48m	60m	72m	84m	96m	108m	120m	180m	240m	360m	Interpolation
Austria	Jan/89	Jan/89	Jan/89	May/02	Jan/89	May/02	Jan/89	May/02	May/02	Jan/89	Feb/12		Aug/97	Jan/89
Australia	Sep/90	Jun/72	Jun/72	Mar/05	Jun/72	Mar/05	Mar/87	Mar/05	Mar/05	Jun/72	Jun/72			Jun/72
Switzerland	Jan/88	Jan/88	Jan/88	May/02	Jan/88	May/02	Jan/88	May/02	May/02	Jan/88	Apr/11	Jan/88	Jan/98	Jan/88
Germany	Jun/72	Jun/72	Jun/72	Jun/72	Jun/72	Jun/72	Jun/72	Jun/72	Jun/72	Jun/72		Dec/93	Jun/88	Jun/72
France	Jan/84	Mar/85	Jan/78	May/02	Jan/84	May/02	Jan/85	May/02	May/02	Jun/72	Jul/92	Jan/99	Feb/89	Jan/84
United Kingdom	Jan/79	Jan/79	Jun/72	Aug/08	Jun/72	Aug/08	Jan/80	Aug/08	Aug/08	Jun/72	Jan/80	Jun/72	Jan/80	Jun/72
Hong Kong	Jan/08	Nov/91	Oct/93	Feb/12	Sep/94		Nov/95			Oct/96	Aug/07			Nov/95
India	Jan/93	Sep/11	Feb/12	Feb/12	Nov/94	Feb/12	Feb/12	Feb/12	Feb/12	Jun/72	Feb/12		Feb/12	Sep/11
Malasya	Jun/72		Jan/92		Jan/92					Jun/72		Jan/92		Jan/92
Sweden	Jul/82	Jan/87	Jan/84	May/02	Jan/84	May/02	Jan/87			Jun/72	May/93	Oct/10	Mar/09	Jan/84
South Africa			Jun/72							Jun/72	Sep/00	Jan/86	Sep/00	Sep/00

We estimate local one-year risk-free rates back to 1973 via regressions with US yields and exchange rate changes as predictors:

$$\ln(1 + R^f_{i,t:t+12}) = a_0 + a_1 \ln\left(\frac{S_{i,t+12}}{S_{i,t}}\right) + a_2 \ln(1 + R^f_{US,t:t+12}) + \omega_{i,t:t+12}, \tag{A1}$$

where $R^f_{i,t:t+12}$ and $R^f_{US,t:t+12}$ are the one-year local and US interest rate at time t, and $S_{i,t}$ denotes the exchange rate—number of units of local currency i per US dollar—at the same point in time. For each market, we estimate this regression at the monthly frequency using all available information. Table IX presents the results.

Table IX
Regressions to Estimate Risk-Free rates back to June 1973

The table presents the results from regressing a risk-free rate in country i on the US risk-free rate and the exchange: $\ln(1 + R^f_{i,t:t+12}) = a_0 + a_1 \ln\left(\frac{S_{i,t+12}}{S_{i,t}}\right) + a_2 \ln(1 + R^f_{US,t:t+12}) + \omega_{i,t:t+12}$. $R^f_{i,t:t+12}$ and $R^f_{US,t:t+12}$ are the one-year local and US interest rate at time t, and $S_{i,t}$ denotes the exchange rate—number of units of local currency i per US dollar—at the same point in time.

Market	R2	Start	End	N
Austria	62.3%	01/31/1989	12/31/2020	384
Australia	67.6%	06/30/1972	12/31/2020	583
Switzerland	59.4%	01/31/1988	12/31/2020	396
Germany	68.2%	06/30/1972	12/31/2020	583
France	74.8%	01/31/1984	12/31/2020	444
United Kingdom	80.3%	06/30/1972	12/31/2020	583
Hong Kong	83.2%	11/30/1995	12/31/2020	302
India	52.9%	01/31/1993	12/31/2020	336
Malasya	27.8%	06/30/1972	12/31/2020	583
Sweden	73.1%	07/31/1982	12/31/2020	462
South Africa	50.3%	09/30/2000	12/31/2020	244

The key takeaway is that the exchange and the US interest rate do a good job of predicting foreign interest rates. The average R^2 of Eq. A1 across all markets is 61%. For developed markets, it is 70%.

Appendix B. The State Vector

Appendix to the section "A Global State Vector".

Appendix A. Factor Timing Outside the US

The key motivation for the choice of the state vector in Giglio et al. (2021) comes from Haddad et al. (2020). Haddad et al. (2020) claim that the dividend yield of principal component portfolios (of anomalies) can predict their future returns. This has been shown in the US. As a preliminary analysis, before estimating many local models, we test whether this hypothesis holds for the markets in our sample.

To do this, for each market, we compute returns and dividend yields of the principal components of the corresponding market's anomalies. Then, we evaluate the claim in Haddad et al. (2020); namely, the dividend yields of such principal components predict their returns. We do so by running the following regressions:

$$r^{pc}_{j,t:t+12} = a + bDY^{pc}_{j,t} + \xi_t$$

Where $r^{pc}_{j,t:t+12}$ represents the log return ofthe j-th principal component from period t to $t+12$, $DY^{pc}_{j,t}$ represents the dividend yield of the same j-th principal component at time t. If the claim in Haddad et al. (2020) holds internationally, we should expect to find a positive and significant estimate of b, and a high R^2 (i.e., comparable to the one in the US).

The results shown in Table X are clear: Almost every estimate of b is positive and significant. Moreover, the average R^2 is 15%, a quantity comparable to 20% in the US. This suggests that the evidence brought forward by Haddad et al. (2020) seems to work internationally.

Table X
Return Predictability Regressions

This table presents the results of the predictability regressions: $r^{pc}_{j,t:t+12} = a + by^{pc}_{j,t}$. For completeness, we include the market. t-statistics (in parenthesis) are computed using Newey and West (1987) robust standard errors with a maximum of six lags.

		r^{m}	r^{pc1}	r^{pc3}	r^{pc3}	r^{pc4}
AT	b	10.18	5.53	7.02	5.15	8.95
	t-stat	(2.36)	(3.48)	(3.50)	(1.67)	(4.15)
	R^2 (%)	0.06	0.17	0.17	0.04	0.20
AU	b	10.64	4.09	6.66	-0.27	0.00
	t-stat	(4.08)	(2.67)	(5.11)	-(0.14)	(0.00)
	R^2 (%)	0.12	0.11	0.27	0.00	0.00
CH	b	8.55	6.03	2.21	0.94	1.90
	t-stat	(2.41)	(2.50)	(0.86)	(0.50)	(1.35)
	R^2 (%)	0.07	0.08	0.01	0.00	0.01
DE	b	12.03	5.12	6.33	3.19	-1.00
	t-stat	(2.58)	(3.23)	(2.90)	(1.25)	-(0.31)
	R^2 (%)	0.09	0.09	0.10	0.01	0.00
FR	b	13.07	0.81	4.32	0.47	2.26
	t-stat	(2.98)	(0.57)	(2.84)	(0.30)	(2.24)
	R^2 (%)	0.12	0.00	0.05	0.00	0.03
GB	b	17.30	3.94	-0.38	6.33	6.16
	t-stat	(4.27)	(3.50)	-(0.13)	(2.96)	(3.96)
	R^2 (%)	0.22	0.11	0.00	0.11	0.19
HK	b	28.66	4.28	5.33	0.50	-2.29
	t-stat	(6.06)	(1.61)	(2.82)	(0.24)	-(1.30)
	R^2 (%)	0.38	0.03	0.07	0.00	0.01
IN	b	58.37	4.50	0.06	11.06	-2.00
	t-stat	(7.32)	(3.07)	(0.03)	(3.18)	-(1.32)
	R^2 (%)	0.50	0.22	0.00	0.34	0.02
MY	b	15.18	8.50	1.10	-1.57	-0.27
	t-stat	(4.24)	(1.81)	(0.69)	-(1.36)	-(0.22)
	R^2 (%)	0.18	0.06	0.00	0.01	0.00
SE	b	11.84	3.34	3.44	2.71	-1.74
	t-stat	(2.31)	(0.76)	(2.28)	(1.25)	-(1.57)
	R^2 (%)	0.10	0.02	0.05	0.01	0.01
TW	b	5.49	4.26	1.69	3.95	-0.20
	t-stat	(1.89)	(2.01)	(0.51)	(2.13)	-(0.11)
	R^2 (%)	0.06	0.06	0.00	0.03	0.00
US	b	18.47	11.59	4.56	3.11	-1.86
	t-stat	(4.68)	(2.00)	(1.64)	(1.43)	-(1.66)
	R^2 (%)	0.21	0.14	0.05	0.02	0.01
ZA	b	8.92	-7.26	1.67	7.21	-0.44
	t-stat	(2.78)	-(3.27)	(0.91)	(3.18)	-(0.48)
	R^2 (%)	0.05	0.13	0.01	0.19	0.00

Appendix B. Constructing the State-Vector

The state-vector F_t contains returns and dividend yields of an equally market portfolio and PC portfolios of anomalies:

$$F_t = \begin{bmatrix} F_{r,t} \\ \\ F_{y,t} \end{bmatrix} = \begin{bmatrix} r_t^m \\ r_{1,t}^{pc} \\ r_{2,t}^{pc} \\ r_{3,t}^{pc} \\ r_{4,t}^{pc} \\ \\ y_t^m \\ y_{1,t}^{pc} \\ y_{2,t}^{pc} \\ y_{3,t}^{pc} \\ y_{4,t}^{pc} \end{bmatrix}.$$

Equally weighted market portfolio. The first element in the F_t, $r_{m,t}$, is the 12-month log (excess) return of an equally weighted market portfolio (local and US market). Let $R_{m,t:(t+1)}$ be the one-month return of the local market in local currency (i.e., in pounds), and $R_{t:(t+1)}^{m,US}$ be the one-month return of the US market, also in local currency (i.e., in pounds). Recall that we assume perfect hedge. Then:

$$r_t^m \equiv r_{(t-12):t}^{m,EW} - r_{(t-12):t}^{f} \tag{B1}$$

Where $r_{t:(t+12)}^{f}$ is the one year log risk free rate, $r_{(t-12):t}^{m,EW} = \sum_{s=t}^{t+12} r_{(s-12):(s-11)}^{m,EW}$ is the 12-month cumulative sum of the one-month log return $r_{t:(t+12)}^{m,EW} = \ln(1 + R_{t:(t+1)}^{m,EW})$ of an equally weighted portfolio defined by $R^{m,EW}_{t:(t+1)} = 0.5 \times (R^{m}_{t:(t+1)} + R^{m,US}_{t:(t+1)})$.

The p-th element of the state vector ($y_{\mathrm{m},t}$) is the the yield as defined by Giglio et al. (2021), of an equally weighted market portfolio between the local market and the US.

Let DY_t be the dividend yield of the market in local currency (i.e., in pounds), and $DY^{m,US}_t$ be the one-month return of the US market, also in local currency (i.e., in pounds). Recall that we assume perfect hedge. Then:

$$y^m_t = \ln\left(1 + \frac{DY^m_t + DY^{m,US}_t}{2}\right) \tag{B2}$$

Principal component portfolios. $r_{pcj,t}$ represent the 12 month log return on long minus short anomalies with weights derived from a principal component decomposition on the one month log returns of long minus short anomalies. Let $r^l_{i,(t-1):t}$ be the one month log return of the long (l) leg of anomaly i. Let $r^s_{i,(t-1):t}$ the one month log return of the short (s) leg of anomaly i. Then, the long minus short log return of anomaly i is given by: $r^{ls}_{i,t-1:t} \equiv r^l_{(t-1):t} - r^s_{(t-1):t}$

We run principal components on the variance-covariance matrix of:

$$r^{ls}_{(t-1):t} = [r^{ls}_{1,(t-1):t}, r^{ls}_{2,(t-1):t}, \dots r^{ls}_{N,(t-1):t}], \tag{B3}$$

and obtain the eigenvectors $w = [w_1, w_2, \dots w_N]$, where w_j is the eigenvector associated with the j-th eigenvalue. Then we use w to construct: $r^{pc}_{(t-12):t} = w' \times r^{ls}_{(t-12):t}$, where $r^{pc}_{(t-12):t} = [r^{pc}_{1,(t-12):t}, r^{pc}_{2,(t-12):t}, \dots r^{pc}_{N,(t-12):t}]$. Similarly, for the dividend yields we have that $y^{pc}_t = w' \times y^{ls}_t$, where $y^{pc}_t = [y^{pc}_{1,t}, y^{pc}_{2,t}, \dots y^{pc}_{N,t}]$.

Appendix C. The Informational Content of Local PCs

One might wonder if we could use the US model for every other market. One way of shedding some light on this is by testing whether the principal components derived from the US substitute the ones derived from local anomalies. Therefore, we estimate the following regressions:

$$r^{m}_{(t-12):t} = r^{m,US}_{1,(t-12):t} + r^{pc,US}_{1,(t-12):t} + r^{pc,US}_{2,(t-12):t} + r^{pc,US}_{3,(t-12):t} + r^{pc,US}_{4,(t-12):t} + error \tag{B4}$$

$$r^{pc}_{1,(t-12):t} = r^{m,US}_{1,(t-12):t} + r^{pc,US}_{1,(t-12):t} + r^{pc,US}_{2,(t-12):t} + r^{pc,US}_{3,(t-12):t} + r^{pc,US}_{4,(t-12):t} + error \tag{B5}$$

$$r^{pc}_{2,(t-12):t} = r^{m,US}_{1,(t-12):t} + r^{pc,US}_{1,(t-12):t} + r^{pc,US}_{2,(t-12):t} + r^{pc,US}_{3,(t-12):t} + r^{pc,US}_{4,(t-12):t} + error \tag{B6}$$

$$r^{pc}_{3,(t-12):t} = r^{m,US}_{1,(t-12):t} + r^{pc,US}_{1,(t-12):t} + r^{pc,US}_{2,(t-12):t} + r^{pc,US}_{3,(t-12):t} + r^{pc,US}_{4,(t-12):t} + error \tag{B7}$$

$$r^{pc}_{4,(t-12):t} = r^{m,US}_{1,(t-12):t} + r^{pc,US}_{1,(t-12):t} + r^{pc,US}_{2,(t-12):t} + r^{pc,US}_{3,(t-12):t} + r^{pc,US}_{4,(t-12):t} + error \tag{B8}$$

Figure **??** shows the R^2 for each of these 4 equations, per market. For example, the UK market portfolio (GB) $r^{m}_{(t-12):t}$ can be explained with an R^2 of 98% by $r^{m,US}_{1,(t-12):t}$, $r^{pc,US}_{1,(t-12):t}$, $r^{pc,US}_{2,(t-12):t}$, $r^{pc,US}_{3,(t-12):t}$, and $r^{pc,US}_{4,(t-12):t}$., but the return of the third principal component $r^{pc}_{3,(t-12):t}$ can only be explained by those same variables with an R^2 of less than 25%. In general, the patterns suggest that the returns of principal components of US anomalies explain relatively well the returns of first principal components of local anomalies, but this association becomes much weaker as we move onto the returns of the subsequent principal components of local anomalies.

We repeated the exact same analysis for yields y and estimated the following equations:

$$y_t^m = y_{1,t}^{m,US} + y_{1,t}^{pc,US} + y_{2,t}^{pc,US} + y_{3,t}^{pc,US} + y_{4,t}^{pc,US} + error \tag{B9}$$

$$y_{1,t}^{pc} = y_{1,t}^{m,US} + y_{1,t}^{pc,US} + y_{2,t}^{pc,US} + y_{3,t}^{pc,US} + y_{4,t}^{pc,US} + error \tag{B10}$$

$$y_{2,t}^{pc} = y_{1,t}^{m,US} + y_{1,t}^{pc,US} + y_{2,t}^{pc,US} + y_{3,t}^{pc,US} + y_{4,t}^{pc,US} + error \tag{B11}$$

$$y_{3,t}^{pc} = y_{1,t}^{m,US} + y_{1,t}^{pc,US} + y_{2,t}^{pc,US} + y_{3,t}^{pc,US} + y_{4,t}^{pc,US} + error \tag{B12}$$

$$y_{4,t}^{pc} = y_{1,t}^{m,US} + y_{1,t}^{pc,US} + y_{2,t}^{pc,US} + y_{3,t}^{pc,US} + y_{4,t}^{pc,US} + error \tag{B13}$$

Figure 5 shows the R^2 resulting from the estimation of for such regressions. The patterns are even stronger than the ones we found in the returns analysis:

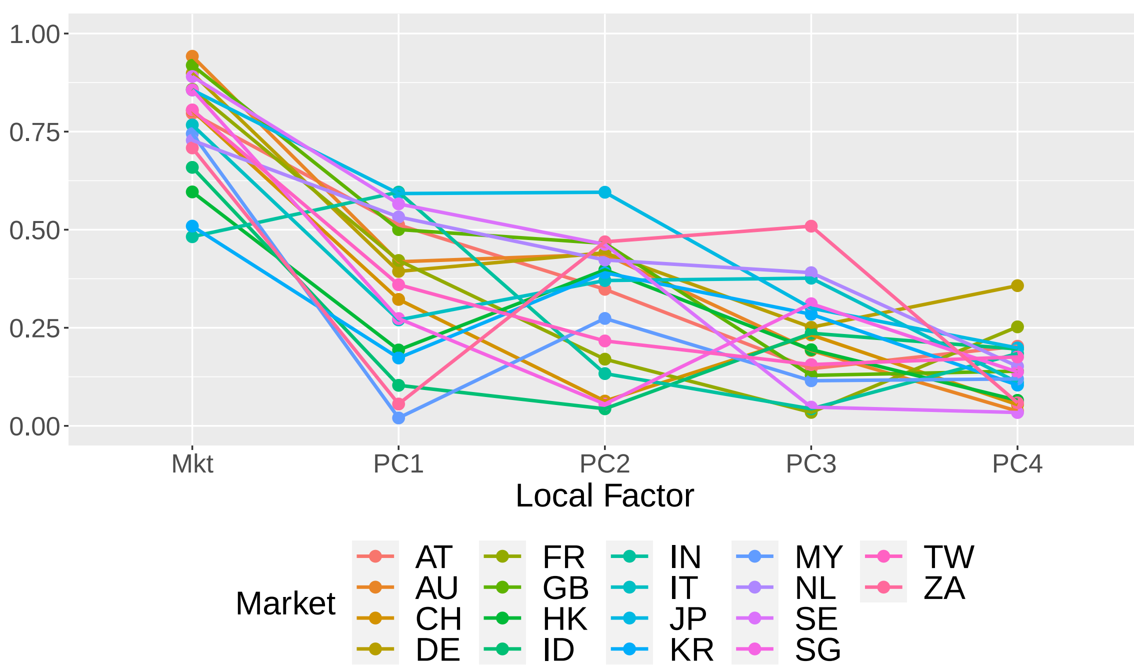


Figure 5 Local PC Overlapping analysis: Yields. The figure shows the R^2 for the specifications described in the text.

Appendix C. Estimation

Appendix to the section "Estimation".

Appendix A. The VAR

The starting point is a linear factor model, F_t, with p pricing portfolios, $k = 2p$ rows, that has homoskedastic normally distributed error terms, u_{t+1} with VCV matrix $\Sigma = \mathbb{V}_t(u_{t+1})$.

$$\underset{(k\times 1)}{F_{t+1}} = \underset{(k\times 1)}{c} + \underset{(k\times k)}{\rho}\, F_t + \underset{(k\times 1)}{u_{t+1}} \tag{C1}$$

$$\begin{pmatrix} F_{r,t+1} \\ F_{y,t+1} \end{pmatrix} = \begin{pmatrix} c_r \\ c_y \end{pmatrix} + \begin{pmatrix} \mathbf{0}_{p\times p} & \rho_{r,y} \\ \mathbf{0}_{p\times p} & \rho_{y,y} \end{pmatrix} \begin{pmatrix} F_{r,t} \\ F_{y,t} \end{pmatrix} + \begin{pmatrix} u_{r,t+1} \\ u_{y,t+1} \end{pmatrix} \tag{C2}$$

The first p rows of F_t are excess returns and the last p rows are the dividend yields of the same portfolios. $F_{r,t}$ and $F_{y,t}$ are returns and yields of 4 portfolios. The realized excess capital gains of the p pricing portfolios are given by:

$$\underset{(p\times 1)}{\Delta p_{t+1}} - r_{f,t} = \underset{(p\times 1)}{\gamma_0} + \underset{(p\times k)}{\gamma_1}\, F_t + \underset{(p\times k)}{\gamma_2}\, u_{t+1}, \tag{C3}$$

with:

$$\gamma_2 = \begin{pmatrix} \mathbf{I}_{p\times p} & -\mathbf{I}_{p\times p}. \end{pmatrix} \tag{C4}$$

For the corresponding dividend yields we have $y_t = F_{y,t}$:

$$\underset{(p\times 1)}{y_t} = \underset{(p\times 1)}{b_0} + \underset{(p\times k)}{b_1}\underset{(k\times 1)}{F_t} \tag{C5}$$

$$y_t = b_0 + \begin{pmatrix} b_{1,r} & b_{y,1} \end{pmatrix} \begin{pmatrix} F_{r,t} \\ F_{y,t}, \end{pmatrix} \tag{C6}$$

with:

$$b_0 = \mathbf{0}_{p\times 1} \tag{C7}$$

$$b_1 = \begin{pmatrix} b_{1,r} & b_{y,1} \end{pmatrix} = \begin{pmatrix} \mathbf{0}_{p\times p} & \mathbf{I}_{p\times p}. \end{pmatrix} \tag{C8}$$

Total log return return, r_{t+1}, is the sum of capital gains, Δp_{t+1} and the divided yield y_{t+1}. Because this is an identity that holds both ex-post and ex-ante, we can write log returns, r_{t+1}, as a linear function of F_t and the shock u_{t+1}:

$$r_{t+1} = \left(\frac{P_{t+1} + D_{t+1}}{P_t}\right) = \ln\left(\frac{P_{t+1}}{P_t}\right) + \ln\left(1 + \frac{D_{t+1}}{P_{t+1}}\right) \tag{C9}$$

$$\begin{aligned}
&\equiv \Delta p_{t+1} + y_{t+1} \\
&= (r_{f,t} + \gamma_0 + \gamma_1 F_t + \gamma_2 u_{t+1}) + (b_0 + b_1 F_{t+1}) \\
&= (r_{f,t} + \gamma_0 + \gamma_1 F_t + \gamma_2 u_{t+1}) + (b_0 + b_1(c + \rho F_t + u_{t+1})) \\
&= (r_{f,t} + \gamma_0 + \gamma_1 F_t + \gamma_2 u_{t+1}) + (b_0 + b_1 c + b_1 \rho F_t + b_1 u_{t+1})
\end{aligned}$$

$$= r_{f,t} + \underbrace{(\gamma_0 + b_0 + b_1 c)}_{\beta_0} + \underbrace{(\gamma_1 + b_1 \rho)}_{\beta_1} F_t + \underbrace{(\gamma_2 + b_1)}_{\beta_2} u_{t+1} \tag{C10}$$

with:

$$\beta_0 = c_r \tag{C11}$$

$$\beta_1 = \begin{pmatrix} \mathbf{0}_{p\times k} & \rho_{r,y} \end{pmatrix} \tag{C12}$$

$$\beta_2 = \begin{pmatrix} \mathbf{I}_{p\times p} & \mathbf{0}_{p\times p} \end{pmatrix} \tag{C13}$$

The last two parameters are:

$$\gamma_0 = c_r - b_1 c \tag{C14}$$

$$\gamma_1 = \begin{pmatrix} \mathbf{0}_{p\times p} & \rho_{r,y} \end{pmatrix} - b_1 \rho. \tag{C15}$$

We assume the following dynamics for the log SDF:

$$\underset{(1\times1)}{m_{t+1}} = -\underset{(1\times1)}{r_{f,t}} - \frac{1}{2}\underset{(1\times k)}{\lambda_t'}\underset{(k\times k)}{\Sigma}\underset{(k\times1)}{\lambda_t} - \underset{(1\times k)}{\lambda_t'}\underset{(k\times1)}{u_{t+1}} \tag{C16}$$

$$m_{t+1} = -r_{f,t} - \frac{1}{2}\begin{pmatrix}\lambda_{r,t} & \lambda_{y,t}\end{pmatrix}\begin{pmatrix}\Sigma_{rr} & \Sigma_{ry} \\ \Sigma_{yr} & \Sigma_{yy}\end{pmatrix}\begin{pmatrix}\lambda_{r,t} \\ \lambda_{y,t}\end{pmatrix} + \begin{pmatrix}\lambda_{r,t} & \lambda_{y,t}\end{pmatrix}\begin{pmatrix}u_{r,t+1} \\ u_{y,t+1}\end{pmatrix} \tag{C17}$$

The prices of risk follow:

$$\underset{(k\times1)}{\lambda_t} = \underset{(k\times1)}{\lambda} + \underset{(k\times k)}{\Lambda}\underset{(k\times1)}{F_t} \tag{C18}$$

$$\begin{pmatrix}\lambda_{r,t} \\ \lambda_{y,t}\end{pmatrix} = \begin{pmatrix}\lambda_r \\ \mathbf{0}_{p\times1}\end{pmatrix} + \begin{pmatrix}\mathbf{0}_{p\times p} & \Lambda_{ry} \\ \mathbf{0}_{p\times p} & \mathbf{0}_{p\times p}\end{pmatrix}\begin{pmatrix}F_{r,t} \\ F_{y,t}\end{pmatrix} \tag{C19}$$

In total, we end up with $2p$ (c) + $k \times k$ (ρ) + p (λ_r) + $p \times p$ (Λ_{ry}) + $k \times k$ (Σ) parameters to estimate. With $2p = k = 8$, we have 156 parameters to estimate. We label the parameter vector θ.

Appendix B. The Objective Function

The objective function is to choose the parameter vector θ to minimize the Euler equation errors for all $i = 1, 2, ..., I$ portfolios.

$$\mathbb{E}_t\left[e^{m_{t+1}+\Delta p^i_{t+1}+y^i_{t+1}}\right] = 1 \ \ \forall i \tag{C20}$$

We write the equation with i's to make it clear that this equation refers to one asset at the time. Because the random variables $m_{t+1}, \Delta p^i_{t+1}, y^i_{t+1}$ are normally distributed, we can restate the Euler equation as:

$$\mathbb{E}_t\left[m_{t+1} + \Delta p^i_{t+1} + y^i_{t+1}\right] + \frac{1}{2}\mathbb{V}_t\left[m_{t+1} + \Delta p^i_{t+1} + y^i_{t+1}\right] = 0\forall i \tag{C21}$$

Two tricks are useful to see how the Euler restriction is used in the estimation. First, separate the restriction into one that applies to the p pricing portfolios and one that applies to the r additional portfolios. Second, stack the asset-specific Euler Equations into a vector. Because the expectation of a vector of elements is the stacked vector of the expectations of its elements, we let $\mathcal{A}_t = \mathbb{E}_t\left[m_{t+1} + \Delta p_{t+1} + y_{t+1}\right]$ denote the vector of means whose i-th element is $\mathbb{E}_t\left[m_{t+1} + \Delta p^i_{t+1} + y^i_{t+1}\right]$. For the second term, define $\mathcal{B}_t \equiv \mathbb{V}_t\left[m_{t+1} + \Delta p_{t+1} + y_{t+1}\right]$.

We can express $\mathcal{A}_t, \mathcal{B}_t$ as functions of the model parameters. We separate between the p pricing portfolios and the r additional portfolios. Starting with the p pricing portfolios, let $\mathcal{A}_{p,t}$ denote the first term in Eq. XX. By plugging in Eq. XX and Eq. YY we get:

$$\begin{aligned}
\mathcal{A}_{p,t} &= \mathbb{E}_t\left[(-r_{f,t} - \frac{1}{2}\lambda_t'\Sigma\lambda_t - \lambda_t'u_{t+1}) + (r_{f,t} + \gamma_0 + \gamma_1 F_t + \gamma_2 u_{t+1}) + (b_0 + b_1 F_{t+1})\right] && \text{(C22)}\\
&= \mathbb{E}_t\left[(-\frac{1}{2}\lambda_t'\Sigma\lambda_t - \lambda_t'u_{t+1}) + (\gamma_0 + \gamma_1 F_t + \gamma_2 u_{t+1}) + (b_0 + b_1(c + \rho F_t + u_{t+1}))\right] && \text{(C23)}\\
&= \mathbb{E}_t\left[-\frac{1}{2}\lambda_t'\Sigma\lambda_t + (\gamma_0 + \gamma_1 F_t) + [b_0 + b_1(c + \rho F_t)]\right] && \text{(C24)}\\
&= -\frac{1}{2}\lambda_t'\Sigma\lambda_t + (\gamma_0 + \gamma_1 F_t) + [b_0 + b_1(c + \rho F_t)]. && \text{(C25)}
\end{aligned}$$

Similarly for the second term:

$$\begin{aligned}
\mathcal{B}_{p,t} &= \mathbb{V}_t\left[(-r_{f,t} - \frac{1}{2}\lambda_t'\Sigma\lambda_t - \lambda_t'u_{t+1}) + (r_{f,t} + \gamma_0 + \gamma_1 F_t + \gamma_2 u_{t+1}) + (b_0 + b_1 F_{t+1})\right] && \text{(C26)}\\
&= \mathbb{V}_t\left[(-\frac{1}{2}\lambda_t'\Sigma\lambda_t - \lambda_t'u_{t+1}) + (\gamma_0 + \gamma_1 F_t + \gamma_2 u_{t+1}) + (b_0 + b_1(c + \rho F_t + u_{t+1}))\right] && \text{(C27)}\\
&= \mathbb{V}_t\left[-\lambda_t'u_{t+1} + (\gamma_2 + b_1)u_{t+1}\right] && \text{(C28)}\\
&= \lambda_t'\Sigma\lambda_t + (b_1 + \gamma_2)\Sigma(b_1 + \gamma_2)' - 2(b_1 + \gamma_2)\Sigma\lambda_t && \text{(C29)}
\end{aligned}$$

The $p \times 1$ vector of Euler equations is therefore:

$$
\begin{aligned}
0 &= \mathcal{A}_{p,t} + \frac{1}{2}\operatorname{diag}\left(\mathcal{B}_{p,t}\right) && \text{(C30)}\\
&= -\frac{1}{2}\lambda_t'\Sigma\lambda_t + (\gamma_0 + \gamma_1 F_t) + [b_0 + b_1(c + \rho F_t)] + \\
&\quad \frac{1}{2}\operatorname{diag}\left(\lambda_t'\Sigma\lambda_t + (b_1+\gamma_2)\Sigma(b_1+\gamma_2)' - 2(b_1+\gamma_2)\Sigma\lambda_t\right) && \text{(C31)}\\
&= -\frac{1}{2}\lambda_t'\Sigma\lambda_t + (\gamma_0 + \gamma_1 F_t) + [b_0 + b_1(c + \rho F_t)] + \\
&\quad \frac{1}{2}\left(\lambda_t'\Sigma\lambda_t + \operatorname{diag}\underbrace{\left((b_1+\gamma_2)\Sigma(b_1+\gamma_2)'\right)}_{\equiv\Omega} - 2(b_1+\gamma_2)\Sigma\lambda_t\right) && \text{(C32)}\\
&= (\gamma_0 + \gamma_1 F_t) + [b_0 + b_1(c + \rho F_t)] - 2(b_1+\gamma_2)\Sigma\lambda_t + \operatorname{diag}(\Omega) && \text{(C33)}
\end{aligned}
$$

Matching coefficients gives $p + p \times k$ restrictions. With $2p = k$ we have 36 restrictions and 156 parameters to estimate.

$$
0 = (\gamma_0 - \gamma_2\Sigma\lambda) + b_0 + b_1(c - \rho\Sigma\lambda) + \frac{1}{2}\operatorname{diag}(\Omega) \qquad \text{(C34)}
$$

$$
0 = (\gamma_1 - \gamma_2\Sigma\Lambda) + b_1(\rho - \Sigma\Lambda) \qquad \text{(C35)}
$$

Having specified the dynamics of the p pricing portfolios we add r additional portfolio. The returns on these portfolios are less than perfectly correlated with the SDF because of the residual unpriced risk attached to them. Following the notation in Giglio et al. (2021) we refer the unpriced risk as measurement errors. We use the notation $\tilde{\gamma}$ to distinguish these parameters from their corresponding parameters γ for the pricing portfolios. The dynamics of the log-prices of the r additional portfolios is:

$$
\underset{(r\times 1)}{\Delta p_{t+1}} - r_{f,t} = \underset{(r\times 1)}{\tilde{\gamma}_0} + \underset{(r\times k)}{\tilde{\gamma}_1} F_t + \underset{(r\times k)}{\tilde{\gamma}_2} u_{t+1} + \underset{(r\times 1)}{\nu_{t+1}}. \qquad \text{(C36)}
$$

The dynamics of the yields is given by:

$$\underset{(r\times 1)}{y_t} = \underset{(r\times 1)}{\tilde{b_0}} + \underset{(r\times k)}{\tilde{b_1}} F_t + \underset{(r\times 1)}{\epsilon_t} \tag{C37}$$

Log total returns are given by:

$$\underset{(r\times 1)}{r_{t+1}} - r_{f,t} = \underset{(r\times 1)}{\tilde{\beta_0}} + \underset{(r\times k)}{\tilde{\beta_1}} F_t + \underset{(r\times k)}{\tilde{\beta_2}} u_{t+1} + \underset{(r\times 1)}{\varepsilon_{t+1}}, \tag{C38}$$

By proceeding in the same way as before, we first express the intercept, slopes, and shocks of the total return as a function of the other parameters and their shocks:

$$\tilde{\beta_0} = \tilde{\gamma_0} + \tilde{b_0} + \tilde{b_1} c \tag{C39}$$

$$\tilde{\beta_1} = \tilde{\gamma_1} + \tilde{b_1}\rho \tag{C40}$$

$$\tilde{\beta_2} = \tilde{\gamma_2} + \tilde{b_1} \tag{C41}$$

$$\varepsilon_{t+1} = \epsilon_{t+1} + \nu_{t+1} \tag{C42}$$

It is important to notice that $\tilde{\beta_2}$ is restricted in the same way that β_2 is restricted. The next step is to express the mean and and variance of the Euler equations of the r portfolios as functions of the model parameters. Let $\mathcal{A}_{r,t}$ denote the first term in Eq. XX. By plugging in Eq. XX and Eq. YY we get:

$$\begin{aligned}
\mathcal{A}_{r,t} &= \mathbb{E}_t\left[(-r_{f,t} - \frac{1}{2}\lambda_t'\Sigma\lambda_t - \lambda_t' u_{t+1}) + (r_{f,t} + \tilde{\gamma_0} + \tilde{\gamma_1} F_t + \tilde{\gamma_2} u_{t+1} + \nu_{t+1}) + (\tilde{b_0} + \tilde{b_1} F_{t+1} + \epsilon_{t+1})\right] \\
&= \mathbb{E}_t\left[(-\frac{1}{2}\lambda_t'\Sigma\lambda_t - \lambda_t' u_{t+1}) + (\tilde{\gamma_0} + \tilde{\gamma_1} F_t + \tilde{\gamma_2} u_{t+1} + \nu_{t+1}) + (\tilde{b_0} + \tilde{b_1}(c + \rho F_t + u_{t+1}) + \epsilon_{t+1})\right] \\
&= \mathbb{E}_t\left[-\frac{1}{2}\lambda_t'\Sigma\lambda_t + (\tilde{\gamma_0} + \tilde{\gamma_1} F_t) + [\tilde{b_0} + \tilde{b_1}(c + \rho F_t)]\right] && \text{(C43)} \\
&= -\frac{1}{2}\lambda_t'\Sigma\lambda_t + (\tilde{\gamma_0} + \tilde{\gamma_1} F_t) + [\tilde{b_0} + \tilde{b_1}(c + \rho F_t)], && \text{(C44)}
\end{aligned}$$

which follows from $\mathbb{E}_t[u_{t+1}] = 0$, $\mathbb{E}_t[\epsilon_{t+1}] = 0$, and $\mathbb{E}_t[\nu_{t+1}] = 0$. For the second term, we have:

$$
\begin{aligned}
\mathcal{B}_{r,t} &= \mathbb{V}_t\left[m_{t+1} + \Delta p_{t+1} + y_{t+1}\right] \qquad \text{(C45)}\\
&= \mathbb{V}_t\left[(-r_{f,t} - \frac{1}{2}\lambda_t'\Sigma\lambda_t - \lambda_t' u_{t+1}) + (r_{f,t} + \tilde{\gamma_0} + \tilde{\gamma_1}F_t + \tilde{\gamma_2}u_{t+1} + \nu_{t+1}) + (\tilde{b_0} + \tilde{b_1}F_{t+1} + \epsilon_{t+1})\right]\\
&= \mathbb{V}_t\left[(-\frac{1}{2}\lambda_t'\Sigma\lambda_t - \lambda_t' u_{t+1}) + (\tilde{\gamma_0} + \tilde{\gamma_1}F_t + \tilde{\gamma_2}u_{t+1} + \nu_{t+1}) + (\tilde{b_0} + \tilde{b_1}(c + \rho F_t + u_{t+1}) + \epsilon_{t+1})\right]\\
&= \mathbb{V}_t\left[-\lambda_t' u_{t+1} + (\tilde{\gamma_2} + \tilde{b_1})u_{t+1} + \nu_{t+1} + \epsilon_{t+1}\right] \qquad \text{(dropped variables at } t)\\
&= \mathbb{E}_t\left[\left(-\lambda_t' u_{t+1} + (\tilde{\gamma_2} + \tilde{b_1})u_{t+1} + \nu_{t+1} + \epsilon_{t+1}\right)\left(-\lambda_t' u_{t+1} + (\tilde{\gamma_2} + \tilde{b_1})u_{t+1} + \nu_{t+1} + \epsilon_{t+1}\right)'\right]\\
&= \mathbb{E}_t[\lambda_t' u_{t+1}u_{t+1}'\lambda_t - \lambda_t' u_{t+1}u_{t+1}'(\tilde{\gamma_2} + \tilde{b_1})' - \lambda_t' u_{t+1}\nu_{t+1}' - \lambda_t' u_{t+1}\epsilon_{t+1}'\\
&\quad - (\tilde{b_1} + \tilde{\gamma_2})u_{t+1}u_{t+1}'\lambda_t + (\tilde{b_1} + \tilde{\gamma_2})u_{t+1}u_{t+1}'(\tilde{b_1} + \tilde{\gamma_2})' + (\tilde{b_1} + \tilde{\gamma_2})u_{t+1}\nu_{t+1}'\\
&\quad + (\tilde{b_1} + \tilde{\gamma_2})u_{t+1}\epsilon_{t+1}' - \nu_{t+1}u_{t+1}'\lambda_{t+1} + \nu_{t+1}u_{t+1}'(\tilde{b_1} + \tilde{\gamma_2})' + \nu_{t+1}\nu_{t+1}'\\
&\quad - \epsilon_{t+1}u_{t+1}'\lambda_t + \epsilon_{t+1}u_{t+1}'(\tilde{b_1} + \tilde{\gamma_2})' + \epsilon_{t+1}\nu_{t+1}' + \epsilon_{t+1}\epsilon_{t+1}']\\
&= \lambda_t'\mathbb{E}_t\left[u_{t+1}u_{t+1}'\right]\lambda_t - \lambda_t'\mathbb{E}_t\left[u_{t+1}u_{t+1}'\right](\tilde{\gamma_2} + \tilde{b_1})' - \lambda_t'\mathbb{E}_t\left[u_{t+1}\nu_{t+1}'\right] - \lambda_t'\mathbb{E}_t\left[u_{t+1}\epsilon_{t+1}'\right]\\
&\quad - (\tilde{b_1} + \tilde{\gamma_2})\mathbb{E}_t\left[u_{t+1}u_{t+1}'\right]\lambda_t + (\tilde{b_1} + \tilde{\gamma_2})\mathbb{E}_t\left[u_{t+1}u_{t+1}'\right](\tilde{b_1} + \tilde{\gamma_2})' + (\tilde{b_1} + \tilde{\gamma_2})\mathbb{E}_t\left[u_{t+1}\nu_{t+1}'\right]\\
&\quad + (\tilde{b_1} + \tilde{\gamma_2})\mathbb{E}_t\left[u_{t+1}\epsilon_{t+1}'\right] - \mathbb{E}_t\left[\nu_{t+1}u_{t+1}'\right]\lambda_{t+1} + \mathbb{E}_t\left[\nu_{t+1}u_{t+1}'\right](\tilde{b_1} + \tilde{\gamma_2})' + \mathbb{E}_t\left[\nu_{t+1}\nu_{t+1}'\right]\\
&\quad - \mathbb{E}_t\left[\epsilon_{t+1}u_{t+1}'\right]\lambda_t + \mathbb{E}_t\left[\epsilon_{t+1}u_{t+1}'\right](\tilde{b_1} + \tilde{\gamma_2})' + \mathbb{E}_t\left[\epsilon_{t+1}\nu_{t+1}'\right] + \mathbb{E}_t\left[\epsilon_{t+1}\epsilon_{t+1}'\right], \qquad \text{(C46)}
\end{aligned}
$$

where $\mathbb{E}_t\left[u_{t+1}u_{t+1}'\right] = \Sigma$, $\mathbb{E}_t\left[\epsilon_{t+1}\epsilon_{t+1}'\right] \equiv \Sigma_\epsilon$, and $\mathbb{E}_t\left[\nu_{t+1}\nu_{t+1}'\right] \equiv \Sigma_\nu$. Moreover, both ϵ and ν are idiosyncratic shocks. Thus: $\mathbb{E}_t\left[u_{t+1}\nu_{t+1}'\right] = 0$, $\mathbb{E}_t\left[\epsilon_{t+1}\nu_{t+1}'\right] = 0$, and $\mathbb{E}_t\left[u_{t+1}\epsilon_{t+1}'\right] = 0$. Thus, equation (C46) becomes:

$$
\begin{aligned}
\mathcal{B}_{r,t} &= \lambda_t'\Sigma\lambda_t - \lambda_t'\Sigma(\tilde{\gamma_2} + \tilde{b_1})' - (\tilde{b_1} + \tilde{\gamma_2})\Sigma\lambda_t + (\tilde{b_1} + \tilde{\gamma_2})\Sigma(\tilde{b_1} + \tilde{\gamma_2})' + \Sigma_\nu + \Sigma_\epsilon\\
&= \lambda_t'\Sigma\lambda_t + (\tilde{b_1} + \tilde{\gamma_2})\Sigma(\tilde{b_1} + \tilde{\gamma_2})' - 2(\tilde{b_1} + \tilde{\gamma_2})\Sigma\lambda_t + \Sigma_\nu + \Sigma_\epsilon. \qquad \text{(C47)}
\end{aligned}
$$

The $r \times 1$ vector of Euler equations is therefore:

$$\mathbf{0} = \mathcal{A}_{r,t} + \frac{1}{2}\mathrm{diag}\left(\mathcal{B}_{r,t}\right) \tag{C48}$$

By matching coefficients, we end up with $r + r \times k$ restrictions and r $(\tilde{\gamma_0})$ + $r \times p$ $(\tilde{\gamma_1})$ + $r \times k$ $(\tilde{\gamma_2})$ + r $(\tilde{b_0})$ + $r \times p$ $(\tilde{b_1})$ + $2r$ $(\mathrm{diag}(\Sigma_\epsilon) + \mathrm{diag}(\Sigma_\nu))$ additional parameters.

$$0 = (\tilde{\gamma_0} - \tilde{\gamma_2}\Sigma\lambda) + \tilde{b_0} + b_1(c - \rho\Sigma\lambda) + \frac{1}{2}\left(\mathrm{diag}(\Omega + \Sigma_\nu + \Sigma_\epsilon)\right) \tag{C49}$$

$$0 = (\tilde{\gamma_1} - \tilde{\tilde{\gamma_2}}\Sigma\Lambda) + b_1(\rho - \Sigma\Lambda) \tag{C50}$$

Appendix C. Model Output

The parameters a_n and d_n satisfy the following recursions:

$$a_n = a_{n-1} + \gamma_0^\star + d_{n-1}c^\star + \frac{1}{2}(d_{n-1} + \gamma_2)\Sigma(d_{n-1} + \gamma_2)' + \frac{1}{2}\sigma_\nu \tag{C51}$$

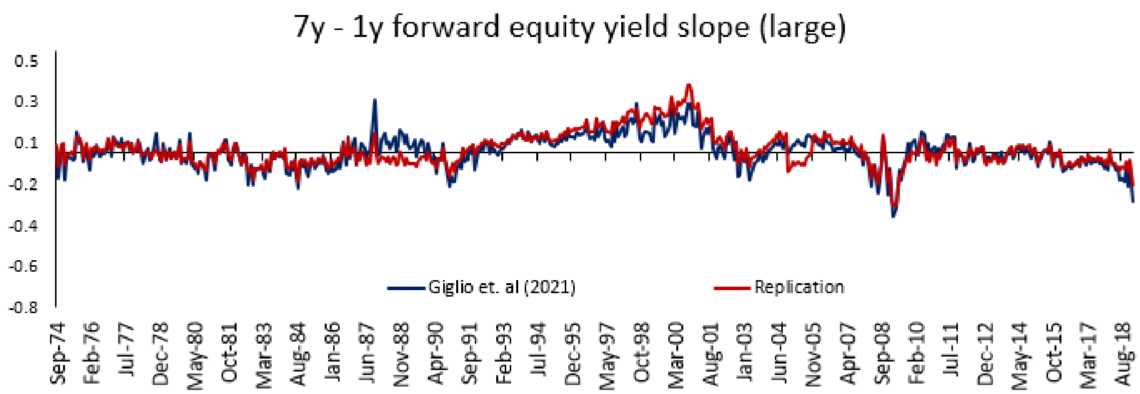
$$d_n = \gamma_1^\star + d_{n-1}\rho^\star. \tag{C52}$$

With initial values $a_{0,1} = b_0 + \frac{1}{2}(\sigma_r^2 - \sigma_\nu^2), d_{0,1} = b_1, a_{0,2} = 0, d_{0.2} = 0, \sigma_r^2 = var(\epsilon_t), \sigma_\nu^2 = var(\nu_t)$. In these formulas, stars indicate risk-neutral parameters.

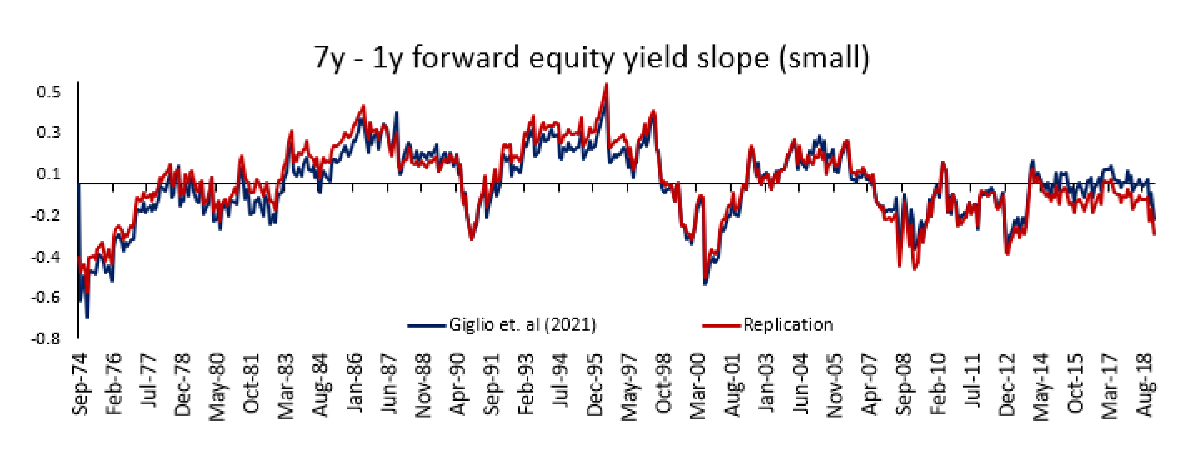
Appendix D. Additional Results

Appendix A. Appendix to the section IV.A

Figure 6 compares the equity yield for large and small companies we estimate with those in GKK. Figure 7 presents the same statistics for value and growth company. Both plots show that the additional assumptions we impose on the VAR system do not affect the inference.

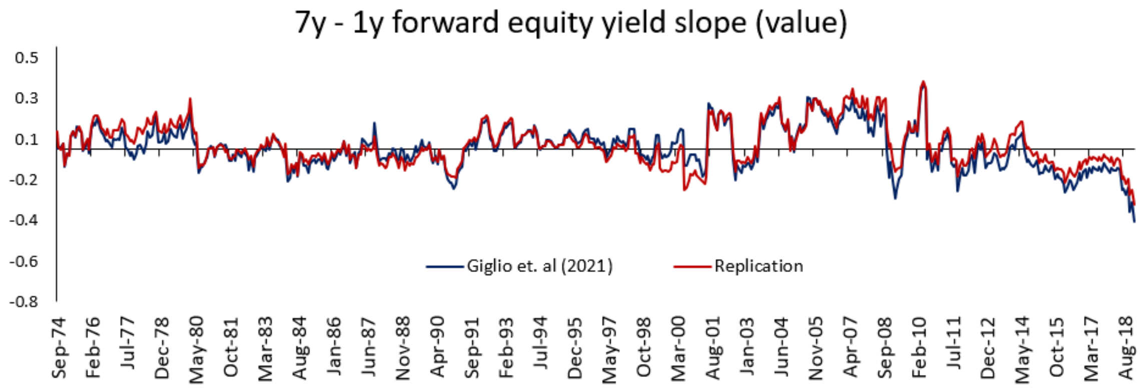


(a) One-year forward equity yields $e^f_{t,1}$

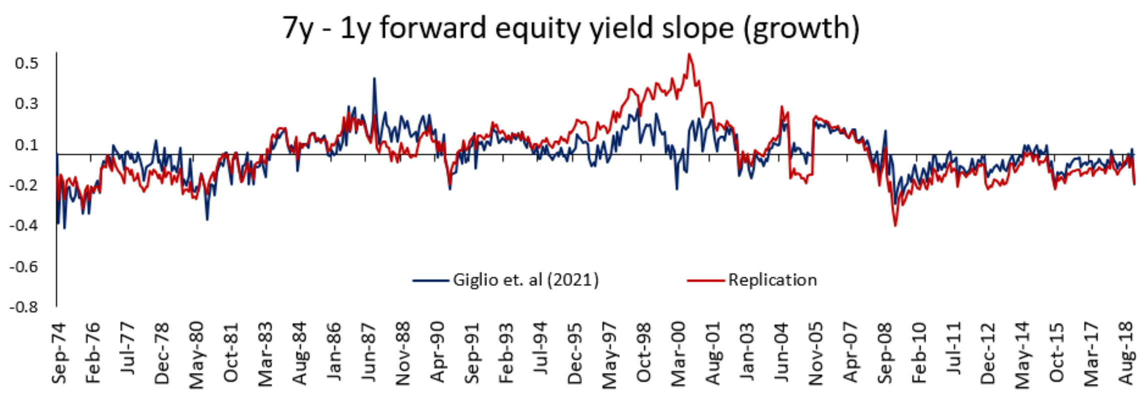


(b) The forward equity yield slope $e^f_{t,7} - e^f_{t,1}$

Figure 6 US Forward Equity Yields For Large and Small Companies
The figure compares the forward yields reported by GKK (blue) against the output from our specification of their model (red). Both specifications use the data provided by GKK.



(a) One-year forward equity yields $e^f_{t,1}$



(b) The forward equity yield slope $e^f_{t,7} - e^f_{t,1}$

Figure 7 US Forward Equity Yields For Value and Growth Companies
The figure compares the forward yields reported by GKK (blue) against the output from our specification of their model (red). Both specifications use the data provided by GKK.

Appendix B. Appendix to the section IV.B

Table XI
Panel Regression: Forward Equity Yields (Big Stocks)

This table reports the results from regressing the slope of the equity forward equity yields ($ef_t^7 - ef_t^1$) on the dummy variable "Bad times". It takes the value of one for the months the dividend price ratio is above the time series median and is market specific. Statistical significance is indicated by ***, **, and * for the 0.01, 0.05, and 0.10 levels. Standard errors are based on the Robust Covariance Matrix Estimator developed by Driscoll and Kraay (1998).

	Forward Equity Yield Slope: $ef_t^7 - ef_t^1$				
Bad times	-0.107^{***}	-0.084^{***}	-0.066^{***}	-0.091^{***}	-0.094^{***}
	(0.005)	(0.007)	(0.007)	(0.007)	(0.009)
Constant	0.067^{***}		0.052^{***}		
	(0.004)		(0.005)		
Markets:	All	All	US	All ex-US	All
Excluded Markets:	Non	Non	Non-US	US	US, UK, FR
Market fixed effects:	No	Yes	No	Yes	Yes
Time fixed effects:	No	Yes	No	Yes	Yes
Observations	3,394	3,394	532	2,862	2,237
R^2	0.112	0.052	0.137	0.058	0.051

Table XII
Panel Regression: Forward Equity Yields (Small Stocks)

This table reports the results from regressing the slope of the equity forward equity yields ($ef_t^7 - ef_t^1$) on the dummy variable "Bad times". It takes the value of one for the months the dividend price ratio is above the time series median and is market specific. Statistical significance is indicated by ***, **, and * for the 0.01, 0.05, and 0.10 levels. Standard errors are based on the Robust Covariance Matrix Estimator developed by Driscoll and Kraay (1998).

	Forward Equity Yield Slope: $ef_t^7 - ef_t^1$				
Bad times	-0.071^{***}	-0.051^{***}	0.055^{***}	-0.057^{***}	-0.087^{***}
	(0.008)	(0.009)	(0.015)	(0.010)	(0.013)
Constant	0.005		-0.012		
	(0.006)		(0.011)		
Markets:	All	All	US	All ex-US	All All
Excluded Markets:	Non	Non	Non-US	US	US, UK, FR
Market fixed effects:	No	Yes	No	Yes	Yes
Time fixed effects:	No	Yes	No	Yes	Yes
Observations	3,394	3,394	532	2,862	2,237
R^2	0.022	0.011	0.023	0.013	0.023

Table XIII
Panel Regression: Forward Equity Yields (Value Stocks)

This table reports the results from regressing the slope of the equity forward equity yields ($ef_t^7 - ef_t^1$) on the dummy variable "Bad times". It takes the value of one for the months the dividend price ratio is above the time series median and is market specific. Statistical significance is indicated by ***, **, and * for the 0.01, 0.05, and 0.10 levels. Standard errors are based on the Robust Covariance Matrix Estimator developed by Driscoll and Kraay (1998).

	Forward Equity Yield Slope: $ef_t^7 - ef_t^1$				
Bad times	-0.090^{***}	-0.036^{***}	-0.012	-0.034^{***}	-0.079^{***}
	(0.008)	(0.011)	(0.010)	(0.012)	(0.015)
Constant	0.032^{***}		0.007		
	(0.006)		(0.007)		
Markets:	All	All	US	All ex-US	All
Excluded Markets:	Non	Non	Non-US	US	US, UK, FR
Market fixed effects:	No	Yes	No	Yes	Yes
Time fixed effects:	No	Yes	No	Yes	Yes
Observations	3,394	3,394	532	2,862	2,237
R^2	0.032	0.004	0.003	0.003	0.014

Table XIV
Panel Regression: Forward Equity Yields (Growth Stocks)

This table reports the results from regressing the slope of the equity forward equity yields ($ef_t^7 - ef_t^1$) on the dummy variable "Bad times". It takes the value of one for the months the dividend price ratio is above the time series median and is market specific. Statistical significance is indicated by ***, **, and * for the 0.01, 0.05, and 0.10 levels. Standard errors are based on the Robust Covariance Matrix Estimator developed by Driscoll and Kraay (1998).

	Forward Equity Yield Slope: $ef_t^7 - ef_t^1$				
Bad times	-0.099^{***}	-0.083^{***}	-0.035^{***}	-0.096^{***}	-0.107^{***}
	(0.007)	(0.010)	(0.010)	(0.011)	(0.014)
Constant	0.067^{***}		0.035^{***}		
	(0.005)		(0.007)		
Markets:	All	All	US	All ex-US	All
Excluded Markets:	Non	Non	Non-US	US	US, UK, FR
Market fixed effects:	No	Yes	No	Yes	Yes
Time fixed effects:	No	Yes	No	Yes	Yes
Observations	3,394	3,394	532	2,862	2,237
R^2	0.049	0.024	0.024	0.030	0.030

Table XV
Decomposition of the equity forward equity yield (Big stocks)

The table presents the results from regressing the slope of the equity forward equity yield ($ef_t^7 - ef_t^1$) as well as its two terms on the dummy variable "Bad times". The first term is the risk premium on the 7-years maturity strip in excess of the 1 year maturity strip, $\theta_t^{(7)} - \theta_t^{(1)}$. The second term is long-term expected dividend growth in excess of short-term dividend growth, $g_t^{(7)} - g_t^{(1)}$. The "Bad-times" dummy variable takes the value of one for the months the dividend price ratio is above the time series median and is market specific. Statistical significance is indicated by ***, **, and * for the 0.01, 0.05, and 0.10 levels. Standard errors are based on the Robust Covariance Matrix Estimator developed by Driscoll and Kraay (1998).

Dependent variable	$ef_t^7 - ef_t^1$	$\theta_t^7 - \theta_t^1$	$g_t^7 - g_t^1$
Bad-times	-0.084^{***}	0.004	0.088^{***}
	(0.015)	(0.003)	(0.015)
Market fixed effects:	Yes	Yes	Yes
Calendar time fixed effects:	Yes	Yes	Yes
Observations	3,394	3,394	3,394
R^2	0.052	0.001	0.053

Table XVI
Decomposition of the equity forward equity yield (Small stocks)

The table presents the results from regressing the slope of the equity forward equity yield ($ef_t^7 - ef_t^1$) as well as its two terms on the dummy variable "Bad times". The first term is the risk premium on the 7-years maturity strip in excess of the 1 year maturity strip, $\theta_t^{(7)} - \theta_t^{(1)}$. The second term is long-term expected dividend growth in excess of short-term dividend growth, $g_t^{(7)} - g_t^{(1)}$. The "Bad-times" dummy variable takes the value of one for the months the dividend price ratio is above the time series median and is market specific. Statistical significance is indicated by ***, **, and * for the 0.01, 0.05, and 0.10 levels. Standard errors are based on the Robust Covariance Matrix Estimator developed by Driscoll and Kraay (1998).

Dependent variable	$ef_t^7 - ef_t^1$	$\theta_t^7 - \theta_t^1$	$g_t^7 - g_t^1$
Bad-times	-0.051^{***}	0.002	0.053^{**}
	(0.020)	(0.013)	(0.021)
Market fixed effects:	Yes	Yes	Yes
Calendar time fixed effects:	Yes	Yes	Yes
Observations	3,394	3,394	3,394
R^2	0.011	0.00001	0.005

Table XVII
Decomposition of the equity forward equity yield (Value)

The table presents the results from regressing the slope of the equity forward equity yield ($ef_t^7 - ef_t^1$) as well as its two terms on the dummy variable "Bad times". The first term is the risk premium on the 7-years maturity strip in excess of the 1 year maturity strip, $\theta_t^{(7)} - \theta_t^{(1)}$. The second term is long-term expected dividend growth in excess of short-term dividend growth, $g_t^{(7)} - g_t^{(1)}$. The "Bad-times" dummy variable takes the value of one for the months the dividend price ratio is above the time series median and is market specific. Statistical significance is indicated by ***, **, and * for the 0.01, 0.05, and 0.10 levels. Standard errors are based on the Robust Covariance Matrix Estimator developed by Driscoll and Kraay (1998).

Dependent variable	$ef_t^7 - ef_t^1$	$\theta_t^7 - \theta_t^1$	$g_t^7 - g_t^1$
Bad-times	-0.036^{*}	-0.003	0.033
	(0.021)	(0.007)	(0.023)
Market fixed effects:	Yes	Yes	Yes
Calendar time fixed effects:	Yes	Yes	Yes
Observations	3,394	3,394	3,394
R^2	0.004	0.0001	0.003

Table XVIII
Decomposition of the equity forward equity yield (Growth)

The table presents the results from regressing the slope of the equity forward equity yield ($ef_t^7 - ef_t^1$) as well as its two terms on the dummy variable "Bad times". The first term is the risk premium on the 7-years maturity strip in excess of the 1 year maturity strip, $\theta_t^{(7)} - \theta_t^{(1)}$. The second term is long-term expected dividend growth in excess of short-term dividend growth, $g_t^{(7)} - g_t^{(1)}$. The "Bad-times" dummy variable takes the value of one for the months the dividend price ratio is above the time series median and is market specific. Statistical significance is indicated by ***, **, and * for the 0.01, 0.05, and 0.10 levels. Standard errors are based on the Robust Covariance Matrix Estimator developed by Driscoll and Kraay (1998).

Dependent variable	$ef_t^7 - ef_t^1$	$\theta_t^7 - \theta_t^1$	$g_t^7 - g_t^1$
Bad-times	-0.083^{***}	-0.005	0.078^{***}
	(0.017)	(0.004)	(0.016)
Market fixed effects:	Yes	Yes	Yes
Calendar time fixed effects:	Yes	Yes	Yes
Observations	3,394	3,394	3,394
R^2	0.024	0.001	0.021

Appendix C. Appendix to the section V.B

Table XIX
Predicting Macroeconomic Variables (Market)

The table presents the results from predicting macroeconomic outcomes observed at time q with short-term risk premia ($\theta^{(1)}_{q-1}$) and growth expectations ($g^{(1)}_{q-1}$). All specifications include the lagged value of the variable we predict. The macroeconomic outcomes include 1) consumption growth, $g^c_{i,q} := C_{i,t}/C_{i,t-q} - 1$, where C_t is consumption at time t, 2) changes in unemployment rate, $\Delta U_{i,q} = U_{i,t} - U_{i,t-q}$, where U_t is the unemployment rate at time t, and 3) growth in industrial production, $g^{IP}_{i,q} := IP_{i,t}/IP_{i,t-q} - 1$, where IP_t is industrial production at time t. All regressions include market-fixed effects. Statistical significance is indicated by ***, **, and * for the 0.01, 0.05, and 0.10 levels. Standard errors are based on the Robust Covariance Matrix Estimator developed by Driscoll and Kraay (1998).

Horizon	Consumption ($g^c_{i,q}$)			Unemployment ($\Delta U_{i,q}$)			Industrial Production ($g^{IP}_{i,q}$)		
(months)	3	6	12	3	6	12	3	6	12
$g^{(1)}_{q-1}$	0.010***	0.014***	0.017**	−0.002*	−0.004*	−0.009**	0.027**	0.036**	0.063**
	(0.002)	(0.004)	(0.006)	(0.001)	(0.002)	(0.003)	(0.008)	(0.011)	(0.021)
$\theta^{(1)}_{q-1}$	0.006	0.011*	0.019	0.004	0.007	0.018*	−0.003	−0.013	−0.024
	(0.003)	(0.005)	(0.012)	(0.002)	(0.004)	(0.009)	(0.027)	(0.036)	(0.053)
$y_{i,q-1}$	−0.068	0.098	0.108	0.311*	0.424***	0.215**	0.046	0.116**	−0.101
	(0.108)	(0.127)	(0.098)	(0.134)	(0.059)	(0.064)	(0.081)	(0.048)	(0.072)
Observations	707	699	685	1,932	1,920	1,896	2,116	2,101	2,071
R^2	0.194	0.331	0.423	0.128	0.221	0.098	0.043	0.062	0.055