Decomposing the Predictive Power of Local and Global Financial Valuation Ratios

Jochen Lawrenz[a] Josef Zorn[b]

Draft December 20, 2017

Abstract

We examine the predictive power of global financial price-to-fundamental ratios for future stock returns in a panel of major developed countries. By disentangling global and local information, we find the global component to be at least equally important and that its importance has increased in recent decades. We further decompose the variability of valuation ratios in discount rate and cash flow driven components and find that the declining predictive power of local ratios goes hand in hand with a diminishing importance of the discount rate component. Our results underscore the relevance of global discount rate news in the time variation of local expected returns.

JEL classification: G12, G15, G17, F36.

Keywords: International stock returns, predictability, financial ratios, discount rate.

[a]University of Innsbruck, Department of Banking and Finance, jochen.lawrenz@uibk.ac.at.

[b]University of Innsbruck, Department of Banking and Finance, josef.zorn@uibk.ac.at.

1. Introduction

Researchers have long been interested in the identification of global factors in international asset pricing. Early literature on the topic has largely focused on the development of different versions of an international capital asset pricing model and the associated question if local markets are integrated or segmented. We approach the topic from a time-series perspective and contribute to the more recent literature on international return predictability. In particular, we investigate the predictive power of global versus local financial valuation ratios in a panel of 12 developed countries. While a number of recent contributions have shown that equity index returns in local markets can partially be predicted by global factors,[1] there is little evidence so far to what extent global and local factors are responsible for the predictability. We attempt to shed light on this question by disentangling the global and local component in financial valuation ratios and by quantifying their respective explanatory power. We find that the global factor appears more important than hitherto thought and detect a distinct time trend. Consistent with the idea of a strengthening market integration,[2] the explanatory power of global factors is substantially stronger in the recent decades. Furthermore, we find substantial time-variation in global predictors, but not in local ones, suggesting that the instability of predictive regressions as documented in the literature[3] is primarily driven by the global component. In an attempt to uncover the driving forces behind these findings, we complement our analysis by decomposing the variability in valuation ratios into a discount rate and a cash flow driven component along the lines of the Campbell and Shiller (1988b) framework. As often suggested in the literature (see e.g. Cochrane, 2005), the evidence of return predictability comes along with the observation that the discount rate variability is much stronger than cash flow related variability. We investigate this relation for local and global valuation ratios and find that while local ratios are driven by both, cash flow and discount rate innovations, global ratios are almost exclusively driven by discount rate innovations. By recognizing that global price ratios can be thought of as weighted average of local ratios, our results imply that aggregate valuation ratios are more strongly driven by the discount rate factor. Our results complement the finding in Vuolteenaho (2002), who shows that national equity index returns are more strongly affected by discount rate news than the disaggregated industry returns, and the contribution by Ammer and Wongswan (2007) who stress the importance of discount rate news on a global level. Our paper brings together

[1] See e.g. Rangvid (2006), Cooper and Priestley (2009, 2013), McMillan (2016), Rapach, Strauss, and Zhou (2013a).

[2] See e.g. Campbell and Hamao (1992), Ammer and Mei (1996), Bekaert and Harvey (1995), Bekaert, Harvey, Lundblad, and Siegel (2011).

[3] See e.g. Dangl and Halling (2012)

both strands of the literature (i.e. return predictability and variance decomposition) in a comprehensive framework and shows that the declining power of local valuation ratios goes along with a declining fraction of variability due to the discount rate component.

The article is organized as follows. Section 2 provides an overview on existent literature. Section 3 tries to formalize the intuition of global and local DR and CF effects. Section 4 introduces data sources and data constructions. In Section 5 we show the main results from predictive regressions, vector autoregressions (VAR) and Bayesian VARs. Section 6 tackles robustness and Section 7 concludes.

2. Literature Review

In this section we outline the literature most closely related to our research question. We distinguish three major stream, (i) return predictability in an international context, (ii) variance decomposition in cash flow news and discount rate news and (iii) global asset pricing studies.

Time variation in expected returns has been tackled by researchers going back to the seminal findings of Campbell and Shiller (1988a). On the international level, one imminent question is to which extent information from outside markets can be associated with local stock index returns. Important contributions come from Harvey (1991), Campbell and Hamao (1992), Bekaert and Hodrick (1992), Solnik (1993), Richards (1995) or Hou, Karolyi, and Kho (2011). These studies focus on the international evidence on return predictability and interlinkages between countries. In particular, Campbell and Hamao (1992) test whether a US financial ratio can predict Japanese returns. More recently, Rapach, Strauss, and Zhou (2013b) find evidence that lagged US returns predict returns in other countries. Related, Lawrenz and Zorn (2017) find improvements in predictability by adding an indicator whether local price-earnings ratios are consistent with global ratios, suggesting that global factors help forecast country returns. This strand of literature motivates our approach in finding a local, country specific factor and a global factor which tracks a fraction of expected returns.

As pointed out by e.g. Albuquerque and Vega (2009), global co-movement of stock markets can be explained by either fundamental macroeconomic linkages or news diffusion. Related to the former explanation, several macroeconomic predictor variables have been tested. Rangvid (2006) constructs a price to industrial production ratio tracking a larger fraction of expected returns than price-earnings and price-dividend ratios. Cooper and Priestley (2009) find similar predictive power using a measure of output gap (log of detrended industrial production). In the global factor context, Cooper and Priestley (2013) define a (world) capital to output ratio closely tied to the world business cycle. This variable tracks variation in expected returns for a group of developed countries, hinting towards a global pattern for return predictability.

Using purely financial predictor variables on a global level such as the price-dividend ratio on the MSCI world market index goes back to e.g. Ferson and Harvey (1993) or Bekaert and Harvey (1995), who use it as predetermined variable in a test of a conditional international CAPM model. More recently, Ammer and Wongswan (2007) use the MSCI world dividend yield in a VAR model and apply the Campbell decomposition. McMillan (2016) also emphasizes the role of local and global information for predictability. Instead of using a genuine global variable, he first follows Rapach et al. (2013b) in taking US data as pivotal and second applies principal component analysis to construct a global factor. In an attempt to identify global and local components, variables are orthogonalized. We take up the approach of orthogonalization, which actually goes back in this particular context to Stehle (1977), as it allows us to quantify the explanatory power of local and global factors and circumvents issues of multicollinearity in multivariate predictive regressions.

Another strand of literature closely tied to our research tries to assess the nature for time-varying expected returns. Against the background of a simple present value idea, it is almost trivial to state that prices will vary either through changing cash flows (CF) or changing discount rates (DR). Making this intuition more rigorous, Campbell (1991) prominently decomposes expected returns into CF and DR innovations. For the US, numerous studies employ this decomposition and find, by and large, that most of the fluctuation in unexpected stock index returns can be associated with DR news.[4] Cochrane (2011) in his AFA presidential address makes the prominent point for discount rates being the sole driver for price-dividend variation. On an international scale, Ammer and Wongswan (2007) stress the DR channel as being more pronounced on the global level, whereas CF news matters more on the local level. They emphasize common risk perception in international equity returns and international co-movement in risk premia. Vuolteenaho (2002) decomposes returns both on the firm level and the aggregated level and finds that at a more disaggregated level, returns are driven largely by the cash flow component whereas for portfolios, the discount rate component is more pronounced. They argue, "[t]his finding suggests that cash flow information is largely firm specific and that expected-return information is predominantly driven by systematic, market-wide components"(Vuolteenaho, 2002, p.259). Our contribution is related to the latter paper by taking the analysis on a higher aggregation level and investigating if national or international valuation ratios are more strongly affected by either

[4] See e.g.Campbell and Ammer (1993), Ammer and Mei (1996), Van Binsbergen and Koijen (2010) or Koijen and Van Nieuwerburgh (2011).

cash flow and discount rate information.

On the methodical side, it has been argued that estimating CF and DR components is subject to instability depending vastly on the specification as emphasized by Chen and Zhao (2009) or Engsted, Pedersen, and Tanggaard (2012). To address such concerns, we employ a Bayesian estimation technique for estimating vector autoregressions (VARs) in the spirit of Hollifield, Koop, and Li (2003) and Balke, Ma, and Wohar (2015).

Coefficient instability has also been documented for predictive regressions. Dangl and Halling (2012) suggest to estimate predictive regressions which explicitly allow time-variation of regression coefficients. By investigating the time-variation from a rolling-window approach, we show that only the global component displays large variability in estimated coefficients, while local predictors appear stable over time. Instability might also arise due to changes in the steady state of predictor variables as noted by Lettau and Van Nieuwerburgh (2008) motivating regime switching procedures as in Zhu (2015). Rapach, Strauss, and Zhou (2010) suggest using forecast combinations to counter instability and thereby linking forecasts to the real economy. Our approach works in the same direction, since we incorporate a global, business cycle related factor in our analysis.

The last strand of literature concerns global asset pricing. Is there a priced risk factor structure across global equity markets? Early studies generally reject the hypothesis of a common stochastic discount factor (SDF) (see e.g. Cumby, 1990; Campbell and Hamao, 1992; Bekaert and Hodrick, 1992). However, studies examining the factor pricing relationships for returns by the world CAPM find support for a common pricing relationship (Harvey, 1991; Ferson and Harvey, 1993). Still, empirical tests for unconditional and conditional versions of the world CAPM yield ambiguous results as shown by Dumas and Solnik (1995) or Adler and Dumas (1983). The existence of a global discount rate which prices local (country) equity markets is still debated upon. As Lewis (2011) summarizes, although international traded assets continue to depend strongly upon local risk factors, both domestic and global risk factors matter for equity returns. Overall, our contribution adds to the debate by quantifying the extent of global factors and relating their importance to the discount rate component.

3. Theoretical Framework

In this section, we provide the theoretical basis for the empirical tests, where we combine local and global factors as determinants for local (country index) returns. The main workhorse in the return predictability literature is the Campbell and Shiller (1988a,b) dynamic dividend discount model, which links the (time-varying) dividend yield to expected returns and dividend growth, $pd_t = const. + \mathbb{E}_t\left[\sum_{j=1}^{\infty}\rho^{j-1}(\Delta d_{t+j} - r_{t+j})\right]$, where lower case letters denote logs and pd_t is the price-dividend ratio, Δd_{t+j} the future dividend growth and r_{t+j} the future return. ρ is a number close to one, $\exp^{p-d}/(1+\exp^{p-d})$. This accounting identity is an approximation being accurate for ratios with variations not too large. Rational bubbles are ruled out under the transversality condition that pd_t does not explode faster than ρ^{-t}, $\lim_{j\to\infty}\rho^j(p_{t+j} + d_{t+j}) = 0$ (see e.g. Lewellen (2004) and Cochrane (2008)). The interpretation of this identity is straightforward. High pd_t ratios must be followed by high dividend growth Δd_{t+j} or low returns r_{t+j} or a combination of both.

Campbell and Shiller (1988a,b) use the pd ratio for the decomposition, but subsequent literature has shown, that the same reasoning leads to analogous expressions for other valuation ratios, such as price-earnings or price-output ratios. Therefore, we use the notation φ as a generic label for a given cash-flow proxy, being either dividends (d), earnings (e) or output (ip for industrial production). Thus, the general price-to-fundamental ratio $p\varphi_t$ has the decomposition

$$p\varphi_t = const. + \mathbb{E}_t\left[\sum_{j=1}^{\infty}\rho^{j-1}(\Delta\varphi_{t+j} - r_{t+j})\right], \tag{1}$$

where $\varphi \in \{d, e, ip\}$. For the pe ratio, the approximation specifies to $pe_t = const. + \mathbb{E}_t\left[\sum_{j=1}^{\infty}\rho^{j-1}(\Delta e_{t+j} - r_{t+j})\right]$, where dividends are substituted by earnings as the cash flow proxy.[5] The case of industrial production ip is motivated by the evidence of Lettau and Ludvigson (2001) that a consumption-aggregate wealth ratio can track variation in expected returns, and Rangvid (2006) who relates a price to GDP ratio to the Campbell and Shiller (1988a,b) identity. The key assumption for this relation is that the non-stationary behavior of dividends is directly related to the output in the economy $d_t = y_t + \nu_t$ where ν_t must be a stationary disturbance term. The specification is then $pip_t = const. + \mathbb{E}_t\left[\sum_{j=1}^{\infty}\rho^{j-1}(\Delta ip_{t+j} - r_{t+j})\right]$. The interpretation is similar as before; high pip_t ratios correspond to either high expected output growth in terms of industrial production or lower expected future returns, or a combination of both.

In order to determine the extent, to which a given price ratio is driven by either cash flow and discount rate information, we follow the literature on the variance decomposition. Multiplying both sides of Eq. (1) by $p\varphi_t - \mathbb{E}[p\varphi_t]$ and taking expectations yields

$$Var(p\varphi_t) = -Cov\left(p\varphi_t, \mathbb{E}_t\left[\sum_{j=1}^{\infty}\rho^{j-1}\Delta\varphi_{t+j}\right]\right) + Cov\left(p\varphi_t, \mathbb{E}_t\left[\sum_{j=1}^{\infty}\rho^{j-1}r_{t+j}\right]\right). \tag{2}$$

[5] Evidently, correctly specified we would need to account for the (log) payout ratio $de = log(D_t/E_t)$, adding the term $(1-\rho)de_{t+j}$ to Δe_{t+j} (see e.g. Chen, Da, and Priestley 2012). However, we test proxies for cash flows and compare their differences throughout the paper.

We extend this variance decomposition to account for both local as well as global information. To extract pure local (L) versus global (G) information from country-specific and global ratios, we orthogonalize them following the approach of Stehle (1977), which has been used in McMillan (2016) more recently,[6] Let $p\varphi_i$ be the country specific predictor variable which is driven by local as well as global information. Furthermore, let $p\varphi_G$ be the global predictor variable. Then, we extract the purely local information by regressing the country-specific ratio on the global one, i.e.

$$\begin{aligned} p\varphi_{i,t} &= a_i + b_i \, p\varphi_{G,t} + e_{i,t}, \\ e_{i,t} &\equiv p\varphi_L. \end{aligned} \tag{3}$$

By regressing $p\varphi_i$'s on $p\varphi_G$ the residual is orthogonal to $p\varphi_G$. We define this residual as the purely local ratio $p\varphi_L$ (stacked vector). On the one hand, orthogonalization allows us to disentangle truly global information from the local ratios, and on the other hand it avoids problems of multicollinearity in the multivariate regression approach.

By generalizing Eq. (2), we are able to perform a variance decomposition including global and local information for horizon k. For the global ratio we get

$$\begin{aligned} Var(p\varphi_{G,t}) = &- Cov\left(p\varphi_{G,t}, \mathbb{E}_t\left[\sum_{j=1}^{k} \rho^{j-1} \Delta\varphi_{G,t+j}\right]\right) - Cov\left(p\varphi_{G,t}, \mathbb{E}_t\left[\sum_{j=1}^{k} \rho^{j-1} \Delta\varphi_{L,t+j}\right]\right) \\ &+ Cov\left(p\varphi_{G,t}, \mathbb{E}_t\left[\sum_{j=1}^{k} \rho^{j-1} r_{t+j}\right]\right) \\ &+ Cov\left(p\varphi_{G,t}, p\varphi_{L,t+k}\right) + Cov\left(p\varphi_{G,t}, p\varphi_{G,t+k}\right), \end{aligned} \tag{4}$$

where the first line captures the covariance with global and local cash flow variation, the second line captures global discount rate innovations and the third line captures autocovariance and covariance with the local ratio. As $k \to \infty$ the last two terms should approach zero.

This variance decomposition can be inferred from a vector autoregression (VAR). Consider a first order VAR with predictor variable $p\varphi$, fundamental variable φ, and returns r,

$$r_{t+1} = a_r + b_r p\varphi_t + \varepsilon^r_{t+1}, \tag{5}$$

$$\Delta\varphi_{t+1} = a_\varphi + b_\varphi p\varphi_t + \varepsilon^\varphi_{t+1}, \tag{6}$$

[6] We employ the orthogonalization procedure to disentangle local from global information. Overall, and importantly, results of the paper are qualitatively the same when using non-orthogonalized ratios.

$$p\varphi_{t+1} = a_x + \phi p\varphi_t + \varepsilon^x_{t+1}, \tag{7}$$

where Δ is a backward difference operator. In parsimonious notation this reads

$$\begin{bmatrix} Y_{t+1} \\ Z_{t+1} \end{bmatrix} = A + \Gamma \begin{bmatrix} Y_t \\ Z_t \end{bmatrix} + \varepsilon_{t+1}, \tag{8}$$

where we split the variables $p\varphi_t$ into a state vector Y which includes local return, cash flow and predictor variables and a state vector Z which includes global cash flow and predictor variables.

Due to potential multicollinearity between different predictor variables, we choose to use a model including dp, pe and pip separately. The setting for the dividend yield then reads $Y = [dp^L_t, \Delta d^L_t, r_t]'$ and $Z = [dp^G_t, \Delta d^G_t]'$. A is the intercept vector. Γ is the coefficient matrix. The variance of the global dividend yield due to cash flow is given by:

$$-\,Cov\left(dp^G_t, \mathbb{E}_t\left[\sum_{j=1}^{\infty} \rho^{j-1} \Delta d^L_{t+j}\right]\right) = -e_2' \Gamma (I - \rho\Gamma)^{-1}\ \Sigma_{Y,Z} e_4 \tag{9}$$

and

$$-\,Cov\left(dp^G_t, \mathbb{E}_t\left[\sum_{j=1}^{\infty} \rho^{j-1} \Delta d^G_{t+j}\right]\right) = -e_5' \Gamma (I - \rho\Gamma)^{-1}\ \Sigma_{Y,Z} e_4 \tag{10}$$

with the unconditional covariance matrix of Y_t and Z_t, $\Sigma_{Y,Z} = devec[(I - \Gamma \otimes \Gamma)^{-1} vec(\Sigma)]$.

The variance due to discount rate fluctuations can be determined by

$$Cov\left(dp^G_t, \mathbb{E}_t\left[\sum_{j=1}^{\infty} \rho^{j-1} r_{t+j}\right]\right) = -e_3' \Gamma (I - \rho\Gamma)^{-1}\ \Sigma_{Y,Z} e_4. \tag{11}$$

We refrain from including further variables such as interest rates, yield spreads or exchange rates due to ambiguous results in the literature (see e.g. Campbell and Ammer (1993), Ammer and Mei (1996)). Ammer and Wongswan (2007) show that these variables are less relevant for explaining expected return variation.

4. Data

We use monthly data for 12 developed countries including Austria, Belgium, Canada, Denmark, France, Germany, Ireland, Japan, Netherlands, Switzerland, UK and US. The global ratios are based on the MSCI World. Return indices, price indices, dividend yields and price-earnings ratios are gathered from Thomson Reuters' Datastream. Data for industrial production are from the OECD database. Our sample extends over the period 1975M1 to 2014M4 and all prices are in $US.[7]

To construct the price to industrial production ratio (*pip*) we follow Rangvid (2006). However, in order to make sure our subsequent analysis is not spurious, we detrend the ratio using two different methods. First, in the benchmark case, we detrend the ratio linearly with a trend t for each cross-section,

$$(p_t - ip_{t-1}) = \alpha + \beta t + u_t. \tag{12}$$

The second specification adds a quadratic term as in Cooper and Priestley (2009),

$$(p_t - ip_{t-1}) = \alpha + \beta t + \gamma t^2 + u_t. \tag{13}$$

5. Results

5.1. *Predictive regressions*

In this section, we present results from univariate predictive regressions. In a pooled panel approach we run the following equation for the sample of $i = 1, \ldots, 12$ countries,

$$r_{i,t+1} = \alpha_k + \mathbf{G}_t' \, \beta_k \; + \; \mathbf{L}_{i,t}' \, \gamma_k \; + \; u_{i,t+1}, \tag{14}$$

where $\mathbf{G} = [dp_G, pe_G, pip_G]'$ denotes the vector of lagged global predictor variables and $\mathbf{L} = [dp_L, pe_L, pip_L]'$ being the vector of lagged local predictor variables. $r_{i,t+1}$ denotes the one period ahead return. All variables are in logs. By pooling variables, we include additional cross-sectional information and thus mitigate the endogeneity effect of the predictive variables.[8] Panel Corrected Standard Errors (PCSE) computed from Seemingly Unrelated Regressions (SUR) are used for inference (see e.g. Beck and Katz (1995) or Ang and Bekaert (2007)). We choose these standard errors over the Newey and West (1987) methodology, since they are more conservative.

Table 1 summarizes results of predictive regressions for various specifications including

[7] Analogous to Ammer and Wongswan (2007) we find similar results when returns are measured in local currencies.

[8] As noted by Hjalmarsson (2010), the pooled estimator is unbiased as long as no fixed effects are included. As a (unreported) cross-check we estimated a fixed effects model finding no meaningful differences in the results.

local and global dp, pe and pip ratios. Row (i) shows the usual predictive regression including the country specific dp, pe and pip ratios. All three variables exhibit a highly significant positive coefficient and R^2s between 0.13 and 0.19% on a monthly basis. This is in line with the literature on global in-sample tests. Country specific ratios do seem to forecast returns for the 1 month ahead horizon.[9] In row (ii), we include the (orthogonalized) local ratios dp_L, pe_L and pip_L. Again, the predictive coefficients are highly significant. However, R^2s are lower compared to the previous specification. In row (iii), we include the global ratios dp_G, pe_G and pip_G. Interestingly, global ratios do exhibit significant predictive power for country returns. R^2s are between 0.02% and 0.1%. Particularly for dp and pip ratios, we can see that local and global ratios exhibit about the same predictive power. In row (iv), we include both the local and the global ratio as predictor variables. In this specification, both local and global ratios significantly predict the 1-month ahead return. We achieve even higher R^2 in this specification, ranging from 0.16% to 0.25%. This evidence underscores the importance of global factors in predicting country returns.

[Insert Table 1 near here]

5.2. Variance decomposition (VAR)

To capture the influence of discount rate and cash flow variability on local and global variables, we decompose the variance implied by the VAR following Ammer and Wongswan (2007) and in particular Ang (2012) for ratios.

Table 2 shows the variance decomposition for each ratio based on estimations from Eqs. (9) and (10) for cash flows and Eq.(11) for discount rates. For all global ratios, most of the variance is due to discount rate innovations (dp_G, pe_G, pip_G). For local ratios, the picture is different. Both, discount rate and local cash flow innovations influence local ratios. Particularly, for dp_L and pe_L, cash flow fluctuation is capturing more of the variance, 47.47 versus 34.38 and 66.09 versus 25.46 respectively. For pip_L, however, the discount rate channel seems more important in explaining variance. This might be due to the macroeconomic nature of the variable and the proximity of output being actual cash flow. Global cash flow components do not seem to influence ratios' variance a lot. The relatively high covariance terms between local and global ratios (columns 4 and 5) arise due to commonalities between the ratios themselves. Although local and global components are orthogonalized, they still share a common pattern.[10] Overall, the findings suggest that global ratios fluctuate mainly

[9] (Unreported) Results on longer horizon predictions are qualitatively the same both for the univariate predictions and for the variance decompositions in the subsequent sections.

[10] We ran the decomposition with local or global components alone finding no major differences with respect

due to DR innovations whereas local ratios fluctuate due to CF and DR innovations. These findings are in line with evidence from Ammer and Wongswan (2007) who detect a similar pattern for global and local components in returns. They note that "results are broadly consistent with co-movement in future discount rates arising from perceptions of common elements of risk in international equity markets" (p.211). Indeed, our results point in a similar direction, since DR determine the fluctuation of a global ratio which subsequently predicts index returns. CF, on the contrary, determine local ratios exclusively. This is in line with evidence from Vuolteenaho (2002), who stresses the importance of CF news for firm level stock returns. The more stock returns are aggregated, CF fluctuation can be diversified away.

Figure 1 shows impulse response functions for local and global ratios following the Cholesky decomposition.[11] Similar to the variance decomposition, the graphs on the left hand side emphasize the response of local ratios to return and cash flow innovations over ten periods (months). Both channels trigger a response of the ratio. On the right hand side, responses of global ratios are depicted. Here, mainly return (DR) innovations triggers a response of the ratios.

We further test whether there is some kind of lead-lag relationship between global and local ratios. As outlined in the variance decomposition, the covariance terms between innovations in local (global) ratios and global (local) ones are relatively high in magnitude. Since global ratios are defined by aggregated cash flows from local ratios, they are interdependent. However, prices as the numerator (or denominator for *dp*) are determined both by local and global influences. Table 3 shows Granger causality tests for local and global ratios.[12] In the bottom panel, we test pairwise Granger causality. Results are somewhat ambiguous. While for *dp* ratios the Granger causality goes from global to local, results for the other ratios are unclear. The same is true for panel causality tests which test Granger causality homogeneously. Overall, the tests show a tendency towards better predictability of local ratios by global ones. This constitutes further evidence on the importance of global factors in explaining expected returns locally and the existence of a global discount rate.

[Insert Table 2 near here]

[Insert Table 3 near here]

to the DR and CF components. Also, unreported results from simulated data show that the orthogonalization does not mechanically give rise to large covariance terms between the local and global term.

[11] We employ the Cholesky ordering $[r, x_G, x_L, \Delta o_G, \Delta o_L]$. Importantly, results are robust to different orderings, exchanging local with global counterparts.

[12] We used orthogonalized and non-orthogonalized local ratios for the tests yielding virtually the same test results.

[Insert Figure 1 near here]

5.3. *Evidence across time (BVAR)*

In this section, we present evidence across time. Motivated by possible parameter instability of DR and CF components implied by the VAR, particularly in smaller samples (see e.g. Chen and Zhao, 2009), we use a Bayesian Vector Autoregression (BVAR). Although VARs are prominently used in the literature to capture DR and CF components, several authors point to distinct weaknesses (see e.g. Engsted et al. (2012)). One of it being biased classical estimates. BVARs make it possible to estimate robust parameters through shrinkage towards a prior distribution of estimates. Also, one can alter the prior specification to get an idea of the stability of estimates. For these reasons, we estimate the influence of DR and CF variation in a BVAR in the spirit of Hollifield et al. (2003) and Balke et al. (2015). Consider a stacked version of Eq. (8),

$$B = C\,\Gamma + U, \qquad U \sim \mathcal{MN}(0, \Sigma \otimes I), \tag{15}$$

where B includes global and local variables (Y and Z) at time t. C includes lagged global and local variables (Y and Z) at $t-1$. U follows a matrix Normal distribution. The OLS estimates for location and dispersion are

$$\hat{\Gamma} = (C'C)^{-1}C'B \tag{16}$$

and

$$\hat{\Sigma} = \frac{1}{T}(B - C\hat{\Gamma})'(B - C\hat{\Gamma}) \tag{17}$$

with $\text{Var}(vec(\Gamma)) = \hat{\Sigma} \otimes (C'C)^{-1}$. The prior is modeled as normal-inverse-Wishart ($\mathcal{NIW}$),

$$p_1(\Gamma, \Sigma^{-1}) = p(\text{vec}(\Gamma))\; p(\Sigma^{-1}), \tag{18}$$

where

$$p(\text{vec}(\Gamma)) \propto f_{\mathcal{N}}^{k^2}(\text{vec}(\Gamma_0), D_0^{-1})\; I(\Gamma \in \Omega), \tag{19}$$

and

$$p(\Sigma^{-1}) = f_{\mathcal{W}}^{k}(v_0, E_0^{-1}). \tag{20}$$

$f_{\mathcal{N}}^{k^2}$ is the k^2-variate Normal pdf with prior mean $\text{vec}(\Gamma_0)$ and covariance matrix D_0^{-1} (proportional to Σ^{-1}). $f_{\mathcal{W}}^{k}$ is the k-dimensional Wishart pdf where $I(\Gamma \in \Omega)$ is an indicator function

for the region Ω. Without restriction on Γ, $\Omega = R^{k\times k}$. Γ_0, D_0, v_0 and E_0 are hyperparameters to be specified for the prior distribution.
Combining the likelihood function of the VAR in Eq. (15) with the prior in Eqs. (18)-(20), we obtain the joint posterior for Γ and Σ^{-1},

$$p(\Gamma, \Sigma^{-1}|B, C) \propto p_1(\Gamma, \Sigma^{-1}) \cdot p(B|C, \Gamma, \Sigma^{-1}). \tag{21}$$

Consequently, the posterior can be decomposed into the conditional densities for vec(Γ) and Σ^{-1}, respectively

$$p(\text{vec}(\Gamma)|B, C, \Sigma^{-1}) \propto f_{\mathcal{N}}^{k^2}(\text{vec}(\tilde{\Gamma}), \tilde{D}^{-1}) I(\Gamma \in \Omega), \tag{22}$$

$$p(\Sigma^{-1}|B, C, \Gamma) = f_{\mathcal{W}}^{k}(\tilde{v}, \tilde{E}^{-1}), \tag{23}$$

where $\text{vec}(\tilde{\Gamma}) = \tilde{D}^{-1}[(\Sigma^{-1} \otimes (C'C)) \cdot \text{vec}(\Gamma) + D_0 \cdot \text{vec}(\Gamma_0)]$, $\tilde{D} = \Sigma^{-1} \otimes (C'C) + D_0$, $\tilde{E} = SSE + E_0$, $\tilde{v} = T + v_0$ and $SSE = (B - C\Gamma)'(B - C\Gamma)$. Since we employ natural conjugate priors whose posterior has the same distributional family as the prior distribution, we can solve the Bayesian VAR analytically.

The prior in the base case is specified as follows. We demean the variables in the VAR and shrink the estimates towards the mean with the hyperparameter $vec(\Gamma_0) = 0_{k^2}$. For the prior variance, we set the scale matrix D_0 for Σ with a scalar of 0.1 times the identity matrix I_{k^2}. Through this scalar, we can model the overall tightness of the prior covariance matrix. The hyperparameter E_0 is the identity matrix I_k.

Table 4 shows the variance decomposition over time inferred from the BVAR. Percentage numbers are defined as variance proportions of combined DR and CF variance. The first two columns summarize the finding of Table 2 for the whole sample period. For global ratios, subsamples show very similar decompositions as in the whole sample. DR fluctuations dominate global ratios. Local ratios are subject to more variability. Across all local ratios, the relative importance of CF does rise in later periods. Particularly for the subsample 2000-2014, CF account for 80% and 85% of variation for local *dp* and *pe* ratios. For pip_L, cash flow information also rises in importance, though the DR channel still prevails with 75% in the most recent subsample.

Predictability patterns across time for three sub-samples using the BVAR approach are summarized in Table 5. Row (i) shows coefficients for country specific predictor variables. For the first subsample (1975-1987) neither of the predictors are significant with even the wrong sign. For the second period (1987-2000), all three variables significantly predict future returns. R^2s range between 0.63% to 0.72%. In the last subsample (2000-2014), only the *pip* ratio significantly predicts future returns. Specifications in rows (ii) include only the local (orthogonalized) ratios. For the first subsample, the local ratios exhibit higher explanatory power compared to specification (i) as emphasized by R^2. For the second subsample, local ratios generate higher R^2 for the dp ratio but lower explanatory power for pe and pip compared to the country specific ratios in (i). In the last sample (2000-2014), local ratios perform worse than the country specific ones in (i) with lower R^2s. In specification (iii), we test the predictive power of global ratios. In the first subsample, global ratios exhibit highly significant coefficients and R^2s higher than specification (i) and (ii). The picture is similar but slightly weaker for the period 1987-2000. Importantly though, for the last subsample (2000-2014), global ratios show highly significant coefficients and highest R^2. Evidently, based on this analysis, global ratios gained importance in the recent periods. Specification (iv) combines local and global ratios in the predictive system. Again, we can detect a growing dominance of global ratios as being the driver for return predictability. Together, these findings suggest that predictability of future returns shifted from the local component to the global one, which may explain the lack of DR as innovator in local ratios' variance.[13]

Figure 2 provides further insights on the role of global versus local predictors. The three graphs show coefficients for local and global predictors based on dp, pe and pip ratios. We estimate a rolling regression with 10 year in-sample estimation. Solid lines are global predictors' coefficients, while dashed lines are local predictors' coefficients. The shaded area represents one standard error bounds. We inverted the scale of the dp ratios to ease comparisons. For most of the horizon, the local predictive coefficient is below zero and thus helps predict future returns significantly. In the last sample period, though, the local predictor is not significantly different from zero. Contrary, the global coefficient exhibits much more volatility but remains most of the time below zero implying predictive power.

To quantify the importance of local versus global predictor variables, we follow Grömping (2007) and decompose a model's total explanatory value into relative contributions of the regressors (i.e. global versus local predictors). The approach is based on Lindeman, Merenda, and Gold (1980) who first outline the concept of averaging sequential sums of squares over orderings of regressors. Figure 3 summarizes results in terms of bar charts. Interestingly, we detect for the first subsample (1975-1987) that local ratios contribute most to the explanatory power of the model, ranging from 46% to 68%. In the second subsample (1987-2000) only dp local rises by 8%, all other local predictors lose relative predictive importance (31% and 38%). In the last sample, we detect that almost all predictive power comes from the global ratio – in line with results in the previous paragraph. The global predictor has a relative

[13]We stress that the higher predictive power of global ratios is not an artefact associated with the crisis years. We control for the crisis using dummies finding no significant difference in our results.

importance of 89% to almost 100%.

[Insert Table 4 near here]

[Insert Table 5 near here]

[Insert Figure 2 near here]

[Insert Figure 3 near here]

6. Robustness

In this section we provide additional robustness checks against common concerns. We base the subsequent checks on the BVAR model.

6.1. Role of the United States

Many studies demonstrate the US as a pivotal factor in other countries' predictability. Prominently, Rapach et al. (2013b) show that lagged US returns help predict future returns in other countries. Our approach is more general, as we try to capture the global influence on expected returns. Although the US is a major driver of global financial and economic shifts, we test whether our results are sensible to the inclusion of US ratios and returns.

Table 6 shows the BVAR variance decomposition excluding the US. Compared to the variance decomposition including the US, the results are remarkably stable. No major changes in the decomposition can be found. Only local dp ratio percentages change by 5% in the whole sample. Other numbers do not change by more than 2%. This suggests that the evidence is not a pivotal phenomena associated with the leading role of the US. It is truly a global phenomenon.

[Insert Table 6 near here]

6.2. Anglo-Saxon countries

It is often argued that due to their relatively more pronounced market based financial systems, Anglo-Saxon countries are different. In fact, the equity premium is considered to be larger compared to other developed countries (see e.g. Ang and Bekaert, 2007). To check if our results is primarily driven by Anglo-Saxon countries, we extract principal components of returns and country specific ratios (motivated by e.g. McMillan, 2016). Table 7 shows results for the principal component analysis. The first principal component captures 59% of the return dispersion. Interestingly, this component is positive in all countries. We interpret this as further evidence for the importance of a global factor in returns. By replacing the global predictor variable with the first principal component in the VAR we arrive at similar results for the variance decomposition. For the whole sample period, the first principal component of predictor variables varies mostly via the DR channel (90.9%). The second principal component is negative for all but Canada, Japan, UK and US. There might be fundamental differences between Anglo-Saxon countries (and Japan) and the rest of the sample. For ratios, the first component is positive for all countries as well with the exception of *pip* for Ireland. Again, a global component in ratios seems plausible based on this result.

Given these differences, we employ the previous variance decomposition excluding Canada, Japan, UK and US separately. Table 8 summarizes the results. Similar to the exclusion of US only, the results are remarkably robust. Numbers for DR and CF change at the maximum by 6% with no clear additional pattern, suggesting the overall results are truly general for the countries in the sample.

[**Insert Table 7 near here**]

[**Insert Table 8 near here**]

6.3. Individual countries

Table 9 highlights differences across individual countries. Overall, matching previous variance decomposition results, global ratios fluctuate due to discount rate innovations whereas local ratios fluctuate due to CF and DR innovations. Still, some heterogeneity can be detected. While for Austria, global ratios fluctuate almost exclusively due to the DR channel (99%), this number is closer to 85% for Germany. Local ratios display an even higher dispersion ranging from 65% cash flow driven (US) to 9% in Switzerland. The results support the phenomena that a global discount rate is rather uniform across countries but local discount rates and cash flows are much more country specific.

Table 10 shows coefficients and R^2s for individual, country specific, predictive regressions following Eq. (14) and the *dp* ratio as predictor. Similar to preceding research the predictability evidence across countries is weak at best. In fact we cannot detect significant predictability on common confidence levels for any individual country in our sample. Thus, we refrain from interpreting any cross-sectional differences.

[**Insert Table 9 near here**]

[**Insert Table 10 near here**]

6.4. Simulated data

We test the above models using simulated price to fundamental ratios. Through such procedures, we can counter concerns about data mining, spurious relationships and even possible mechanical, tautological relationships particular from the VAR. Since price to fundamentals ratios are generally highly persistent, we model artificial ones following the discrete version of an Ornstein-Uhlenbeck process as the data generating process,

$$dX_t = \theta(\mu - X_t)\,dt + \sigma\,dW_t, \tag{24}$$

where $\theta > 0$ denotes the rate by which shocks dissipate, μ is the equilibrium mean, $\sigma > 0$ the volatility parameter and dW_t is the increment of a Wiener process. The process is mean reverting and converges to a stationary distribution. We match the moments of this process with our empirical estimates of *pe* ratios.[14]

Replacing our sample with simulated ratios for 12 artificial countries and one global simulated ratio yields the following (unreported) results:[15] Point estimates, as expected, show no significant pattern neither in the univariate regression nor in the VAR system. Variance decompositions of (orthogonalized) simulated ratios show no mechanical connection to DR or CF fluctuations, covariances with residuals are virtually zero.

Comparing empirical orthogonalized local ratios with non-orthogonalized, country specific ratios, yields a difference of 25% in the variance decomposition of DR and CF variations over the whole sample. Where for orthogonalized (local) ratios, CF information dominates, for non-orthogonalized (local) ratios, DR are slightly higher. We perceive this as a further hint on the global nature of the discount rate channel.

[14] Mean empirical estimates from *pe* ratios are $\widehat{\theta} = 0.98$, $\widehat{\mu} = 2.96$ and $\widehat{\sigma} = 0.42$.

[15] We both test a separately simulated global ratio and a global ratio constructed as the mean from simulated country ratios.

7. Conclusion

We approach the identification of global factors in international asset pricing from the perspective of time-series predictive regressions of local index returns on financial valuation ratios such as price to fundamental ratios. We orthogonalize local and global ratios in order to clearly disentangle both information sources. We run predictive panel regressions to gauge the explanatory power of local and global ratios and estimate frequentist and Bayesian VAR models to perform a Campbell and Shiller (1988a) variance decomposition in order to quantify the cash flow and discount rate components.

In line with previous literature, we find global price-ratios to significantly predict national index returns. We advance the understanding by disentangling the global component and showing it to be at least equally important as the local ratios. Consistent with the idea of increasing market integration, we detect a distinct time trend in our 1975–2014 sample, showing that the global component gained importance in recent decades. In fact, during the most recent sub-period 2000-2014, only the global ratio turns out to be a significant predictor of local index returns. Furthermore, the temporal development of predictive regression coefficients from a rolling window approach shows that local predictors display only little time-variation, while global predictors display large swings over time. The evidence suggests, that the instability of predictive regressions is mainly driven by the global factor.

Our contribution combines predictive regressions with a cash flow/discount rate variance decomposition. We find that local ratios fluctuate due to variation in both, cash flow and discount rate innovations, while global ratios are almost exclusively driven by the discount rate component. Our results complement related findings by Ammer and Wongswan (2007) and Vuolteenaho (2002). We go beyond the previous literature in showing distinct time trends in the decomposition. In particular, we observe a steady decline in the discount rate component in local ratios. Second, we relate this evidence to the predictability results and show that the lack of local ratios' predictability particularly in the post 2000's era can be associated with global ratios tracking a larger fraction of expected return variation.

Overall, our results support the idea that evidence of stronger predictability can be observed from predictors which are more strongly driven by discount rate innovations. Furthermore, we demonstrate that global predictors became more important in recent decades. The declining predictive power of local predictors goes hand in hand with a decline in the discount rate channel. Our results stress the importance of global discount rate news in the time variation of expected returns and may prove useful in an asset allocation exercise.

References

Adler, M., Dumas, B., 1983. International portfolio choice and corporation finance: A synthesis. The Journal of Finance 38, pp.925–984.

Albuquerque, R., Vega, C., 2009. Economic news and international stock market co-movement. Review of Finance 13, pp.401–465.

Ammer, J., Mei, J., 1996. Measuring international economic linkages with stock market data. The Journal of Finance 51, pp.1743–1763.

Ammer, J., Wongswan, J., 2007. Cash flows and discount rates, industry and country effects and co-movement in stock returns. Financial Review 42, pp.211–226.

Ang, A., 2012. Predicting dividends in log-linear present value models. Pacific-Basin Finance Journal 20, pp.151–171.

Ang, A., Bekaert, G., 2007. Stock return predictability: Is it there? Review of Financial Studies 20, pp.651–707.

Balke, N. S., Ma, J., Wohar, M. E., 2015. A bayesian analysis of weak identification in stock price decompositions. Macroeconomic Dynamics 19, pp.728–752.

Beck, N., Katz, J. N., 1995. What to do (and not to do) with time-series cross-section data. The American Political Science Review 89, pp.634–647.

Bekaert, G., Harvey, C. R., 1995. Time-varying world market integration. The Journal of Finance 50, pp.403–444.

Bekaert, G., Harvey, C. R., Lundblad, C. T., Siegel, S., 2011. What segments equity markets? Review of Financial Studies 24, pp.3841–3890.

Bekaert, G., Hodrick, R. J., 1992. Characterizing predictable components in excess returns on equity and foreign exchange markets. The Journal of Finance 47, pp.467–509.

Campbell, J. Y., 1991. A variance decomposition for stock returns. The Economic Journal 101, pp.157–179.

Campbell, J. Y., Ammer, J., 1993. What moves the stock and bond markets? a variance decomposition for long-term asset returns. The Journal of Finance 48, pp.3–37.

Campbell, J. Y., Hamao, Y., 1992. Predictable stock returns in the United States and Japan: A study of long-term capital market integration. The Journal of Finance 47, pp.43–69.

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

Campbell, J. Y., Shiller, R. J., 1988b. Stock prices, earnings, and expected dividends. The Journal of Finance 43, pp.661–676.

Chen, L., Da, Z., Priestley, R., 2012. Dividend smoothing and predictability. Management Science 58, pp.1834–1853.

Chen, L., Zhao, X., 2009. Return decomposition. Review of Financial Studies 22, pp.5213–5249.

Cochrane, J. H., 2005. Asset Pricing. Princeton University Press, revised ed.

Cochrane, J. H., 2008. The dog that did not bark: A defense of return predictability. Review of Financial Studies 21, pp.1533–1575.

Cochrane, J. H., 2011. Presidential address: Discount rates. The Journal of Finance 66, pp.1047–1108.

Cooper, I., Priestley, R., 2009. Time-varying risk premiums and the output gap. Review of Financial Studies 22, pp.2801–2833.

Cooper, I., Priestley, R., 2013. The world business cycle and expected returns. Review of Finance 17, pp.1029–1064.

Cumby, R. E., 1990. Consumption risk and international equity returns: some empirical evidence. Journal of International Money and Finance 9, pp.182–192.

Dangl, T., Halling, M., 2012. Predictive regressions with time-varying coefficients. Journal of Financial Economics 106, pp.157–181.

Dumas, B., Solnik, B., 1995. The world price of foreign exchange risk. The Journal of Finance 50, pp.445–479.

Dumitrescu, E.-I., Hurlin, C., 2012. Testing for granger non-causality in heterogeneous panels. Economic Modelling 29, pp.1450–1460.

Engsted, T., Pedersen, T. Q., Tanggaard, C., 2012. Pitfalls in {VAR} based return decompositions: A clarification. Journal of Banking & Finance 36, pp.1255–1265.

Ferson, W. E., Harvey, C. R., 1993. The risk and predictability of international equity returns. Review of Financial Studies 6, pp.527–566.

Grömping, U., 2007. Estimators of relative importance in linear regression based on variance decomposition. The American Statistician 61, pp.139–147.

Harvey, C., 1991. The world price of covariance risk. The Journal of Finance 46, pp.111–157.

Hjalmarsson, E., 2010. Predicting global stock returns. Journal of Financial and Quantitative Analysis 45, pp.49–80.

Hollifield, B., Koop, G., Li, K., 2003. A bayesian analysis of a variance decomposition for stock returns. Journal of Empirical Finance 10, pp.583–601.

Hou, K., Karolyi, G. A., Kho, B.-C., 2011. What factors drive global stock returns? The Review of Financial Studies 24, pp.2527–2574.

Koijen, R. S., Van Nieuwerburgh, S., 2011. Predictability of returns and cash flows. Annual Review of Financial Economics 3, pp.467–491.

Lawrenz, J., Zorn, J., 2017. Predicting international stock returns with conditional price-to-fundamental ratios. Journal of Empirical Finance 43, pp.159–184.

Lettau, M., Ludvigson, S., 2001. Consumption, aggregate wealth, and expected stock returns. The Journal of Finance 56, pp.815–849.

Lettau, M., Van Nieuwerburgh, S., 2008. Reconciling the return predictability evidence. Review of Financial Studies 21, pp.1607–1652.

Lewellen, J., 2004. Predicting returns with financial ratios. Journal of Financial Economics 74, pp.209–235.

Lewis, K. K., 2011. Global asset pricing. Annual Review of Financial Economics 3, pp.435–466.

Lindeman, R., Merenda, P., Gold, R., 1980. Introduction to Bivariate and Multivariate Analysis. Scott Foresman & Co.

McMillan, D. G., 2016. Stock return predictability and market integration: The role of global and local information. Cogent Economics & Finance 4, pp.1–18.

Newey, W. K., West, K. D., 1987. A simple, positive semi-definite, heteroskedasticity and autocorrelation consistent covariance matrix. Econometrica 55, pp.703–708.

Rangvid, J., 2006. Output and expected returns. Journal of Financial Economics 81, pp.595–624.

Rapach, D. E., Strauss, J. K., Zhou, G., 2010. Out-of-sample equity premium prediction: Combination forecasts and links to the real economy. Review of Financial Studies 23, pp.821–862.

Rapach, D. E., Strauss, J. K., Zhou, G., 2013a. International stock return predictability: What is the role of the United States? The Journal of Finance 68, pp.1633–1662.

Rapach, D. E., Strauss, J. K., Zhou, G., 2013b. International stock return predictability: What is the role of the united states? The Journal of Finance 68, pp.1633–1662.

Richards, A. J., 1995. Comovements in national stock market returns: Evidence of predictability, but not cointegration. Journal of Monetary Economics 36, pp.631–654.

Solnik, B., 1993. The performance of international asset allocation strategies using conditioning information. Journal of Empirical Finance 1, pp.33–55.

Stehle, R., 1977. An empirical test of the alternative hypotheses of national and international pricing of risky assets. Journal of Finance 32, pp.493–502.

Van Binsbergen, J. H., Koijen, R. S. J., 2010. Predictive regressions: A present-value approach. The Journal of Finance 65, pp.1439–1471.

Vuolteenaho, T., 2002. What drives firm-level stock returns? The Journal of Finance 57, pp.233–264.

Zhu, X., 2015. Tug-of-war: Time-varying predictability of stock returns and dividend growth. Review of Finance 19, pp.2317–2358.

Table 1: Predictive regressions

This table shows one month ahead pooled predictive regressions for combinations of global and local predictor variables based on Eq.(14). t-statistics in parenthesis are based on PCSE SUR standard errors. dp, pe and pip denote local country specific ratios. Full sample 1975 to 2014.

	dp	dp_L	dp_G	R^2	pe	pe_L	pe_G	R^2	pip	pip_L	pip_G	R^2
(i)	0.0050			0.0013	-0.0060			0.0013	-0.0064			0.0019
	(3.114)				-(2.964)				-(3.142)			
(ii)		0.0044		0.0007		-0.0070		0.0012		-0.0068		0.0013
		(2.403)				-(2.989)				-(2.677)		
(iii)			0.0054	0.0006			-0.0034	0.0002			-0.0073	0.0010
			(2.222)				-(1.282)				-(2.497)	
(iv)		0.0044	0.0054	0.0016		-0.0070	-0.0034	0.0016		-0.0068	-0.0065	0.0025
		(2.404)	(2.224)			-(2.989)	-(1.282)			-(2.680)	-(2.063)	

Table 2: Forecast error variance decomposition

This table shows variance decompositions for global and local predictor variables based on Eqs. (9 - 11) including autocovariances. Full sample.

Predictor	DR	CF local	CF global	cov global	cov local	st.err.
dp_L	34.38	47.47	0.01	0.00	18.15	0.16
dp_G	42.12	1.70	0.00	0.06	56.12	0.14
pe_L	25.46	66.09	0.47	0.00	7.98	0.19
pe_G	32.20	2.51	1.13	0.10	64.07	0.15
pip_L	46.50	9.66	3.31	0.00	40.53	0.14
pip_G	53.10	0.02	0.33	0.18	46.36	0.13

Table 3: Granger causality tests

This table shows Granger causality tests between local and global ratios. Panel A tests Granger causality with a common coefficient (stacked) and 2 lags. Panel B employs the Dumitrescu and Hurlin (2012) procedure (individual coefficients) and 2 lags. Full sample.

Panel A: Pairwise Granger Causality Tests

$H0$:	*dp*		*pe*		*pip*	
	F-stat	p-val	F-stat	p-val	F-stat	p-val
local does not cause global	0.702	0.496	8.414	0.000	0.561	0.571
global does not cause local	24.620	0.000	24.423	0.000	1.259	0.284

Panel B: Pairwise Dumitrescu and Hurlin (2012) Panel Causality Tests

$H0$:	*dp*		*pe*		*pip*	
	Zbar-stat	p-val	Zbar-stat	p-val	Zbar-stat	p-val
local does not homog. cause global	0.823	0.411	3.923	0.000	1.000	0.318
global does not homog. cause local	8.450	0.000	10.470	0.000	2.244	0.025

Table 4: Variance decomposition over time from BVAR

This table shows variance decompositions over time from BVAR. Estimation based on Bayesian VAR with Normal-inverse-Wishart prior ($vec(\Gamma_0) = 0_{k^2}$, $D_0 = 0.1 \cdot I_{k^2}$). Numbers are in relative percentages associated with discount rate (DR) or cash flow (CF) innovations.

	75-14		75-87		87-00		00-14	
	DR	CF	DR	CF	DR	CF	DR	CF
dp_L	43%	57%	67%	33%	51%	49%	20%	80%
dp_G	96%	4%	98%	2%	92%	8%	96%	4%
pe_L	28%	72%	36%	64%	33%	67%	15%	85%
pe_G	90%	10%	96%	4%	85%	15%	89%	11%
pip_L	82%	18%	92%	8%	84%	16%	75%	25%
pip_G	100%	0%	100%	0%	100%	0%	100%	0%

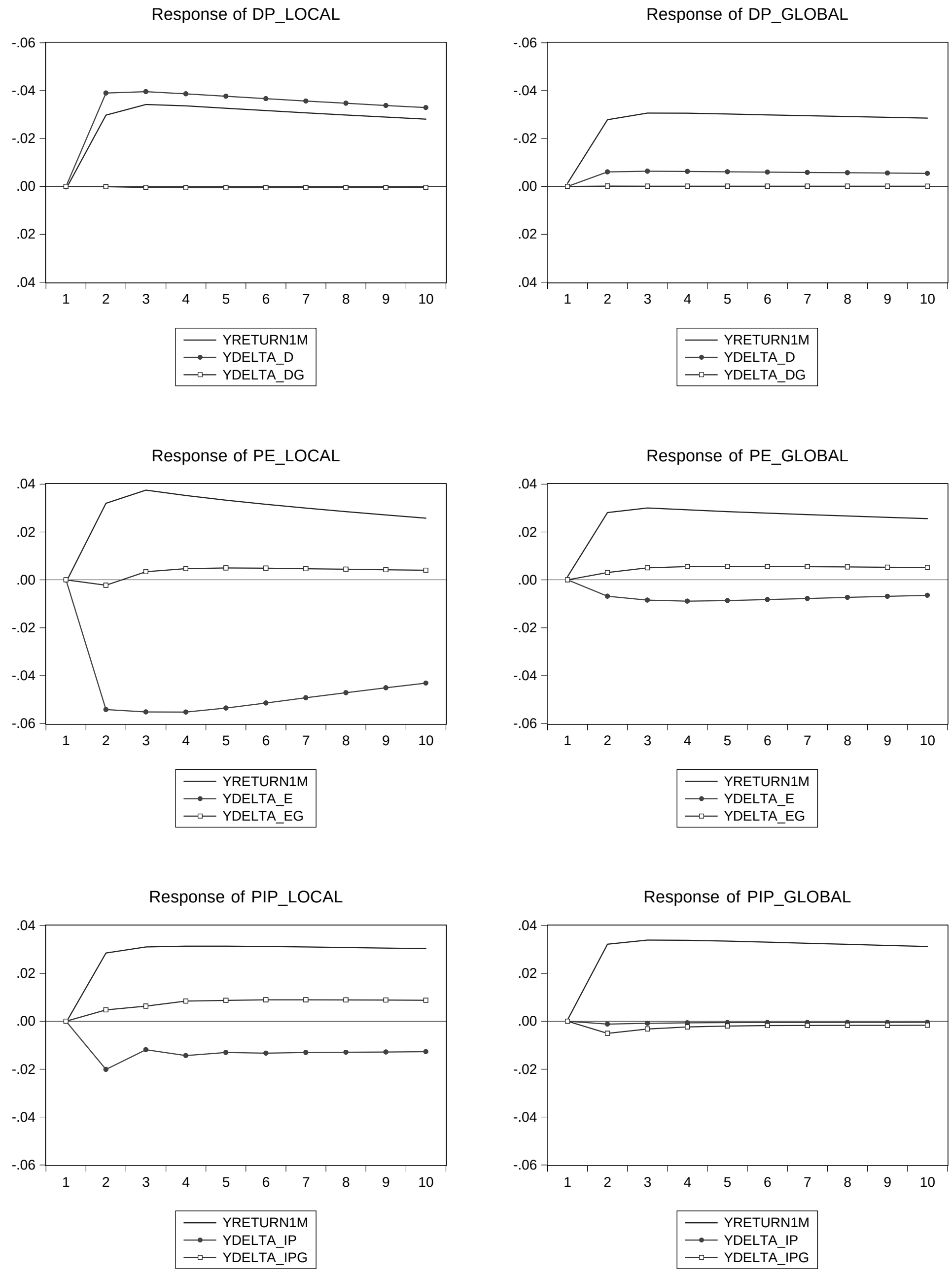

Fig. 1. Impulse response functions - Cholesky factorization

This figure shows impulse response functions for one standard deviation impulses on local and global ratios. Cholesky factorization (combined graph). Ordering: $[r, x_G, x_L, \Delta o_G, \Delta o_L]$. Vertical axes are in units of the response variables. For dp ratios we inverted the vertical axis in order make comparisons to the other variables easier.

Table 5: BVAR predictions across time

This table shows point estimates from a BVAR specification following Eq. (15). Estimation based on Bayesian VAR with Normal-inverse-Wishart prior ($vec(\Gamma_0) = 0_{k^2}$, $D_0 = 0.1 \cdot I_{k^2}$). dp, pe and pip denote (non-orthogonalized) country specific predictor. t-statistics in brackets.

Panel A: 1975-1987	dp	dp_L	dp_G	R^2	pe	pe_L	pe_G	R^2	pip	pip_L	pip_G	R^2
(i)	-0.0022			0.0024	0.0007			0.0028	-0.0042			0.0026
	[-0.628]				[0.177]				[-0.869]			
(ii)		0.0083		0.0032		-0.0124		0.0055		-0.0100		0.0057
		[1.327]				[-2.197]				[-2.052]		
(iii)			-0.0324	0.0093			0.0251	0.0091			0.0285	0.0082
			[-3.532]				[3.340]				[2.681]	
(iv)		0.0085	-0.0325	0.0099		-0.0105	0.0237	0.0106		-0.0085	0.0263	0.0103
		[1.372]	[-3.549]			[-1.858]	[3.127]			[-1.742]	[2.452]	

Panel B: 1987-2000	dp	dp_L	dp_G	R^2	pe	pe_L	pe_G	R^2	pip	pip_L	pip_G	R^2
(i)	0.0060			0.0072	-0.0086			0.0068	-0.0163			0.0063
	[2.164]				[-2.476]				[-2.997]			
(ii)		0.0149		0.0081		-0.0123		0.0058		-0.0108		0.0024
		[2.503]				[-2.038]				[-2.015]		
(iii)			0.0184	0.0069			-0.0485	0.0123			-0.0396	0.0053
			[2.005]				[-4.094]				[-2.770]	
(iv)		0.0144	0.0175	0.0095		-0.0067	-0.0453	0.0125		-0.0149	-0.0486	0.0107
		[2.420]	[1.901]			[-1.083]	[-3.710]			[-2.718]	[-3.318]	

Panel C: 2000-2014	dp	dp_L	dp_G	R^2	pe	pe_L	pe_G	R^2	pip	pip_L	pip_G	R^2
(i)	0.0066			0.0226	-0.0060			0.0217	-0.0134			0.0306
	[1.972]				[-1.411]				[-3.622]			
(ii)		0.0010		0.0209		0.0020		0.0209		-0.0051		0.0229
		[0.192]				[0.356]				[-1.143]		
(iii)			0.0209	0.0276			-0.0192	0.0256			-0.0377	0.0407
			[3.859]				[-3.253]				[-5.384]	
(iv)		0.0013	0.0209	0.0272		0.0029	-0.0194	0.0253		-0.0042	-0.0375	0.0407
		[0.263]	[3.863]			[0.527]	[-3.276]			[-0.940]	[-5.344]	

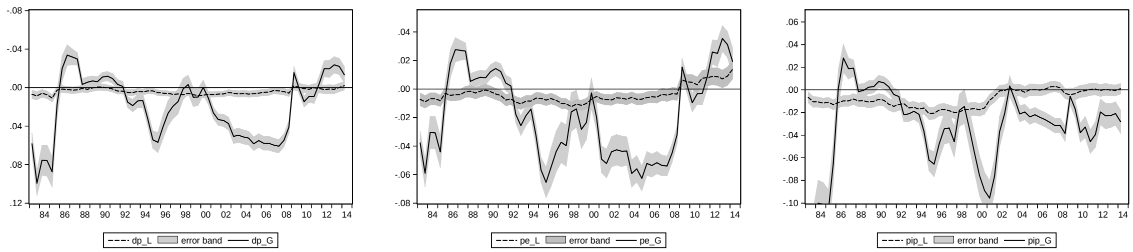

Fig. 2. Rolling prediction

This figure shows coefficients and standard error bands for local and global predictors from a rolling predictive regression (Eq. 14). Window: 12 months, horizon from 1985 to 2014. 1-month ahead forecasts. Axis for *dp* ratios is inverted to ease comparisons.

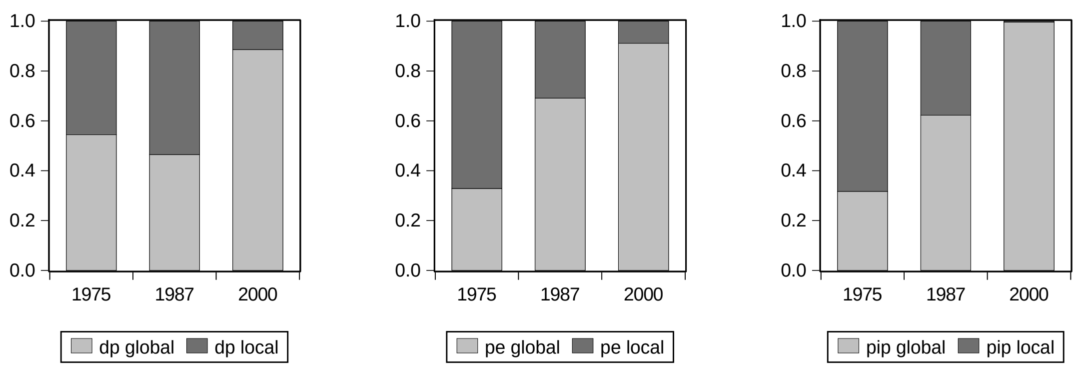

Fig. 3. Relative importance of predictor variables

This figure shows results for the relative importance of local versus global predictor variables across time. Calculations based on Grömping (2007). Decomposition of a model's total explanatory value into relative contributions of the regressors.

Table 6: Variance decomposition over time from BVAR excluding US

This table shows variance decompositions over time excluding the US. Estimation based on Bayesian VAR with Normal-inverse-Wishart prior ($vec(\Gamma_0) = 0_{k^2},\ D_0 = 0.1 \cdot I_{k^2}$). Numbers are in relative percentages associated with discount rate (DR) or cash flow (CF) innovations.

	75-14		75-87		87-00		00-14	
	DR	CF	DR	CF	DR	CF	DR	CF
dp_L	39%	61%	64%	36%	51%	49%	20%	80%
dp_G	96%	4%	99%	1%	92%	8%	96%	4%
pe_L	26%	74%	35%	65%	33%	67%	14%	86%
pe_G	91%	9%	97%	3%	85%	15%	89%	11%
pip_L	82%	18%	92%	8%	84%	16%	76%	24%
pip_G	100%	0%	100%	0%	100%	0%	100%	0%

Table 7: Principal Component Analysis

This table shows the first three principal components (PC1-3) for all returns (r) and ratios dp, pe and pip.

PCA	r			dp			pe			pip		
Cross section	PC1	PC2	PC3	PC1	PC2	PC3	PC1	PC2	PC3	PC1	PC2	PC3
Proportion [%]	59.0	7.8	5.1	62.6	13.6	6.9	57.7	13.6	6.8	63.4	12.1	6.7
Eigenvalue	8.88	1.18	0.77	9.39	2.04	1.04	8.66	2.03	1.02	9.51	1.82	1.01
Austria	0.235	-0.311	0.028	0.117	0.525	0.095	0.063	0.482	0.084	0.309	-0.001	0.032
Belgium	0.279	-0.263	-0.024	0.270	-0.117	-0.170	0.247	0.056	-0.161	0.322	-0.004	0.005
Canada	0.264	0.224	-0.321	0.301	-0.061	-0.070	0.289	-0.051	-0.067	0.311	-0.004	-0.023
Denmark	0.250	-0.175	-0.041	0.248	-0.010	-0.281	0.242	-0.198	-0.009	0.319	-0.007	-0.019
France	0.276	-0.185	-0.032	0.296	0.032	-0.075	0.310	-0.067	-0.026	0.322	-0.005	0.005
Germany	0.282	-0.252	0.037	0.285	0.237	-0.172	0.243	0.256	-0.384	0.322	-0.007	0.000
Ireland	0.263	-0.056	-0.074	0.262	-0.318	-0.123	0.300	-0.073	-0.038	-0.038	0.009	-0.743
Japan	0.186	0.017	0.823	0.215	0.449	-0.108	0.222	0.369	-0.135	0.286	0.002	0.009
Netherlands	0.307	-0.108	-0.042	0.303	-0.167	-0.142	0.322	-0.045	-0.028	0.322	-0.007	-0.006
UK	0.282	0.090	-0.063	0.294	-0.231	0.022	0.307	0.075	-0.007	0.322	-0.011	-0.011
US	0.271	0.191	-0.288	0.280	-0.259	-0.079	0.318	-0.164	0.049	0.320	-0.006	-0.010

Table 8: Variance decomposition over time from BVAR excluding Canada, Japan, UK,US

This table shows variance decompositions over time excluding Canada, Japan, UK and the US. Estimation based on Bayesian VAR with Normal-inverse-Wishart prior ($vec(\Gamma_0) = 0_{k^2}$, $D_0 = 0.1 \cdot I_{k^2}$). Numbers are in relative percentages associated with discount rate (DR) or cash flow (CF) innovations.

	75-14		75-87		87-00		00-14	
	DR	CF	DR	CF	DR	CF	DR	CF
dp_L	40%	60%	66%	34%	52%	48%	21%	79%
dp_G	97%	3%	99%	1%	92%	8%	97%	3%
pe_L	26%	74%	36%	64%	34%	66%	13%	87%
pe_G	92%	8%	97%	3%	83%	17%	91%	9%
pip_L	82%	18%	92%	8%	79%	21%	78%	22%
pip_G	100%	0%	100%	0%	99%	1%	100%	0%

Table 9: Variance decomposition: individual countries

This table shows variance decompositions for individual countries based on Eqs. (9 - 11) using price dividend ratios. Full sample 1975-2014. Numbers in percent.

	DR		CF	
	dp_G	dp_L	dp_G	dp_L
Austria	99.00	53.10	1.00	46.90
Belgium	90.71	38.54	9.29	61.46
Canada	97.04	31.99	2.96	68.01
Denmark	94.87	18.00	5.13	82.00
France	94.94	43.79	5.06	56.21
Germany	84.88	28.66	15.12	71.34
Ireland	94.91	48.02	5.09	51.98
Japan	86.23	49.30	13.77	50.70
Netherlands	90.36	29.75	9.64	70.25
Switzerland	89.91	9.09	10.09	90.91
UK	93.40	43.90	6.60	56.10
US	92.02	65.03	7.98	34.97

Table 10: Return predictability: individual countries

This table shows results for individual countries' 1-month ahead predictive regressions, $r_{i,t+1} = \alpha_k + G_t' \, \beta_k \, + \, L_{i,t}' \, \gamma_k \, + \, u_{i,t+1}$, using price dividend ratios as predictors. Full sample 1975-2014. t-statistics based on PCSE SUR in parenthesis.

	dp_G	dp_L	R^2
Austria	-0.010	-0.012	0.003
	(-0.857)	(-0.857)	
Belgium	0.003	-0.005	0.001
	(0.374)	(-0.340)	
Canada	0.001	0.010	0.001
	(0.157)	(0.649)	
Denmark	-0.003	0.011	0.002
	(-0.330)	(1.034)	
France	0.003	0.026	0.003
	(0.254)	(1.043)	
Germany	0.007	-0.018	0.004
	(0.915)	(-0.921)	
Ireland	0.000	0.003	0.000
	(-0.012)	(0.356)	
Japan	0.018	-0.005	0.008
	(2.013)	(-0.500)	
Netherlands	0.008	0.000	0.002
	(1.034)	(0.023)	
Switzerland	0.003	-0.008	0.001
	(0.399)	(-0.550)	
UK	0.017	0.039	0.013
	(1.463)	(1.446)	
US	0.005	0.010	0.007
	(0.526)	(1.063)	