Local and Global Discount Rates

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Abstract

This article shows that both local and global share prices scaled to fundamentals track a fraction of time variation in expected stock index returns. For 11 developed countries we detect a local and a global discount rate component. Based on a variance decomposition, local ratios fluctuate due to cash-flow and discount rate news whereas global ratios fluctuate nearly exclusively due to discount rate news. Interestingly, in recent periods, the global channel gained importance for return predictability. The overall findings suggest that discount rate news is primarily driven by systematic global components while cash-flow news is largely driven by lower aggregated, firm specific information.

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1. Introduction

We detect two major information channels that explain variation in expected returns for developed countries' stock indices between 1975 and 2014. The first channel is associated with local, country specific information based on both discount rate (DR) and cash-flow (CF) news. The second one is a global channel determined primarily by discount rate news. Both, local and global factors track a fraction of the variation in expected returns. Our conjecture is that there exist components of a *local discount rate* and a *global discount rate* for stock markets. The magnitude of the DR channel compared to the CF channel is closely tied to return predictability. We decompose price to fundamental ratios' variance into DR and CF news innovations. While global ratios are determined by DR news almost exclusively, for local ratios both DR and CF news is relevant. Interestingly, the CF component in local ratios rises throughout our sample compared to the DR component. This incidence goes hand in hand with less return predictability by local ratios. Importantly, this finding is compensated by higher predictive power by global ratios suggesting an increasing role of global factors for local stock indices. Global ratios correlate with the world business cycle hinting on an existence of a global discount rate explained by for instance habits or long-run risk across markets. Our results provide a possible explanation for the mixed international evidence on (time-varying) return predictability, dividend growth predictability and parameter instability.

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 closely tied to our research question. We distinguish three major stream, (i) global return predictability and their instability, (ii) the origin for predictability being cash-flow news or 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 extend information from outside markets can be associated with local stock index returns. Interesting implications have findings in early attempts by Harvey (1991), Campbell and Hamao (1992), Bekaert and Hodrick (1992), Solnik (1993) or Richards (1995). 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 (2013) find evidence that lagged US returns predict returns in other countries. Related, Lawrenz and Zorn (2016) 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.

Closely tied to a global factor are macroeconomic predictor variables. 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 on a global pattern for return predictability.

McMillan (2016) emphasizes the role of local and global (US) information for predictability. He decomposes local and US components of dividend price ratios by orthogonalizing them. This procedure makes estimation in a predictive regression easier since the likelihood of multicollinearity between the variables vanishes. We build upon this approach but instead of taking the US as the global factor we use a true global variable incorporated in the MSCI World.

Our attempt also tries to strengthen the instability of return predictability on the international level. Rangvid, Schmeling, and Schrimpf (2013) detect dividend growth predictability as being the role rather than the exception in global equity markets, particularly for smaller, less developed markets. 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.

Another strand of literature closely tied to our research tries to assess the nature for time-varying expected returns. Whether cash-flow (CF) or discount rate (DR) news influence expected returns is a fundamental question in the finance discipline. An early attempt by Campbell (1991) prominently decomposes expected returns into CF and DR innovations.

For the US, numerous studies employ this decomposition finding, by and large, that most of the fluctuation in unexpected stock index returns can be associated with DR news.[1] Cochrane (2011) in his presidential address makes the point for discount rates being the solely 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 finding as well that lower aggregated returns are driven largely by cash-flows whereas for portfolios discount rates are 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). This evidence in particular motivates us to infer whether discount rates are determined locally or globally or by a combination of both factors.

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).

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) or 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.

Why are discount rates varying? And to what extent are they determined locally or globally? Several models try to explain variations in the market price of risk, including the most prominent ones using habits (Campbell and Cochrane, 1999), long run risk (Bansal and

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

Yaron, 2004) or idiosyncratic risk (George M. Constantinides, 1996).[2] Recently, Cochrane (2016) stresses the commonalities between several examples of models that explain the variability of the market's ability to bear risk. Although the models have very different (microeconomic) assumptions and underlying approaches it is quite striking that their state variables correlate so much between each other. Importantly, these models all capture business cycle correlated risk premia. It should not be surprising in this respect that given the co-movements in international asset prices, particularly in recessions, discount rates also share some co-movement.

3. Theoretical Framework

In this section we provide the theoretical motivation 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,

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

where lower case letters denote logs and $p_t - d_t$ is the price-dividend ratio, Δd_t the dividend growth and r_t the 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 $p_t - d_t$ 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 ratios must be followed by high dividend growth Δd_{t+j} or low returns r_{t+j} or a combination of both.

Assuming earnings being payed out entirely as dividends, this approximation works also for pe ratios,[3]

$$p_t - e_t = const. + \mathbb{E}_t\left[\sum_{j=1}^{\infty} \rho^{j-1}(+\Delta e_{t+j} - r_{t+j})\right], \tag{2}$$

where dividends are substituted by earnings as the cash-flow proxy.

[2] See Cochrane (2016) for a summary of various models capturing time-varying risk aversion.

[3] 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.

It is even possible to relate a macroeconomic variable, industrial production, in this identity. Motivated by the evidence of Lettau and Ludvigson (2001) that a consumption-aggregate wealth ratio can track variation in expected returns, Rangvid (2006) 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. We can therefore write for GDP output (industrial production) y_t,

$$p_t - y_t = const. + \mathbb{E}_t \left[\sum_{j=1}^{\infty} \rho^{j-1} (\Delta y_{t+j} - r_{t+j}) \right]. \tag{3}$$

Again, the interpretation is similar as in Eq.(1) and (2), high $p_t - y_t$ ratios correspond to either high expected output growth in terms of industrial production or lower expected future returns, or a combination of both.

Campbell (1991) provides a similar decomposition for unexpected returns. By moving back one period the identity in Eq.(1) and taking innovations of both sides we obtain $0 = (\mathbb{E}_t - \mathbb{E}_{t-1}) \sum_{j=0}^{\infty} \rho^j (\Delta d_{t+j} - r_{t+j})$. Pulling r_j on the left side yields the unexpected return decomposition,

$$\begin{aligned} r_t - \mathbb{E}_{t-1} r_t &= (\mathbb{E}_t - \mathbb{E}_{t-1}) \left[\sum_{j=0}^{\infty} \rho^j \Delta d_{t+j} - \sum_{j=1}^{\infty} \rho^j r_{t+j} \right] \\ &= N_{CF,t+j} - N_{DR,t+j}, \end{aligned} \tag{4}$$

where $N_{CF,t+j}$ is the revision in expectations about current and future cash-flows. $N_{DR,t+j}$ is the revision in expectations about future discount rates. Positive shocks to returns must come from positive shocks to forecast cash-flow growth or from negative shocks to forecast returns (discount rate), or a combination of both.

Our main innovation is, first, to generalize the decomposition for variables associated with output (cash-flow related),

$$r_t - \mathbb{E}_{t-1} r_t = (\mathbb{E}_t - \mathbb{E}_{t-1}) \left[\sum_{j=0}^{\infty} \rho^j \Delta o_{t+j} - \sum_{j=1}^{\infty} \rho^j r_{t+j} \right], \tag{5}$$

where o emphasizes the output (fundamentals) in the economy proxied by variables such as (i) financial: dividends or earnings and (ii) macroeconomic: GDP or industrial production ip.

Our second, essential, innovation is to tie local and global sources of news to local returns.

Note that changes in output Δo can be decomposed into a global and a local component,

$$\Delta o = \Delta o^{global} + \Delta o^{local} + \nu. \tag{6}$$

Now substitute Eq.(6) into Eq.(5) to obtain a generalized return decomposition,

$$\begin{aligned} r_t - \mathbb{E}_{t-1} r_t = (\mathbb{E}_t - \mathbb{E}_{t-1}) \left[\sum_{j=0}^{\infty} \rho^j \Delta o_{t+j}^{global} - \sum_{j=1}^{\infty} \rho^j r_{t+j}^{global} \right] \\ + (\mathbb{E}_t - \mathbb{E}_{t-1}) \left[\sum_{j=0}^{\infty} \rho^j \Delta o_{t+j}^{local} - \sum_{j=1}^{\infty} \rho^j r_{t+j}^{local} \right] \end{aligned} \tag{7}$$

This identity implies that variation in unexpected returns must come from combinations of global and local cash-flow and discount rate news. However, the identity may not hold due to non-linearities between local and global discount rate components. Keeping this in mind for the subsequent analysis we formalize the relationship even more general,

$$r_t - \mathbb{E}_{t-1} r_t = f[N_{CF,t+j}^{global}, N_{DR,t+j}^{global}, N_{CF,t+j}^{local}, N_{DR,t+j}^{local}], \tag{8}$$

where f denotes the unknown true relationship that ties unexpected returns to innovations in local and global cash-flow and discount rate news.
To infer the magnitude of local and global cash-flow and discount rate news we decompose the variance of price-dividend, price-earnings and price-industrial production ratios. Multiplying both sides of Eq. (1) by $(p_t - d_t) - \mathbb{E}(p_t - d_t)$ and taking expectations yields

$$Var(x_t) = -Cov\left(x_t, \mathbb{E}_t \left[\sum_{j=1}^{\infty} \rho^{j-1} \Delta o_{t+j} \right] \right) + Cov\left(x_t, \mathbb{E}_t \left[\sum_{j=1}^{\infty} \rho^{j-1} r_{t+j} \right] \right), \tag{9}$$

where we replace $(p_t - d_t)$ by x_t denoting any price p to fundamental o ratio.

Following our generalization in Eq.(7) we can do a variance decomposition including global and local information for horizon k. For the global ratio we get

$$\begin{aligned} Var(x_t^{global}) = &- Cov\left(x_t^{global}, \mathbb{E}_t\left[\sum_{j=1}^{k} \rho^{j-1} \Delta o_{t+j}^{global}\right]\right) - Cov\left(x_t^{global}, \mathbb{E}_t\left[\sum_{j=1}^{k} \rho^{j-1} \Delta o_{t+j}^{local}\right]\right) \\ &+ Cov\left(x_t^{global}, \mathbb{E}_t\left[\sum_{j=1}^{k} \rho^{j-1} r_{t+j}\right]\right) \\ &+ Cov\left(x_t^{global}, x_{t+k}^{local}\right) + Cov\left(x_t^{global}, x_{t+k}^{global}\right) \end{aligned} \quad . \tag{10}$$

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

From an asset pricing view a time-varying stochastic discount factor (DR) can be modeled, very general, following a power-utility consumption-based model as demonstrate by Cochrane (2016),

$$DR_{t+1} = \beta \left(\frac{c_{t+1}}{c_t}\right)^{-\gamma} \Phi_{t+1}, \tag{11}$$

with the first term emphasizing marginal consumption and risk aversion γ. The variable Φ_{t+1} varies over time with recessions and therefore is correlated with the business cycle.[4] Since business cycles share some co-movement across countries, we emphasize also from an asset pricing perspective the importance of a global and local component that determine the variable Φ_{t+1} which, in turn, affects DR_{t+1}.

4. Data

We use monthly data for 11 developed countries including Austria, Belgium, Canada, Denmark, France, Germany, Ireland, Japan, Netherlands, 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 Datastream. Data for industrial production are from the OECD database. Our sample reaches from 1985M1 to 2014M4 and all prices are in $US.[5]

To mitigate the possible multicollinearity problem between global and local ratios we

[4]Cochrane (2016) shows that most of the explanations, be it habits, long-run risk, recursive utility, idiosyncratic risk or even behavioral views can be boiled down to a time-varying state variable Φ_{t+1}.

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

orthogonalize them following McMillan (2016),

$$x_i = x_G + e_i, \tag{12}$$

$$e_i \equiv x_L, \tag{13}$$

where x_i is the country specific predictor variable and x_G is the global predictor variable. By regressing x_i's on x_G the residual is orthogonal to x_G. We define this residual as the purely local ratio x_L (stacked vector). Through this procedure we achieve stable uncorrelated predictor variables which we can combine in a predictive regression.

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 three distinct methods. First, in the benchmark case, we detrend the ratio linearly with a trend t for each cross-section,

$$(p_t - ip_{t-1}) = \alpha + \beta t + u_t. \tag{14}$$

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

$$(p_t - ip_{t-1}) = \alpha + \beta t + \gamma t^2 + u_t. \tag{15}$$

In a third specification we use a Hodrick-Prescott filter (Hodrick and Prescott, 1997),

$$\min_{\tau} \left(\sum_{t=1}^{T} ((p_t - ip_{t-1}) - \tau_t)^2 + \lambda \sum_{t=2}^{T-1} [(\tau_{t+1} - \tau_t) - (\tau_t - \tau_{t-1})]^2 \right), \tag{16}$$

with a common smooth parameter for monthly data of λ=129600.

Table 1 shows the correlation matrix for all variables. Global ratios are all highly correlated from 0.775 to 0.955 in absolute terms. For local ratios only *dp* and *pe* display a high (negative) correlation of -0.792. As desired, the orthogonalization of local ratios yields very low correlations to the global ratios.

[Insert Table 1 near here]

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 countries,

$$r_{i,t+1} = \alpha_k + G_t' \, \beta_k \; + \; L_{i,t}' \, \gamma_k \; + \; u_{i,t+1}, \tag{17}$$

where $G = [dp_G, pe_G, pip_G]'$ emphasizes a vector of lagged global predictor variables and $L = [dp_L, pe_L, pip_L]'$ a 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 add additional cross-sectional information and thus mitigate the endogeneity effect of the predictive variables.[6] 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 2 highlights predictive regressions for various specifications including local and global *dp*, *pe* and *pip* ratios. Column (i) shows the usual predictive regression including the country specific *dp* ratio with a highly significant positive coefficient. This is in line with the literature on in-sample tests. R^2 is 0.13%. *dp* ratios do seem to forecast returns for the 1 month ahead horizon. In column (ii) we now include the global ratio dp_G and the orthogonalized local ratio dp_L. Interestingly, both components help to explain variation in future returns on a similar magnitude. Adjusted R^2 rises slightly to 0.155%. This finding suggests that global factors help to explain variation in expected returns. Similar results can be inferred for *pe* ratios as outlined in columns (iii) and (iv). While country specific *pe* ratios do forecast future returns, the inclusion of the global factor enhances the forecast ability with rising R^2. However, the global factor is significant only at the 10% level. Results for the *pip* ratio are even stronger as shown in columns (v) and (vi). R^2 rises from 0.194% to 0.252%. Columns (vii) and (viii) show combinations of different forecast variables. By including *dp* and *pe* ratios in one regression, the global components do seem to dominate in terms of magnitude and significance. Even more, adding all variables in a regression increases R^2 to 0.679%. Again the global components dominate in terms of significance and magnitude of the coefficients. However, one should be cautious about inference due

[6] 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.

to the high correlation of forecasting variables. dp_L and pe_G change sign which might be attributable to a multicollinearity problem in the regression. For this reason we focus on estimations with orthogonal components only in the subsequent analysis.

[Insert Table 2 near here]

5.2. Vector Autoregressions

In this section we employ Vector Autoregressions (VARs) to infer interdependencies of predictor variables, returns and output variables. We follow Campbell (1991) and decompose the variance of variables of interest based on the extension in Eq.(10).

Consider a first order VAR with predictor variables x, output variables o, and returns r,

$$r_{t+1} = a_r + b_r x_t + \varepsilon^r_{t+1}, \tag{18}$$

$$\Delta o_{t+1} = a_o + b_o x_t + \varepsilon^o_{t+1}, \tag{19}$$

$$x_{t+1} = a_x + \phi x + \varepsilon^x_{t+1}, \tag{20}$$

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

$$\begin{bmatrix} Y_{t+1} \\ Z_{t+1} \end{bmatrix} = A + \Gamma \begin{bmatrix} Y_t \\ Z_t \end{bmatrix} + \varepsilon_{t+1}, \tag{21}$$

where we split the variables x_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:

$$-\,Cov\left(dp^G_t, \mathbb{E}_t\left[\sum_{j=1}^{\infty} \rho^{j-1} \Delta d^L_{t+j}\right]\right) = -e_2'\Gamma(I - \rho\Gamma)^{-1}\ \Sigma_{Y,Z} e_4 \tag{22}$$

and

$$-\,Cov\left(dp^G_t, \mathbb{E}_t\left[\sum_{j=1}^{\infty} \rho^{j-1} \Delta d^G_{t+j}\right]\right) = -e_5'\Gamma(I - \rho\Gamma)^{-1}\ \Sigma_{Y,Z} e_4 \tag{23}$$

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 news can be estimated by

$$Cov\left(dp_t^G, \mathbb{E}_t\left[\sum_{j=1}^{\infty}\rho^{j-1}r_{t+j}\right]\right) = -e_3'\Gamma(I-\rho\Gamma)^{-1}\ \Sigma_{Y,Z}e_4. \tag{24}$$

As in Ammer and Wongswan (2007), we specifically do not include further variables such as interest rates, yield spreads or exchange rates since those variables were not found to be relevant for explaining expected return variation (see e.g. Campbell and Ammer (1993) or Ammer and Mei (1996)).

Table 3 shows the estimation output for the first order VAR. In line with the univariate results, both local and global dp ratios forecast returns. As expected dp_L and dp_G are highly persistent with autocorrelations of 0.996 and 0.995 respectively. By and large these results are similar to the US evidence reported in Campbell and Ammer (1993). However, we find also significant predictability of (short term) dividend growth predictability.

To capture the influence of discount rate and cash-flow news on local and global variables we decompose the variance implied by the VAR following Ammer and Wongswan (2007) and Ang (2012) for ratios in particular. Table 4 shows the variance decomposition for each ratio based on estimations from Eqs.(22 & 23) for cash-flows and Eq.(24) for discount rates. For all global ratios most of the variance is due to discount rate innovations (first column). 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 news 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 news 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.[7] Overall, the findings suggest that global ratios fluctuate mainly due to DR news whereas local ratios fluctuate due to CF and DR news. 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 news determines the fluctuation of a global

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

ratio which subsequently predicts index returns. Considering the finding that DR news determines both local and global ratios, we would argue for a local and global discount rate partly responsible for the fluctuation of expected returns. CF news, on the contrary, determines 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 news can be diversified away.

Figure 1 shows impulse response functions for local and global ratios following the Cholesky decomposition.[8] Similar to the variance decomposition the graphs on the left hand side emphasize the response of local ratios to return and cash-flow news 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) news triggers a response of the ratios.

How does the variance decomposition look over time? Table 5 shows the variance decomposition for subsamples including only DR and CF (global and local) covariance terms. Percentage numbers are defined as variance proportions of combined DR and CF variance. The first two columns summarize the finding of Table 4 for the whole sample period. For global ratios subsamples show very similar decompositions as in the whole sample. DR news dominates global ratios with an exception of pip_G during the period 1975-1987 where CF news accounts for 17% of variation. Local ratios are subject to more variability. Across all local ratios, the relative importance of CF news does seem to rise in later periods. Particularly for the subsample 2000-2014, CF news accounts for 82% and 85% of variation for local dp and pe ratios. For pip_L cash-flow news also rises in importance though the DR channel still prevails with 70% in the last subsample.

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 6 shows Granger causality tests for local and global ratios. For this purpose we use country specific ratios (not orthogonalized) in order to rule out possible effects from the orthogonalization procedure.[9] In the bottom panel we test pairwise Granger causality. Results are somewhat ambiguous. Where 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

[8]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.

[9] Unreported tests using orthogonalized ratios yield virtually the same results.

show a tendency towards better predictability of local ratios by global ones. This might be a further hint on the importance of global factors in explaining expected returns locally and the existence of a global discount rate.

[Insert Table 3 near here]

[Insert Table 4 near here]

[Insert Table 5 near here]

[Insert Table 6 near here]

[Insert Figure 1 near here]

5.3. Bayesian Vector Autoregressions

Motivated by possible parameter instability of DR and CF components as highlighted by Chen and Zhao (2009) and inconclusive evidence in the literature 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 news in a BVAR in the spirit of Hollifield et al. (2003) and Balke et al. (2015). Consider a stacked version of Eq. (21),

$$B = C\,\Gamma + U, \qquad U \sim \mathcal{MN}(0, \Sigma \otimes I), \tag{25}$$

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

$$\hat{\Gamma} = (C'C)^{-1}C'B \tag{26}$$

and

$$\hat{\Sigma} = \frac{1}{T}(B - C\hat{\Gamma})'(B - C\hat{\Gamma}) \tag{27}$$

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

$$p_1(\Gamma, \Sigma^{-1}) = p(\text{vec}(\Gamma))\; p(\Sigma^{-1}), \tag{28}$$

where

$$p(\text{vec}(\Gamma)) \propto f_{\mathcal{N}}^{k^2}(\text{vec}(\Gamma_0), D_0^{-1})\; I(\Gamma \in \Omega), \tag{29}$$

and

$$p(\Sigma^{-1}) = f_{\mathcal{W}}^{k}(v_0, E_0^{-1}). \tag{30}$$

$f_{\mathcal{N}}^{k^2}$ 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.(25) with the prior in Eqs. (28)-(30), we obtain the joint posterior for Γ and Σ^{-1},

$$p(\Gamma, \Sigma^{-1}|B, C) \propto p_1(\Gamma, \Sigma^{-1}) \cdot p(B|C, \Gamma, \Sigma^{-1}). \tag{31}$$

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

$$p(\text{vec}(\Gamma)|B, C, \Sigma^{-1}) \propto f_{\mathcal{N}}^{k^2}(\text{vec}(\tilde{\Gamma}), \tilde{D}^{-1}) I(\Gamma \in \Omega), \tag{32}$$

$$p(\Sigma^{-1}|B, C, \Gamma) = f_{\mathcal{W}}^{k}(\tilde{v}, \tilde{E}^{-1}), \tag{33}$$

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 7 shows the variance decomposition over time inferred from the BVAR. Compared to the VAR decomposition the results appear smoother especially in subsamples. No qualitative changes occur to the relative importance of CF versus DR news components. Different though, are estimates for pip_G showing zero percent CF components in all subsamples. The 'outlier' in the period 1975-1987 does not emerge in the BVAR model suggesting a more robust estimation due to shrinkage.

Why is discount rates news less important for local ratios in later samples? Predictability patterns in subsamples using the BVAR approach are shown in Table 8. For the full sample from 1985M1 to 2014M05 local and global components do both track a similar fraction of future returns as suggested by the coefficients in column 1. Interestingly though, in the periods from 2000 to 2014 only global components significantly predict future returns for all three ratios. During 1987-2000 local *dp* ratios significantly predict returns whereas the global component does not. Still, for *pe* and *pip* the global component is more pronounced as emphasized by the magnitude of the coefficient and the t statistic. In the earlier period of 1975-1987 global and local *dp* ratios explain about the same fraction of future returns. For *pe* and *pip* on the contrary, only the local component predicts future returns. Coefficients from global components show even the wrong sign. Adjusted R^2 is higher in later periods for all specifications. 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 news as innovator in local ratios' variance. It seems as due to financial market integration the predictability pattern emerges as a global phenomena determined by market wide discount rate innovations.

[**Insert Table 7 near here**]

[**Insert Table 8 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. (2013) 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 9 shows the BVAR variance decomposition excluding the US. Compared to the variance decomposition including 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 9 near here]

6.2. Anglo-Saxon countries

Are Anglo-Saxon countries different? One might argue that due to their relatively more pronounced market based financial systems stock index returns behave different. In fact, the equity premium is considered to be larger compared to other developed countries (see e.g. Ang and Bekaert (2007)). Inspired by McMillan (2016) we extract principal components of returns and country specific ratios. Table 10 shows results for the principal component analysis. Evidently, 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. The second 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 11 summarizes the results. Similar to the exclusion of US only, the results are remarkably robust. Numbers for DR and CF news 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 10 near here]

[Insert Table 11 near here]

6.3. Role of detrending pip

One critical issue in the construction of the *pip* ratio stems from the detrending method. The previous results are based on detrending *pip* linearly, which is, in our view, the least problematic approach. Still, it is also common to detrend variables non-linear.

Table 12 shows predictive regressions for price to industrial production ratios using different detrending methods. While the local ratio is not affected by the detrending method the global one changes dramatically. The magnitude for the coefficient for pip_G rises by a factor of 4 and a factor of 12 by including a quadratic term and using the HP filter respectively. R^2 rises from 0.25% to 1.86%. This comes as a surprise. For instance, Cooper and Priestley (2013) highlight differences in predictability arising from detrending methods of a output gap measure, though the differences are not as pronounced as our findings. Table 13 shows correlations between predictor variables and the world business cycle. While local ratios show very little correlation with the world business cycle (ip_{cycle}) global ratios do. The more sophisticated the detrending procedure the higher the correlation with the business cycle. pip_G detrended with the Hodrick-Prescott filter has the highest correlation with the business cycle of 0.451. Somehow, the predictability is higher for ratios that are closer tied to the world business cycle. Intuitively, this seems plausible since global DR news is tied to global risk perceptions.

[**Insert Table 12 near here**]

[**Insert Table 13 near here**]

6.4. Simulated data

We test the above models using simulated price to fundamental ratios. Trough 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 an Ornstein-Uhlenbeck process as the data generating process,

$$dX_t = \theta(\mu - X_t)\, dt + \sigma\, dW_t, \tag{34}$$

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 simply match the moments of this process with our empirical estimates of pe ratios.

Replacing our sample with simulated ratios for 11 artificial countries and one global simulated ratio yields the following (unreported) results. 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 news, covariances of residuals are virtually zero. The reverse orthogonalization (regress global ratios on local ones) yields some differences in results. Comparing orthogonalized local ratios with non-orthogonalized, country specific ratios, yields a difference of 25% in the variance decomposition of DR and CF news over the whole sample. Where for orthogonalized ratios CF news dominates, for non-orthogonalized ratios, DR news is slightly higher. This should not come as a surprise though. Trough orthogonalization we diminish the global effect that in turn is closely tied to DR news.

7. Conclusion

We find that both local and global price to fundamental factors track a fraction of expected returns. Local ratios fluctuate due to CF and DR news while the latter is less pronounced in later time periods. Global ratios fluctuate almost exclusively due to DR news. We find that the more a predictor variable fluctuates due to DR news the better the predictability of returns. 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 returns variation. It seems as a global discount factor is emerging due to rising financial integration of markets. This seems plausible given the correlation of global factors to the world business cycle. Our approach may explain the discrepancy of predictability both from a time-series instability perspective due to regime switching and integration and from a cross-sectional perspective due to ambiguous return/dividend growth predictability internationally.

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Table 1: Correlation matrix

This table shows correlation coefficients for variables. Subscripts L and G denote local and global ratios. Δ is the difference operator.

Correlation	r	dp_G	dp_L	pe_G	pe_L	pip_G	pip_L	Δd	Δe	Δip	Δd_G	Δe_G	Δip_G
r	1												
dp_G	0.035	1											
dp_L	0.019	0.061	1										
pe_G	-0.019	-0.955	-0.045	1									
pe_L	-0.026	-0.066	-0.792	0.062	1								
pip_G	-0.031	-0.775	0.007	0.829	-0.024	1							
pip_L	-0.039	0.028	-0.098	-0.036	0.223	0.000	1						
Δd	0.920	0.047	0.038	-0.022	-0.023	-0.040	-0.051	1					
Δe	0.204	-0.041	-0.045	0.032	0.088	0.023	0.010	0.031	1				
Δip	0.026	-0.035	-0.011	0.047	0.017	0.040	0.008	0.043	0.023	1			
Δd_G	0.081	0.089	0.001	-0.057	0.012	0.003	0.013	0.112	-0.048	0.055	1		
Δe_G	-0.002	0.110	0.036	-0.072	-0.029	-0.092	-0.035	0.014	-0.118	-0.081	-0.261	1	
Δip_G	0.071	-0.166	-0.044	0.201	0.073	0.152	0.005	0.070	0.053	0.071	0.153	-0.149	1

Table 2: Predictive regressions

This table shows one month ahead predictive regressions for combinations of global and (orthogonalized) local predictor variables based on Eq.(17). t-statistics in parenthesis are based on PCSE SUR standard errors.

	(i)	(ii)	(iii)	(iv)	(v)	(vi)	(vii)	(viii)
c	0.004	0.004	0.025	0.018	0.009	0.009	-0.078	-0.146
	(2.167)	(1.560)	(4.434)	(2.389)	(10.527)	(11.231)	(-2.785)	(-4.672)
dp	0.005							
	(3.114)							
dp_G		0.005					0.026	0.037
		(2.224)					(3.644)	(4.958)
dp_L		0.004					0.000	-0.001
		(2.404)					(0.119)	(-0.329)
pe			-0.006					
			(-2.964)					
pe_G				-0.003			0.022	0.043
				(-1.282)			(2.880)	(4.840)
pe_L				-0.007			-0.007	-0.004
				(-2.989)			(-1.995)	(-1.136)
pip					-0.006			
					(-3.142)			
pip_G						-0.006		-0.013
						(-2.063)		(-2.490)
pip_L						-0.007		-0.005
						(-2.680)		(-2.062)
Adj. R^2 %	0.130	0.155	0.133	0.164	0.194	0.252	0.319	0.679

Table 3: VAR Estimates for dp

This table shows VAR(1) point estimates for combinations of global and (orthogonalized) local predictor and output variables based on Eq.(21).

	r	dp_G	dp_L	Δd	Δd_G
r	0.089	-0.157	1.129	0.159	0.490
	-0.034	-0.017	-0.014	-0.065	-0.028
	[2.659]	[-9.293]	[81.467]	[2.460]	[17.507]
dp_G	0.007	0.995	0.004	0.018	0.026
	-0.002	-0.001	-0.001	-0.004	-0.002
	[3.249]	[880.055]	[4.653]	[4.144]	[13.857]
dp_L	0.009	0.005	0.996	0.035	-0.005
	-0.003	-0.002	-0.001	-0.006	-0.003
	[3.003]	[3.101]	[801.599]	[5.944]	[-1.954]
Δd	0.001	-0.138	-0.887	0.019	-0.039
	-0.017	-0.009	-0.007	-0.034	-0.014
	[0.074]	[-15.824]	[-123.667]	[0.578]	[-2.703]
Δd_G	-0.001	-0.003	0.002	-0.009	0.192
	-0.006	-0.003	-0.002	-0.011	-0.005
	[-0.213]	[-1.037]	[1.036]	[-0.880]	[41.821]
Adj. R^2	0.011	0.991	0.989	0.018	0.338

Table 4: Forecast error variance decomposition

This table shows variance decompositions for global and (orthogonalized) local predictor variables based on Eqs. (22 - 24 including autocovariances.

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

Table 5: Variance decomposition over time

This table shows variance decompositions over time for global and (orthogonalized) local predictor variables based on Eqs. (22 - 24.

	75-14		75-87		87-00		00-14	
	DR	CF	DR	CF	DR	CF	DR	CF
dp_L	42%	58%	60%	40%	45%	55%	18%	82%
dp_G	96%	4%	99%	1%	91%	9%	97%	3%
pe_L	28%	72%	35%	65%	32%	68%	15%	85%
pe_G	90%	10%	97%	3%	86%	14%	88%	12%
pip_L	78%	22%	86%	14%	79%	22%	70%	30%
pip_G	99%	1%	83%	17%	96%	4%	98%	2%

Table 6: Granger causality tests

This table shows Granger causality tests between local and global ratios.

Panel A: Pairwise Granger Causality Tests						
H:0	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						
H:0	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 7: Variance decomposition over time from BVAR

TRhis table shows variance decompositions over time from BVAR. Estimation based on Bayesian VAR with Normal-inverse-Wishart prior ($vec(\Gamma_0) = 0_{k^2}$, $D_0 = 0.1 \cdot I_{k^2}$).

	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%

Table 8: BVAR predictions across time

This table shows point estimates from BVAR. Estimation based on Bayesian VAR with Normal-inverse-Wishart prior ($vec(\Gamma_0) = 0_{k^2}$, $D_0 = 0.1 \cdot I_{k^2}$).

	75-14			75-87			87-00			00-14		
	Coef	t-stat	R^2	Coef	t-stat	R^2	Coef	t-stat	R^2	Coef	t-stat	R^2
dp_L	0.009	[2.908]	0.011	0.016	[2.521]	0.007	0.015	[2.592]	0.008	0.002	[0.307]	0.028
dp_G	0.007	[3.150]		0.011	[2.871]		0.004	[0.837]		0.022	[4.648]	
pe_L	-0.009	[-3.015]	0.013	-0.018	[-3.088]	0.013	-0.007	[-1.083]	0.012	0.003	[0.527]	0.025
pe_G	-0.009	[-3.616]		0.008	[1.067]		-0.045	[-3.709]		-0.019	[-3.276]	
pip_L	-0.008	[-3.023]	0.011	-0.009	[-1.742]	0.010	-0.015	[-2.718]	0.011	-0.004	[-0.940]	0.041
pip_G	-0.007	[-2.460]		0.026	[2.452]		-0.049	[-3.317]		-0.037	[-5.344]	

Table 9: 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 ($vec(\Gamma_0) = 0_{k^2}$, $D_0 = 0.1 \cdot I_{k^2}$).

	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 10: Principal Component Analysis

This table shows principle components for returns and country specific ratios.

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 11: 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 ($vec(\Gamma_0) = 0_{k^2}$, $D_0 = 0.1 \cdot I_{k^2}$).

	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 12: Detrending methods and predictive regressions

This table shows one month ahead predictive regressions using different detrending methods for the pip ratio. Estimation following Eq.(17). t-statistics in parenthesis are based on PCSE SUR standard errors.

	(i)	(ii)	(iii)
c	0.009	0.009	0.009
	(11.236)	(11.226)	(11.301)
pip_L	-0.007	-0.007	-0.006
	(-2.814)	(-2.794)	(-2.496)
$pip_G^{(t)}$	-0.006		
	(-2.265)		
$pip_G^{(t+t^2)}$		-0.025	
		(-5.010)	
$pip_G^{(HP)}$			-0.073
			(-9.497)
$Adj.R^2[\%]$	0.25	0.63	1.86

Table 13: Correlation with business cycle

This table shows the correlation matrix for predictor variables and the global business cycle ip_{cycle}.

	ip_{cycle}	pip_G^{trend}	$pip_G^{trend^2}$	pip_G^{HP}	pip_L	dp_G	dp_L	pe_G	pe_L
ip_{cycle}	1								
pip_G^{trend}	0.251	1							
$pip_G^{trend^2}$	0.381	0.588	1						
pip_G^{HP}	0.451	0.479	0.819	1					
pip_L	0.071	0.000	0.028	0.035	1				
dp_G	-0.195	-0.774	-0.471	-0.376	0.028	1			
dp_L	-0.059	0.008	-0.008	-0.019	-0.096	0.061	1		
pe_G	0.081	0.828	0.454	0.315	-0.036	-0.955	-0.045	1	
pe_L	0.012	-0.025	0.009	0.035	0.223	-0.066	-0.792	0.062	1

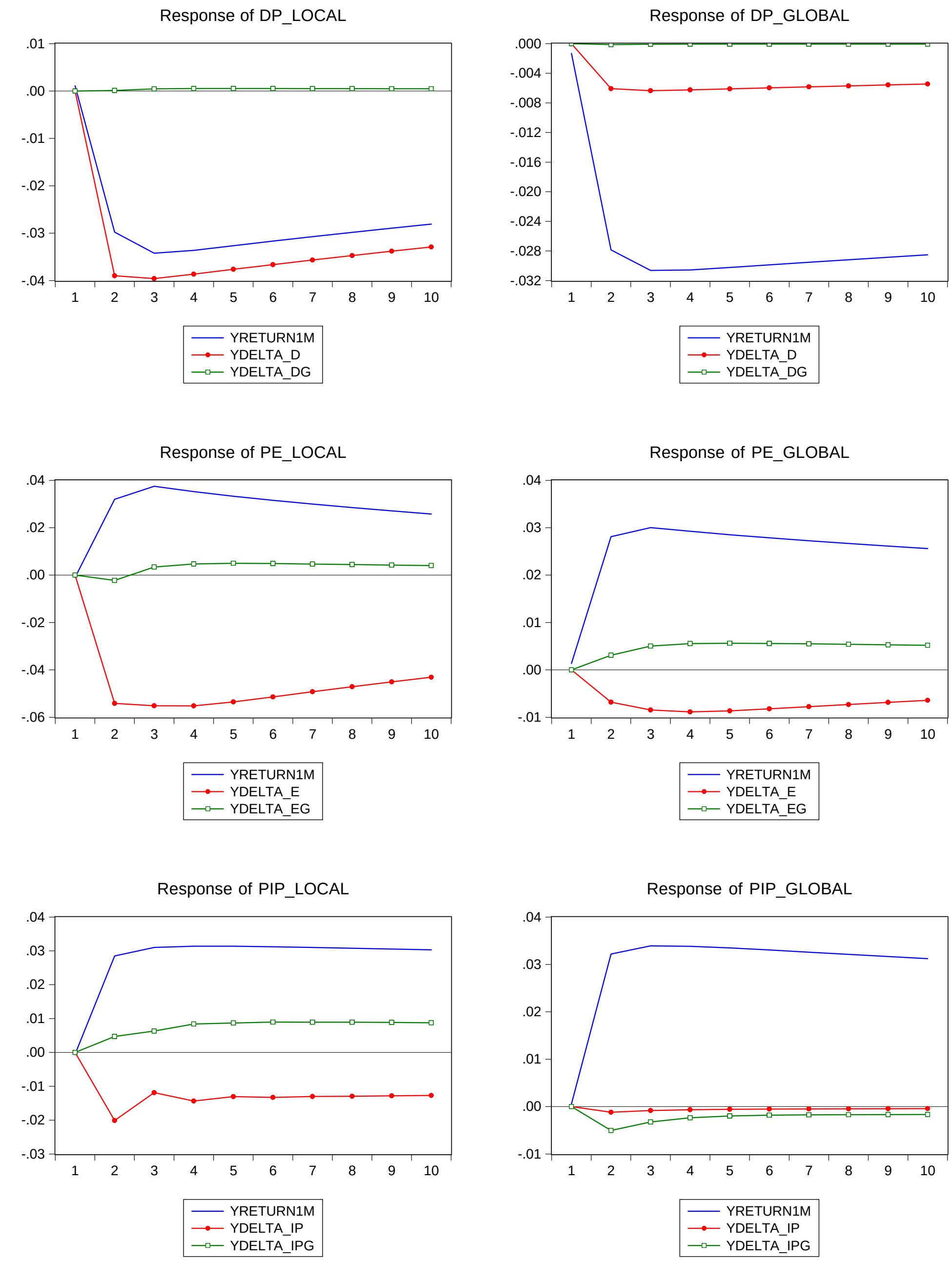

Fig. 1. Impulse response functions - Cholesky factorization

This figure shows impulse response functions for one standard deviation impulses. Cholesky factorization (combined graph).