Stock-Bond Correlations, Macroeconomic Regimes and Monetary Policy*

An International Perspective

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Abstract

This paper documents a strong association between stock-bond (SB) correlations and monetary policy regimes for a sample of 10 developed markets. Negative stock-bond correlations are associated with periods of accommodating monetary policy, but only in times of low inflation. Irrespective of the inflation and/or growth regime, stock-bond correlations are always positive when monetary policy is restrictive. Pure inflation and growth regimes instead have little explanatory power for stock-bond correlations. Our findings are consistent with recent theoretical research that attributes an important role not only to the cyclicality of inflation but also to monetary policy stance for understanding the dynamics of stock-bond correlations.

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1 Introduction

While US stock and bond return correlations have been predominantly positive over the last 40 years, there have been persistent episodes of large negative stock-bond correlations, in particular since the end of the 1990s. Panel A of Figure 1 shows that US stock-bond correlations were about 20% during the 1970s, increased to, on average, 40% during the 1980s and first half of the 1990s, to drop to, on average, minus 20% since 1998. Correlations varied substantially though over these sub periods: Correlations were as high as +70% in the fall of 1994 and as low as -67% in Q2-2003 and Q3-2012. Panel B of Figure 1 shows that stock-bond correlations in other developed markets followed a remarkably similar pattern, suggesting that one or more common factor(s) are driving international stock-bond correlations.

Recent papers have come up with various explanations for the large variation in stock-bond correlations, and especially for the persistent negative spells observed since the end of the 1990s. First, a number of papers (see e.g. Connolly et al. (2005), Baur and Lucey (2009)) ascribe negative stock-bond return correlations to flight-to-safety (FTS) episodes, during which increased stock market uncertainty induces investors to flee stocks in favor of bonds. FTS spells, however, typically take less than three days (see e.g. Baele et al. (2014)), indicating that FTS alone cannot explain the much longer negative stock-bond correlation episodes. Second, Baele et al. (2010) show using a dynamic factor model that stock and bond illiquidity helps explain episodes of negative stock-bond correlations while many macroeconomic fundamentals do not. Using a DCC-MIDAS model, **?** also find equity liquidity to be an important driver of stock-bond correlations. Third, several papers link sign switches in stock-bond correlations explicitly to time variation in the covariance between output (consumption) and inflation. Bekaert and Engstrom (2010) show that the on average positive correlation between equity and bond yields is due to the high incidence of stagflationary periods. In recessions, increasing economic uncertainty and risk aversion push up the equity risk premium, and hence also equity yields. Because expected inflation also happens to be high in recessions, bond yields increase through their expected inflation and, potentially, their inflation risk premium components, and positive correlations emerge between equity and bond yields and inflation. Their model also implies correlations to be low during periods of procyclical inflation, such as during the 2008-2009 global financial crisis. Campbell et al. (2009) develop a pricing model for stock and bond returns and assign a latent variable to capture the covariance between nominal variables and the real economy, which, in turn, helps to produce negative co-movements between bond and stock returns. Similar to Bekaert and Engstrom (2010), Burkhardt and Hasseltoft (2012)

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also relate stock-bond correlation to inflation being pro- or countercyclical. When inflation is countercyclical, both equities and bonds are risky and move positively with inflation risk, inducing a positive correlation. When instead inflation is procyclical, equity and bond risk premia are negatively correlated as nominal bonds act as a hedge, inducing a negative stock-bond correlation. They provide some evidence that inflation indeed switched from being countercyclical to being procyclical around the year 2000, about the time when also stock-bond correlations became negative. In a similar vein, Dergunov et al. (2017) build on the work of David and Veronesi (2013) and show that inflation may be relevant for the pricing of real assets like equities because low consumption growth tends to be associated with either very high or very low inflation. This does not only imply that extreme values for inflation imply a higher probability of the economy being in a bad state, but also that positive inflation shocks may be interpreted as being either good or bad news about the future economy. Finally, a recent paper by Ermolov (2014) uses the "Bad Environment Good Environment" (BEGE) model of Bekaert and Engstrom (2015) to relate both good and bad demand and supply shocks to stock-bond correlations. Supply shocks, either good or bad, help explain the positive correlations in the 1970s, 1980s, and 1990s, while demand shocks in combination with smaller supply shocks explain some but not all of the negative correlations observed since the year 2000.

The empirical backing for these channels seems, however, not overwhelming. For instance, in the model of Campbell et al. (2009), the parameters governing time variation in stock-bond returns are borderline significant at best. Also, the paper does not formally test to what extent changes in their covariance factor match the sign switches in stock-bond correlations. Similarly, the empirical relationship between the cyclicality of inflation and stock-bond correlations as predicted in the model by Burkhardt and Hasseltoft (2012) becomes much weaker when inflation and consumption shocks are modeled separately from stock and bond returns. While Ermolov (2014)'s BEGE model has many attractive features, it only generates (bad) demand shocks that are sufficiently large to explain large negative correlations during the short period 2008-2009, leaving the remaining frequent spells of negative correlations since 2000 unexplained. The empirical model of Dergunov et al. (2017) has similar issues, as the very low inflation / growth regime that they associate with negative stock-bond correlations is only observed briefly around 2008.

The first contribution of our paper is to revisit the link between stock-bond correlations and inflation and output regimes in an international context. One of the potential explanations for the poor empirical relation between macro fundamentals and stock-bond correlations is the lack of power of tests that focus on a single

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country, typically the US. Similarly, for a theory to be valid, it should not just explain stock-bond correlations in the US, but also in other markets. We estimate both integrated and segmented market versions of our models. In integrated bond and equity markets, one would expect global rather than local macroeconomic regimes to drive stock-bond correlations. In (partially) segmented markets instead, (also) local inflation and output regimes should be the main drivers of stock-bond correlations.

We proceed as follows. We start by estimating both univariate and bivariate regime-switching models on both global and local inflation and the output gap. The univariate models allow us to distinguish between high, intermediate, and low inflation and output regimes, and the bivariate model between spells of pro- and countercyclical inflation. Subsequently, we regress realized stock-bond correlations on the obtained macroeconomic regime dummies. Unlike e.g. Burkhardt and Hasseltoft (2012) and Song (2014), we estimate the macroeconomic regimes and their relationship with stock-bond correlations separately, to avoid that macroeconomic regimes are identified as to fit the stock-bond correlations. As such, our estimates provide a conservative estimate of the importance of macroeconomic regimes for stock-bond correlations.

We find evidence for three inflation regimes, which we characterize as low, intermediate, and high inflation states, and two output regimes ('recessions' versus 'expansions'). Despite using alternative identification methods and data from different countries, we do not find evidence for a switch to a procyclical inflation regime around the year 2000. In fact, despite using various models and business cycle measures, we do not find any evidence for a procyclical inflation regime over our entire sample in any country, casting doubt on theories explaining switches to negative stock-bond correlations around that time by switches from a counter- to a procyclical inflation regime. We do, however, for several countries find short-lived switches during 2001, 2008-2009, and 2012 towards less negative (but still not positive) correlations between output gap and inflation shocks. Bekaert et al. (2015) identify these periods as times during which demand shocks temporarily gained importance relative to supply shocks.

We do find stock-bond correlations to be lower and often negative in low inflation regimes, while they are positive and large in intermediate and high inflation regimes. The switch to the low inflation regime precedes, however, the switch to negative stock-bond correlations around 2000 with several years. Estimated stock-bond correlations within the low inflation regime, while often negative, are small in magnitude and fail to match the often extreme negative stock-bond correlations observed in the post-1998 period. Moreover, because nearly all countries switched to the low inflation regime in the first half of the 1990s and remained there ever since, inflation regimes alone cannot explain the large time variation in stock-bond correlations that we have observed in the post 1995 period. Finally, while we do find stock-bond correlations to be slightly negative in recessions and positive in expansions when global recession dummies are used, we find the output dummies to explain very little of the variation in stock-bond correlations.

These findings suggest that pure macro regimes explain relatively little of the variation in stock-bond correlations. Inspired by recent work by Campbell et al. (2014) and Song (2014), the second and main contribution of this paper is to investigate to what extent changes in monetary policy (MP) regimes, potentially interacted with these macro regimes, are more successful determinants of stock-bond correlations. We were further encouraged by Panel A of Figure 1, which shows a striking overlap between periods of low to negative stock-bond correlations and spells of negative monetary policy gaps (indicating accommodating MP stance). To test the relationship between stock-bond correlations and MP more formally, we first estimate a monetary policy rule where the central bank's reaction to inflation and output stabilization changes over time. In the accommodating regime, output stabilization dominates while in the restrictive regime the central bank is mainly focused on controlling inflation. Our main finding is that stock-bond correlations tend to be strongly negative when monetary policy is accommodating, but only in times of low inflation. Irrespective of the inflation or output regime, stock-bond correlations turn positive as soon as monetary policy turns restrictive. The intuition is simple. In the low inflation state, investors are mainly concerned about the economy entering into a deflationary spiral. Accommodating monetary policy reduces the likelihood of this bad state, and instead makes positive inflation shocks more likely, leading to a drop in bond prices. At the same time, by reducing the likelihood of a deflationary state, a credible MP stimulus also raises growth expectations and hence stock prices. In addition to a pure cash flow effect, accommodating policy may lead to increasing equity prices through its dampening effects on both economic uncertainty and risk aversion, and hence risk premia (see e.g. Bekaert and Hoerova (2013)), amplifying the initial CF induced increase in equity prices. When instead MP is restrictive, central banks are expected to react strongly to inflation shocks by (more than proportionally) raising short-term interest rates. This does not only lead to a drop in bond prices, but also to lower real output and equity prices, and hence a positive stock-bond correlation.

Finally, in an epilogue we confront the model's correlation estimate (using data until December 2013) with the updated out-of-sample observed stock-bond correlations of the 10 local markets. Although the out-of-sample period from January 2014-March 2017 is characterized by high financial and geopolitical uncertainty, our regression model correctly predicted the average US correlation level over this period.

The remainder of the article is organized as follows. Section 2 presents some stylized facts on stock-bond correlations across the globe. Section 3 presents the empirical models used to identify macro and inflation regimes. Subsequently, in Section 4, we investigate the relationship between the macro and inflation regimes and international stock-bond correlations. Section 5 links stock-bond correlations to the pure monetary policy regimes. In Section 6, we test the relationship between stock-bond correlations and interactions between the macro and monetary policy regime dummies. Section 7 provides an epilogue to our results and concludes.

2 International Stock-Bond Correlations

2.1 Measuring Stock-Bond Correlations

Our main analysis is mostly at the monthly and quarterly frequency, which is the frequency at which data on the economic state variables are available. It may also be the highest frequency at which a fundamentals-based model is expected to have explanatory power. Rather than simply using monthly (quarterly) stock-bond returns to estimate monthly (quarterly) stock-bond correlations, we follow Baele et al. (2010) and Asgharian et al. (2014) and use the richness of daily data and the DCC-MIDAS model of Colacito et al. (2009). This model decomposes variances and correlations at the daily frequency into a high-frequency (daily) and low-frequency component. The high-frequency variance component follows a standard GARCH(1,1) model; the low frequency monthly (quarterly) component is a weighted average of past monthly (quarterly) realized variances. As in the original MIDAS papers, the weights are described by a flexible Beta function. While this function can in principle take many forms, we find its shape as implied by the estimated decay parameter to be exponentially decreasing. We provide more details on the model and on the estimation results in Appendix A. As we will discuss below, for several countries, daily bond data are only available as from the end of the 1980s / early 1990s. For those countries, we extend the sample by applying the standard DCC model of Engle (2002) to available monthly or quarterly data.

2.2 Stock and Bond Return Data

Our data set consist of daily total equity index and 10-year benchmark bond returns for 10 developed markets, namely the US, Canada, Japan, UK, Germany, France, the Netherlands, Belgium, Italy, and Spain. These countries exhibit substantial differences in their inflation and growth dynamics, as well as in their exposure to the global financial crisis in 2007-2008 and the subsequent sovereign debt crisis in Europe. For the US, we use the NYSE-AMEX-NASDAQ value-weighted returns including dividends from the CRSP Stock File Indexes, and the returns on 10-year government bonds taken from the CRSP US Treasury and Inflation module. For the other markets, we use Datastream International's total market indexes to calculate daily total equity returns, and their 10-year benchmark bond indices to calculate bond returns. All returns are denominated in local currency. Our daily sample runs until December 2013, but has different starting points for different countries. As can be seen from the first row of Table A.1 of A our longest series are for the US, starting in June 1961. For several other countries, however, the sample starts at the end of the 1980s / early 1990s, mainly because of the lack of daily bond returns. To maximize sample length, we complement our daily data with monthly stock and bond returns[1]. This allows us to extend the sample until January 1970s for all countries except Japan (1983), Italy (1991), and Spain (1980). Tables A.1 and A.2 of Appendix A present summary statistics for both the daily and monthly data.

2.3 Stock-Bond Correlations: Stylized Facts

Figure 2 plots the full-sample long-run correlations for each country separately. As mentioned above, these are based on a DCC-MIDAS model for sample periods for which daily data is available, and on the simple DCC model when only monthly data is available. It is striking that all markets shift from persistently positive and often large stock-bond correlations to about zero correlation around 1998, and strong and persistent spells of negative correlations since then. The strong commonality suggests that global rather than local factors are driving international stock-bond correlations. The only exception to the rule is Japan, where correlations dropped to negative values already in mid-1993. Since the early 1990s, the Japanese economy

[1]We download for each country 10-year government bond yields from the Federal Reserve Bank of St. Louis Economic Data database. These government bond yields are converted to monthly total returns using $R_{B,t} = \frac{Y_{B,t-1}}{12} - D_t \times \triangle Y_{B,t}$, where $R_{B,t}$ is the government bond's total return at month t, $Y_{B,t-1}$ is the yield of the government bond at time t and $\frac{Y_{B,t-1}}{12}$ is the carry of the government bond over the month t, $\triangle Y_{B,t}$ is the difference $Y_{B,t} - Y_{B,t-1}$ and D_t is the modified duration of the bond at month t. The modified duration is computed assuming that the bond has a maturity of 10 years at month t and has a coupon equal to the $Y_{B,t}$.

has been characterized by low growth and persistent periods of deflation. We do notice more extreme negative correlations for safe haven countries such as the US, Germany, and the Netherlands during the global financial crisis. In contrast, correlations in peripheral euro countries such as Italy and Spain have risen substantially during the sovereign debt crisis, as concerns about potential sovereign defaults were negatively affecting both bond and equity markets.

3 Regime Identification

In Section 4, we relate stock-bond correlations to inflation and output regimes. This section shows how those regimes are identified. Subsection 3.2 discusses simple univariate Regime-Switching (RS) models. Subsection 3.3 presents a bivariate RS model for output and inflation that allows us to distinguish between periods of procyclical and countercyclical inflation. We start, however, with a description of the macroeconomic data.

3.1 Macroeconomic Data

We calculate inflation as the year-on-year percentage changes in monthly consumer price indices (CPI, all items). As a measure of real output, we use monthly real seasonally-adjusted industrial production (IP, Total Industry) series. Both the CPI and IP series are from the OECD (2014). The sample starts in the 1950s for all countries but Canada (Jan. 1961), The Netherlands (April 1960), and Spain (Jan. 1965). The sample ends in December 2013. We use IP instead of GDP as the latter is only available at the quarterly instead of the monthly frequency. Our global inflation and industrial production proxies are based on the first principal component of the CPI and IP indices. We do check the robustness of our results to GDP-weighted global inflation and output series. To facilitate the identification of expansions and contractions, our preferred output measure is the IP output gap, calculated as the percentage difference between the observed (log of) real industrial production and the unobserved (log of) potential industrial production. We follow Döpke and Changny (2001) and Funke (1998) and measure potential IP using an unobserved components model. We refer to Appendix B for a detailed description of this model and for estimation results.

3.2 Univariate Regime Switching Models

We model the dynamics of the random series x_t, with x being the level of either inflation or the output gap, using a regime-switching in mean and volatility model:

$$x_t = \mu_{x,St} + \sigma_{x,S_t}\varepsilon_t, \quad \varepsilon_t \sim N(0,1) \tag{3.1}$$

where μ_{x,S_t} represents the regime dependent mean of series x, and σ_{x,S_t} the corresponding regime dependent volatility. We consider cases where the number of regimes (K) is either 2 or 3. The process S_t follows a first-order Markov chain with K regimes with transition probabilities:

$$p(S_t = i|S_{t-1} = j) = P_{ij} \tag{3.2}$$

Let $\tilde{x}_T = [x_T x_{T-1} ... x_1 x_0]^T$ and let θ denote the parameters of the likelihood f. Following Hamilton (1994), the likelihood can be written as:

$$f(\tilde{x}_T;\theta) = \prod_{t=1}^{T}\left(\sum_{i=1}^{K} f(x_t|I_{t-1}, S_t = i;\theta)\, p(S_t = i|I_{t-1};\theta)\right) \tag{3.3}$$

where the ex-ante probability $p_{it} = p(S_t = i|I_{t-1};\theta)$ is calculated as:

$$p_{it} = \sum_{j=1}^{K} P_{ij}\left[\frac{f(x_{t-1}|S_{t-1} = j, I_{t-2};\theta)\, p(S_{t-1} = j|I_{t-2};\theta)}{\sum_{m=1}^{K} f(x_{t-1}|S_{t-1} = m, I_{t-2};\theta)\, p(S_{t-1} = m|I_{t-2};\theta)}\right] \tag{3.4}$$

We start up the algorithm by setting $p(S_1 = i|I_0)$ equal to the ergodic probabilities.

3.3 Pro/Countercyclical Inflation Regimes

3.3.1 The Ravn and Sola (1995) Model

To investigate the potential link between stock-bond return correlations and inflation being pro- or countercyclical, we estimate as in Ravn and Sola (1995) the following bivariate model for inflation π and output gap y changes:

$$\begin{gathered}\triangle\pi_t = \mu_\pi(S_t^\pi) + \xi_{\pi,t} \\ \triangle y_t = \mu_y(S_t^y) + \xi_{y,t} \\ [\xi_{\pi,t}, \xi_{y,t}]^T \sim N(0, \Sigma(S_t^\pi, S_t^y))\end{gathered} \tag{3.5}$$

Both S_t^π and S_t^y can take on two states: either inflation (output) is in the high (h) or in the low (l) regime. Let S_t be a 4 state latent regime variable that combines the 4 possible inflation/output regimes:

$$S_t = \{(\pi_h, y_h), (\pi_l, y_h), (\pi_h, y_l), (\pi_l, y_l)\} \tag{3.6}$$

Accounting for changes in the mean is particularly important here as Ravn and Sola (1995) have shown that covariance estimates, our main parameters of interest here, will generally be biased unless changes in the mean are accounted for. We model the state-dependent covariance matrix as:

$$\Sigma_{S_t} = \begin{pmatrix} \sigma_\pi^2(S_t) & \sigma_{\pi,y}(S_t) \\ \sigma_{\pi,y}(S_t) & \sigma_y^2(S_t) \end{pmatrix} \tag{3.7}$$

We identify spells of pro- and countercyclical inflation as regimes that feature positive (negative) covariances between output and inflation shocks, respectively. Finally, assuming that inflation and output each follow their own independent regime process[2], the 4 by 4 transition probability matrix is determined by the 4 probabilities of staying in the low or high regime $(P_{y_h}, P_{y_l}, P_{\pi_h}, P_{\pi_l})$, and given by:

$$\prod^{indep} = \begin{bmatrix} P_{y_h}P_{\pi_h} & (1-P_{y_l})P_{\pi_h} & P_{y_h}(1-P_{\pi_l}) & (1-P_{y_l})(1-P_{\pi_l}) \\ (1-P_{y_h})P_{\pi_h} & P_{y_l}P_{\pi_h} & (1-P_{y_h})(1-P_{\pi_l}) & P_{y_l}(1-P_{\pi_l}) \\ P_{y_h}(1-P_{\pi_h}) & (1-P_{y_l})(1-P_{\pi_h}) & P_{y_h}P_{\pi_l} & (1-P_{y_l})P_{\pi_l} \\ (1-P_{y_h})(1-P_{\pi_h}) & P_{y_l}(1-P_{\pi_h}) & (1-P_{y_h})P_{\pi_l} & P_{y_l}P_{\pi_l} \end{bmatrix} \tag{3.8}$$

To estimate the model's 16 parameters, we follow the same procedure as described in Section 3.2.

3.3.2 An alternative regime-switching model

A potential disadvantage of the Ravn and Sola (1995) model is that correlations can only differ across output/inflation mean/volatility regimes. To our knowledge, however, there is no economic theory that directly links inflation cyclicality to either the level or volatility of output and inflation. As an alternative, we present a simple regime-switching model that allows the relationship between output and inflation to

[2]Relaxing the independent regime assumption would increase the number of parameters by 8, as the 4 by 4 transition probability matrix would have 12 rather than 4 free parameters. Given the relative short sample, we did not pursue such model.

switch independently from output and inflation volatility.

$$\begin{aligned}\triangle y_t &= c_y\left(S_t^y\right) + \sigma_y\left(S_t^y\right)\varepsilon_{y,t}, \quad \varepsilon_{y,t} \sim N(0,1) \\ \triangle \pi_t &= c_\pi\left(S_t^\pi\right) + \beta\left(S_t^{cov}\right)\varepsilon_{y,t} + \sigma_\pi\left(S_t^\pi\right)\varepsilon_{\pi,t}, \quad \varepsilon_{\pi,t} \sim N(0,1)\end{aligned} \tag{3.9}$$

The latent state variables S_t^y and S_t^π govern the time variation in output and inflation volatility, respectively. As in the Ravn and Sola (1995) model, we allow means to be different across the volatility regimes. A separate state variable S_t^{cov} determines the covariation (β) between output and inflation shocks. We allow for two states in both inflation and output volatility, i.e. $S_t^y = \{low, high\}$ and $S_t^\pi = \{low, high\}$ and in the output-inflation beta, i.e. $S_t^{cov} = \{low, high\}$. Because we furthermore assume that the three regime variables move independently over time, we can conveniently express the transition probability matrix as:

$$\prod^{indep} = \begin{bmatrix} P_v^y & (1-Q_v^y) \\ (1-P_v^y) & Q_v^y \end{bmatrix} \otimes \begin{bmatrix} P_v^\pi & (1-Q_v^\pi) \\ (1-P_v^\pi) & Q_v^\pi \end{bmatrix} \otimes \begin{bmatrix} P_{cov} & (1-Q_{cov}) \\ (1-P_{cov}) & Q_{cov} \end{bmatrix} \tag{3.10}$$

where P_v^y and P_v^π, and Q_v^y and Q_v^π represent the probabilities that output and inflation volatility stay in the low and high regime, respectively, and P_{cov} and Q_{cov} the probability that the output-inflation beta remains in the low and high regime, respectively.

3.4 Estimation Results

3.4.1 Univariate models

Estimation of Regimes in Realized Inflation Table 1 shows the estimation results for a three-state regime switching model on monthly local and global realized annual inflation rates. Figure 3 plots the corresponding inflation rates and regimes over time. We first discuss the global inflation regimes, and subsequently the local ones.

The final column of Table 1 reports the estimation results for the global inflation rate, calculated as the first principal component of the local inflation rates[3]. The model identifies three clearly distinguishable regimes[4]. Regime 1 features both low inflation (1.9%) and low inflation volatility (0.5%). Inflation in the second 'intermediate inflation' regime amounts to 4.2%, and inflation volatility to 0.9%. Both average inflation (10.5%) and inflation volatility (2.7%) are much higher in the third

[3]The first principal component explains 79.5% of the total variance of the inflation rates in our sample, and is a well-balanced weighted combination of the local inflation rates (results available upon request). We verified that our findings are robust to using GDP instead of PCA-weights.

[4]We verified that the regime-dependent inflation estimates are statistically different from one another.

'high inflation' regime. The low and high inflation regimes both have an expected regime duration of about 11 years, compared to about 5 years for the medium inflation regimes. The final graph of Figure 3 shows that the high inflation regime started in the early 1970s and ended in 1983 with Volcker's successful conquest of (US) inflation. Intermediate inflation was observed in the periods 1962-1972 and 1983-1993. Except for the short inflation surge in mid-2008, as of 1994, global inflation has been persistently in the low inflation regime.

Estimation results for local inflation largely mimic those for global inflation, with some noticeable exceptions. First, while countries are often at the same time in the same regime, the within-regime inflation levels often differ substantially. Low inflation ranges from 0% in Japan to 3% in Spain. Both for intermediate and high inflation regimes, Germany has the lowest inflation rates (2.8% and 5.3%), while Spain has the highest (7.1% and 16.1%). Second, while many countries are (except for some short-lived jumps) exclusively in the low inflation regime since the early 1990s, we observe more frequent regime shifts during this period predominantly in the US, but also in Belgium and the Netherlands.

Estimation of Regimes in Real Output Gap Table 2 reports estimation results for a two-state regime-switching mean and variance model for both local and global IP output gaps. Figure 3 plots the corresponding output gaps and regimes over time. Similar to our global inflation measure, the global output gap is calculated as the first principal component of the local IP output gaps.[5] Note that we did also estimate 3-state versions of our model; because we did not find statistically significant differences in average output gaps between the intermediate and high regimes, we simply report results for a 2-regime version[6]. We observe economically and statistically significant differences in average output gap between the first 'recession' regime and the second 'expansion' regime. For all countries except Belgium and the Netherlands (where the difference is statistically insignificant), the recession regime is characterized by a significantly higher output gap volatility than the expansion regime. The difference across regimes in output gap is smallest in the Netherlands (1.02%) and France (1.05%) but largest in Italy (2.08%) and Canada (2.22%). Expansion regimes take on average slightly longer than recession regimes (4.1 versus 3.2 years). The difference is particularly large for the global output gap (8.7 versus 3.3 years). Figure 3 plots the local and global output gaps together with

[5]The first principal component explains 65.74% of total variation of cross-country IP output gaps across the 10 countries. We verified that our findings are robust to using GDP instead of PCA-weights.

[6]Because of the presence of nuisance parameters under the null, testing for 3 against 2 regimes cannot be performed using standard approaches such as a likelihood ratio test.

their estimated regimes. The plots confirm that the low output gap regimes largely overlap with known recession periods.

3.4.2 Estimation of Pro/countercyclical Inflation Regimes

Section 3.3 described two models to identify periods of pro- and countercyclical inflation. Table 3 contains the estimation model of the Ravn and Sola (1995) model. Table 4 presents the results for our alternative regime-switching model. Rather than discussing the estimation results for each model in detail, we focus on what is most relevant for this paper, namely that we find no evidence for a switch to a procyclical inflation state as from the year 2000 onward. The estimated correlations in the Ravn and Sola (1995) model (Table 3, Panel C) are nearly always negative. Of the 44 estimated correlations (4 correlations per country/global), only 8 are positive but close to zero and statistically insignificant. These findings are corroborated by the estimates of the alternative RS model. While we find evidence of two regimes in the inflation-growth beta of all countries, none of these betas is actually positive: betas are either close to zero (regime 1) or large and negative (regime 2). A closer look at the regime probabilities over time (not reported) shows, moreover, that neither correlations nor betas systematically switched to a higher (less negative) regime in 2000. We do notice though for several countries some short-lived switches to less negative correlation (beta) regimes during 2001, 2008-2009, and in 2012. Interestingly, Bekaert et al. (2015) identify these periods as episodes during which demand shocks temporarily dominated supply shocks.

The differences between our and Burkhardt and Hasseltoft (2012)'s findings are striking. Our results are qualitatively unaffected when we use, as they do, real consumption growth instead of real IP growth, or when we estimate our model at the quarterly rather than at the monthly frequency, or when we also include lags of output and inflation changes in the mean specification. We are able to replicate their findings only when we stack inflation, the output gap, and stock and bond returns in one system, and impose the macro variables to share the same regime as the stock and bond returns. Jointly modeling the macro variables and asset returns is problematic, however, as the macroeconomic parameters are chosen to also match stock and bond return dynamics, in this particular case the switch towards a negative stock-bond correlation regime since the early 2000s. Just as Burkhardt and Hasseltoft (2012), we find the regime with negative stock-bond correlations to have a positive covariance (correlation) between output gap and inflation shocks. The small size and poor significance of the output/inflation correlation parameters casts doubts, however, on any theory giving a central role to this parameter for explaining stock-bond correlations.

4 Stock-Bond correlation and Macroeconomic Regimes

4.1 Empirical Setup

In this section, we formally test whether stock-bond correlations are systematically different across inflation regimes, output regimes, or a combination of both. More specifically, we regress the (Fisher-transformed[7]) stock-bond correlations $\tilde{\rho}_{SB,c,t}$ for country c estimated previously using the DCC-MIDAS model (see Section 2) on the different country-specific regime dummies:

$$\tilde{\rho}_{SB,c,t} = \sum_{i=1}^{N} \gamma_i \times D^{z(g)}_{c,i,t} + \varepsilon^{z}_{SB,i,t} \tag{4.1}$$

where $D^{z(g)}_{c,i,t}$ equals one when the probability that the process for macro variable(s) z in country c or at the global level (g) at time t is in state $i = 1, .., N$, is larger than 50%. We do not include an intercept, so that the parameter estimates (γ_i's) capture the average stock-bond correlations across the different regimes. We base inference on Newey-West standard errors (24 lags) to correct for the substantial serial correlation in the dependent variable. To compare the fit across specifications, we report the regressions' adjusted R^2, the Mean Absolute Difference (MAD) between the fitted and empirically observed correlations (from the MIDAS model), as well as the % of observations that the fitted and observed correlations share the same sign (hit rate).

Rather than estimating Equation (4.1) country by country, we also estimate two panel versions of it. In a first specification, we regress local stock-bond correlations on local macroeconomic regime dummies assuming that the γ's are constant across countries. According to this specification, local stock-bond correlations differ only to the extent that the local macroeconomic indicators are in a different regime. A second panel regression uses both constant γ's and global regime dummies. In this extremely stylized model, correlations are constant across countries but vary over time with the global regime variables.

[7]We calculate the Fisher (Fisher (1915)) transformed correlation $\tilde{\rho}_{SB,c,t}$ at time t as $\tilde{\rho}_{SB,c,t} = \frac{1}{2}ln\left(\frac{1+\rho_{SB,c,t}}{1-\rho_{SB,c,t}}\right)$, with $\rho_{SB,c,t}$ the corresponding DCC-MIDAS conditional correlation.

4.2 Empirical Findings

4.2.1 Stock-bond correlation and inflation regimes

Table 5 reports estimation results from country-by-country regressions of local stock-bond correlations on three local (Panel A) or three global (Panel B) inflation regime dummies. The final column also reports estimates from two panel regressions that keep the parameters constant across countries (fixed effect panel regressions), either using local (Panel A) or global (Panel B) inflation regime dummies. Overall, we find stock-bond correlations to be lowest and mostly negative (but statistically insignificant) in the low inflation regime, and positive (and significant) in the intermediate and high inflation regimes. We find the most negative (and statistically significant) correlations in the low local and global inflation regime for Japan (-26.2% and -28.9%, respectively). Stock-bond correlations are either similar across the intermediate and high inflation regime, or higher in the high inflation regime[8]. In most countries, using global inflation dummies leads to a better fit than using local dummies. In fact, the model that imposes the same correlations to all countries (fixed effect panel model with global inflation dummies) has a substantially better fit than the panel model with local inflation dummies. In unreported results, we found that local inflation dummies do not have additional explanatory power for stock-bond correlations once global inflation dummies are accounted for.

These findings are generally consistent with the model of David and Veronesi (2013). In a low inflation environment, positive inflation shocks decrease investor beliefs of being in a bad deflationary state. This subsequently leads to higher expectations about future output and inflation, and hence to negative stock-bond correlations. In a very high inflation regime instead, positive inflation shocks confirm investors' fears of being in a bad stagflationary regime. This moves both stock and bond prices down, leading to positive stock-bond correlations.

In terms of fit, however, this model performs rather poor. While the model predicts the sign of stock-bond correlations rather well, Mean Absolute Deviations (MAD) in percent remain rather large, ranging from 15.4% in Japan to 31% for Italy. The poor fit is illustrated in Figure 5, which compares the fitted correlations with their empirical counterparts. In most countries, the switch to the low inflation regime precedes the drop in stock-bond correlations with several years. In fact, in the 4 years following the drop towards a low global inflation regime in 1993, stock-bond correlations were at their historical peak in most countries, Japan being the exception. Moreover, while the model fits the level of positive correlations reasonably

[8] Only in France and Belgium, and only when global inflation dummies are used, stock-bond correlations are slightly higher in the intermediate compared to the high inflation regime.

well, it does not match the magnitude nor dynamics of negative correlations during the last 15 years of our sample.

4.2.2 Stock-bond correlation and output gap regimes

Table 6 shows the estimation results from a regression of local stock-bond correlations on two dummies capturing the state (recession/expansion) of either the local (Panel A) or global (Panel B) business cycle. Figure 6 compares the fitted correlations from the dummy model with the empirically observed ones. Using local output dummies, we find no systematic relationship between the state of the economy and stock-bond correlations. Correlations are higher during recessions for the US, France, Italy, and Spain, but lower for Japan, Germany, the UK, The Netherlands, Belgium, and Canada. This is confirmed by the panel estimation using local dummies, which estimates very similar correlations[9] in the recession and output regimes (10% versus 13.6%). When global dummies are used, we find stock-bond correlations to be lower and mostly negative in the recession state than in the expansion state for all countries but Italy and Spain. Low or negative correlations are, however, with the exception of Japan, never statistically significant. Figure 6 shows that the fit of the output dummy model for stock-bond correlations is poor. This is also confirmed by the higher MAD relative to the inflation dummy model, and the much lower regression R^2's. The MAD for the global panel model (27.6%) is even slightly worse than for a model that simply assumes correlations to be constant within countries (27.3%), while the hit ratio is only marginally better (65.4% vs. 65.5%). To conclude, output dummies, at least not alone, cannot explain much of the variation in international stock-bond correlations.

4.2.3 Stock-bond correlation and output/inflation regimes

As discussed in Section 3.4.2, we did not detect any episode of persistently procyclical inflation. We did, however, find regimes during which the correlation between output gap and inflation shocks was less negative. While we do not have a model to identify supply and demand shocks, a less negative (close to zero, typically) correlation between output gap and inflation shocks is consistent with an environment in which demand shocks gain in importance relative to supply shocks (which still dominate). Because demand shocks push inflation and output in the same direction, these periods may be associated with lower stock-bond correlations. When we, however, relate stock-bond correlations to dummies based on either the

[9] We cannot reject the null hypothesis that stock-bond correlations are the same across states.

Ravn and Sola (1995) or our alternative model, we only find positive coefficients that are moreover not statistically different from one another[10]. Not surprisingly, (adjusted) R^2's are close to zero, MAD's high, and hit ratios low.

Table 7 instead investigates the extent to which *interactions* between the output and inflation regimes explain stock-bond correlations. In the global panel model (last column of panel B), similar to Dergunov et al. (2017), the only state to feature an, on average, negative stock-bond correlation (of about -13.8%) is the low inflation / low growth regime. This is a bad state to be in, as heightened risk aversion may lead to a flight-to-quality that pushes equity prices down and Treasury bond prices up. In the model of David and Veronesi (2013), negative (positive) inflation shocks within this regime may further increase (decrease) the likelihood of a bad deflationary regime; either way this leads to negative stock-bond correlations.

At the individual country level, we observe more pronounced negative correlations in this regime for countries with a high credit rating, but positive correlations in markets with more fragile public finances, like Italy and Spain. In these markets, a flight-to-safety occurred not only away from local equities but also out of local Treasury bonds. Note that the average correlation within this regime is often imprecisely estimated, and only significant at the 5% (10%) level in 2 (6) out of 10 countries. Notice furthermore that the fitted correlation is also low (about zero) in the low inflation / expansion state, suggesting that low inflation is the key driver of low stock-bond correlations. In all other states, the fitted correlation is positive and in between 20% to 30%. In terms of fit though, the results are disappointing. Despite having twice the number of regime dummies, this model has only a marginally better fit (in terms of MAD and hit statistic) but a lower (adjusted) R^2. Results are qualitatively similar for the model estimated using local regime dummies.

5 Stock-Bond Correlations and Monetary Policy Regimes

The previous sections showed that inflation and growth regimes as such cannot explain the large time variation in stock-bond correlations, and especially not the large negative correlations observed since the end of the 1990s. We now investigate to what extent the monetary policy regime, potentially interacted with inflation and output regimes, affect stock-bond correlations.

The relationship between stock-bond correlations and monetary policy was recently stressed by Campbell et al. (2014) and Song (2014). Campbell et al. (2014)

[10]These results are available upon request.

show, using a New Keynesian model with habit formation, that a switch to accommodating monetary policy in combination with a decreased volatility of supply shocks and increased volatility of the long-term inflation target contributed to negative stock-bond correlations in the post-2000 period. Song (2014) develops and estimates a long-run risk model featuring regime-switches in both monetary policy stance and the correlation between long-run growth and the inflation target. He finds that while switches to accommodating monetary policy contributed to lower stock-bond correlations, it is only when a switch towards a procyclical inflation regime is taken into account that negative stock-bond correlations are obtained. However, as Ermolov (2014) points out, Song (2014) may overstate the role of macroeconomic shocks as he estimates the macroeconomic dynamics and asset prices jointly. By estimating them jointly, parameters driving the (noisy) macro variables may be set in such a way as to also fit the asset prices, resulting in a general overstating of the role of the macro variables for explaining asset prices.

To investigate the relationship between monetary policy and stock-bond correlations, we proceed as follows. In Section 5.1, we estimate a simple regime-switching monetary policy rule that allows us to distinguish between periods of accommodating and restrictive monetary policy, and between spells of passive (rule-following) and discretionary monetary policy. Subsequently, in Section 5.2, we relate the global and local MP regimes to stock-bond correlations, and test whether switches between restrictive and accommodating monetary policy help explain corresponding switches between positive and negative stock-bond correlations. In a subsequent section, we will combine the MP dummies with the inflation and output dummies, and test the explanatory power of these interacted dummies for stock-bond correlations.

5.1 Monetary Policy Regimes: Identification

To distinguish between accommodating and restrictive monetary policy regimes, we estimate a simple monetary policy rule[11] (see e.g. Clarida et al. (1999)):

$$i_t = \rho i_{t-1} + (1-\rho)\left[\alpha + \beta\left(S_t^{MP}\right)\pi_t + \gamma\left(S_t^{MP}\right)y_t\right] + \epsilon_{t,i}, \quad \epsilon_{t,i} \sim N\left(0, \sigma_t^2\left(S_t^V\right)\right) \tag{5.1}$$

[11] As an alternative, we also identified monetary policy regimes based on the residuals from a fixed parameter MP rule, where either we use the parameters from the original Taylor rule or from the "Yellen version", which imposes a higher γ. The main drawback of these alternative specifications is that they do not allow for shifts in the monetary policy style. Also, parameters are calibrated for the US, and may not be applicable to other markets.

where i_t is the nominal observed (country-specific) monetary policy rate.[12] The parameter ρ captures the degree of lagged dependence in the interest rate. For higher values of ρ , it takes the central bank longer to adjust interest rates fully to the new target. Parameters β and γ govern the reaction of short-term interest rates to inflation (π_t) and the output gap (y_t), respectively, and α is a constant that captures the steady state real interest rate. To distinguish between accommodating and restrictive monetary policy, we condition the reaction of monetary policy to inflation (β) and output (γ) on a latent regime variable S_t^{MP}. During restrictive monetary policy regimes, the central bank reacts more strongly to inflation and relatively less to the output gap. The opposite occurs during periods of accommodating monetary policy. Finally, by letting the $\epsilon_{i,t}$'s variance depend on a latent regime variable S_t^V, we additionally distinguish between periods with lower or higher degrees of discretionary monetary policy.

Table 8 reports estimation results for all countries as well as for the global monetary policy rate, calculated as the first principal component of the policy rates of the US, Germany, the UK, and Japan[13]. Figure 7 plots the smoothed probability of being in the accommodating monetary policy regime. In our estimations, we set ρ equal to zero, as the extremely high persistence of monthly interest rates rendered our estimates unstable. We do find similar results though for a specification including ρ estimated on (slightly less persistent) quarterly rates. We find the estimates for α, an estimate of the steady state real interest rate to range from 1.11% in Japan to 3.00% in Canada. In regime 1, central banks react more strongly to inflation ($\beta_1 > \beta_2$) but less so to the output gap ($\gamma_1 < \gamma_2$). While many individual estimates are only borderline or not significant, the difference between β's and γ's across regimes is sufficiently large to soundly reject the null of equal parameters across regimes. For all countries except Japan (0.947), we find β_1 to be larger than 1, indicating that central banks in regime 1 adjust interest rates with more than the pure inflation rate. We also find substantial differences between the level of volatility of the rule's residual, indicating that monetary policy has gone through spells of more rule-based or more discretionary monetary policy. Figure 7 shows that monetary policy was for nearly all countries predominantly restrictive during the 1980s and 1990s but accommodating during the 1970s and since the early 2000s. In Japan, also the 1990s are identified as a period of mostly accommodating mon-

[12] As a proxy for the monetary policy rate, we use the Effective Federal Funds Rate for the US, short-term repo rates for the continental European countries, and the monthly policy rates as reported by the Bank of England (UK), Bank of Japan, and Central Bank of Canada.

[13] The first principal component explains more than 80% of the total variation in central bank policy rates. The results are robust for other weighting schemes as well (GDP weighted or equally weighted).

etary policy. Despite being based on a simpler model, our identified MP regimes for the US largely overlap with those identified in Campbell et al. (2014) and Baele et al. (2015). Figure 8 shows that monetary policy also frequently switched between active and passive (rule-based) spells. Overall, we observe, however, much more cross-country dispersion in the activeness compared to the monetary policy stance regimes.

As a robustness check, we also estimated the MP rule using data until 2008, i.e. before interest rates moved towards the zero lower bound. From 2008 on, we simply assume MP to be in the accommodating and discretionary regime. Figures 7 and 8 compare regime identification between the full and restricted sample. We hardly find any differences in the identification of accommodating/restrictive MP regimes. In some countries, however full sample estimates identify periods of passive rather than discretionary MP.

5.2 Monetary Policy Regimes and Stock-Bond Correlations

Table 9 reports estimation results from country-by-country regressions of local stock-bond correlations on the local (Panel A) and global (Panel B) monetary policy dummies. The final column also reports estimates from two fixed effects panel regressions, either using local (Panel A) or global (Panel B) monetary policy dummies. Irrespective of whether local or global MP regimes are used, our results indicate accommodating monetary policy to be associated with negative stock-bond correlations, and restrictive monetary policy with positive ones. For instance, in the panel model using global MP regime dummies, the average stock-bond correlation is -11.5% when MP is accommodating compared to 28.1% when it is restrictive (both significant at the 1% level). In the country-by-country regressions, again using global MP regime dummies, we find the stock-bond correlation to be negative for all countries but France in the accommodating regime, but positive and large for all countries in the restrictive MP regime. The effect is always significant for the restrictive MP regime, but only in France and The Netherlands in the accommodating regime. In terms of model fit, we find the MP dummy model, despite being a 2- rather than a 3-regime model, to perform better than the inflation dummy model in terms of R^2 and MAD, and only marginally worse at predicting the correct correlation sign. Still, overall fit remains relatively poor.

In unreported results, we also interacted the monetary policy stance indicators with dummies capturing whether MP was in the passive or active regime. While we do find some support for our hypothesis that stock-bond correlations should be more negative in the active / accommodating regime compared to the passive

/ accommodating regime, we do not find any improvement in model fit. Finally, our results are robust to using MP dummies identified using the pre-2008 sample only. This is not surprising given the full and restricted sample estimates were very similar.

6 Macro, Monetary Policy Regimes and Stock-Bond Correlations

6.1 Panel Regressions

The previous sections indicated that while inflation and monetary policy regimes on a standalone basis are somewhat related to stock-bond correlations, their explanatory power remains rather low. Supported by recent work by Song (2014) and Campbell et al. (2014), we now investigate to what extent a combination of macro and monetary policy regimes explains international stock-bond correlations. We proceed as follows. First, we create 12 dummies capturing the various combinations of the 2 output, 3 inflation, and 2 monetary policy regimes. We denote the dummies based on the global regimes by D_G, and those based on the local regimes by D_{L_c}. Second, we run an (unbalanced) panel regression of the (Fisher-transformed) country-level stock-bond correlations on either the Global or Local dummies[14]:

$$\tilde{\rho}_{SB,c,t} = D'_{L_c/G,t}\gamma + \varepsilon_{ct} \tag{6.1}$$

Importantly, to avoid in-sample overfitting, we impose the γ's to be the same across countries. In the most extreme case, we additionally use global regime dummies, which implies stock-bond correlations will be identical (but still time-varying) across countries, and the regression will set the γ's as to best fit the average stock-bond correlation across all countries. When instead local regimes are used, local stock-bond correlations will be different across countries, but only to the extent that countries are in a different regime at different points in time.

6.2 Empirical Results

Panels A and B of Table 10 report β estimates for the global and local dummy models, respectively, as well as average model-fit statistics. Panel C reports country-specific model-fit statistics, both for the global and local dummy model. A first striking result of Panel A of Table 10 is that large negative correlations are observed

[14]No intercept is included as the dummies sum up to one.

only in times of low inflation and accommodating monetary policy. Estimated average correlations (or β) in this low inflation / accommodating MP regime are similar between expansion (-28.6%) and recession periods (-26.5%). We also observe correlations close to zero in the intermediate inflation/accommodating monetary policy regime (-1.9%)[15]. Instead, correlations are large and strictly positive when monetary policy is restrictive. In the low inflation / low growth regime, restrictive MP leads to stock-bond correlations that are nearly 63% points higher compared to when MP is accommodating (34.3% vs -28.6%). This difference remains large also for the other regime combinations: 51% in the low inflation / high growth regime (24.5% vs -26.5%) and 32% in the intermediate inflation / high growth regime (30.3% vs -1.9%). In the high inflation regime, stock-bond correlations are in the tight range 25%-29%, irrespective of the growth and monetary policy regime. The last column shows that states associated with negative correlations occur in about 35% of our sample.

Despite being tightly parameterized - all countries have the same fitted correlation - the fit of this model surprisingly good. Adding monetary policy interactions to the panel model with only inflation/output states more than doubles the R^2 (59% vs 26.3%), increases the hit ratio from 76.7% to 88.9%, and lowers the Mean Absolute Deviation from 22.6% to 17.5%. Panel C shows that the fit is better for the core European countries (France, Germany, Belgium, Netherlands), the UK, and Canada, but worse for the European periphery countries (Spain, Italy) and Japan. This is not surprising, as the latter countries were more affected by the global financial crisis and in particular the subsequent sovereign debt crisis relative to the benchmark countries, while Japan's business cycle has been somewhat disconnected from the global one since it entered a period of low inflation and suppressed growth in the early 1990s.

As can be seen from Panel B of Table 10, we obtain qualitatively similar results when local rather than global dummies are used. In fact, we now find that any state with accommodating monetary policy that has either low or intermediate inflation, is associated with negative stock-bond correlations, including in the intermediate inflation/low growth regime that was not observed for the global dummies. The cross-country average predicted percentage of months with negative correlations is 44.6%, which is about 10 percentage points higher than for the global model. Consistent with our previous results, model fit worsens substantially when local rather than global dummies are used. The average R^2 across countries drops from

[15]Because we only observe the intermediate inflation / accommodating MP regime in expansions, we cannot say anything about correlation levels associated with this regime during recessions.

59% for the global dummy model to 39% compared to a model with local dummies; the average hit ratio and MAD decrease (increase) accordingly. Panel C shows that, at the individual country level MAD is substantially worse for the local dummy model. Not surprisingly, the exceptions are the two European periphery countries (Spain, Italy, only MAD) and Japan (only hit ratio).

In unreported results, we also investigated to what extent local regimes have additional explanatory power over and above global regimes. As a first test, we ran a panel regression of the residual correlations from the global panel model on the local interacted dummies. TheR^2 of this panel regression is just 2.3%. The hypothesis that all dummies are jointly significantly different from zero is rejected at the 5% level (but just not at the 10% level). This seems to indicate that indeed local regimes have little to add to global regimes. Even for countries that are thought of as being different from the others (Japan, Spain and Italy), country-level R^2s are lower than 5%. As an alternative, we first ran a panel regression of stock-bond correlations on local regimes, and subsequently a panel regression of residual correlations from this local panel model on global dummies. TheR^2 of this regression is much higher, namely 23.4%. A Wald tests rejects the hypothesis that all parameter estimates are jointly zero at the 1% level. These results seem to back our claim that global regimes are more important drivers for stock-bond return correlations than local regimes[16].

We also tested to what extent our results are robust to using US regimes as proxy for global regimes. Despite the limited overlap between the global and US regimes (only about 34%), results are qualitatively similar between a US and a global panel model. In particular, also in the US panel model negative stock-bond correlations are associated with accommodating MP in the low to intermediate inflation states. The US model's R^2 is substantially lower though (44% versus 59% for the global model). Subsequently, we tested whether local regimes have additional power for fitting stock-bond correlations not explained by the US panel model. The R^2 of such panel regression is 7.8%; a Wald test cannot reject the null hypothesis that all parameters are zero at the 5 percent level. In our view, this does not reflect the additional value of local regimes for understanding stock-bond correlations, but

[16]We do find a more important role for local regimes when we no longer assume parameters to be constant across countries (country-level rather than panel regressions). That is, correlations can be different across countries not only because their realized regime is different, but also because the parameters linking regimes to correlations can be different across countries. As expected, the influence is higher when we impose countries to have the same exposure to global regimes, i.e. when we use correlation residuals from the global panel model rather than from country-level regressions of local correlations on global dummies. We, however, strongly believe that this exercise is too prone to overfitting. After all, we fit local stock-bond correlations to 12 dummies in a first step and to 12 additional dummies in the second step. Moreover, we find limited consistency in parameter signs across countries. For this reason, we have decided not to pursue this further.

merely that US regimes are not the best measure to capture global economic states.

Figure 12 compares the fitted to the empirically observed correlations for the different markets, both for the local and global dummy model. The global dummy model captures well the switch from positive to negative correlations around the year 2000. The switch to negative correlations occurred earlier for Japan, reflecting its move to a low inflation / low growth regime already in the early 1990s. While our model generates substantial positive and negative correlations, we do not match the extreme positive correlations in the early 1990s nor the at times extreme negative correlations observed since 2000. In particular the extreme negative correlations may be due to shifts in investor sentiment and associated flights to safety that are unlikely captured by macro-fundamentals (see e.g. Baele et al. (2014)). Naturally, our global model also does not fit - and is not meant to do - the rapid increase in stock-bond correlations in Spain and Italy during and after the sovereign debt crisis. In these markets, innovations in sovereign default premia - normally close to zero - rapidly became the dominating drivers of bond returns. In the midst of the crisis, increasing premia pushed down bond prices at the same time as equities dropped, leading to positive stock-bond correlations. When subsequently sovereign default concerns alleviated, both bonds and equities recovered, and again positive correlations were observed. Once default premia would restore in Italy and Spain, we expect their stock-bond correlation dynamics to align again with those in the core European (global) markets.

6.3 Interpretation

Our results indicate that negative stock-bond correlations are associated with periods of accommodating monetary policy in combination with low to intermediate inflation. Correlations are always positive in the high inflation regime, irrespective of monetary policy stance.

In a low inflation state, investors are mainly worried about the economy entering into a deflationary spiral. Accommodating monetary policy reduces the likelihood of this happening, and instead makes positive inflation shocks more likely, leading to a drop in bond prices (inflation effect). At the same time, a lower likelihood of deflation also reduces the likelihood of a recession. This increases equity prices through a rise in expected cash flows (cash flow effect). Here, inflation signals good economic prospects as in David and Veronesi (2013). At the same time, as shown by Bekaert and Hoerova (2013), accommodating monetary policy tends to reduce both economic uncertainty and risk premia, leading to a further rise in equity prices (discount rate effect). Notice that also risk premia in the bond market may decrease, which would increase bond prices. Our finding of a negative stock-bond correlation indicates that the inflation effect dominates the risk premium effect.

Deflation may not be perceived as a large issue in times when inflation is low but monetary policy is restrictive. It seems fair to assume that if deflation would be a real concern, MP policy would be accommodating. In this regime, MP is expected to react strongly to inflation shocks by (more than proportionally) raising short-term interest rates. This does not only lead to a drop in bond prices, but also to lower real output and equity prices, and hence a positive stock-bond correlation.

The high inflation regime is exclusively observed during the 1970s and early 1980s, a period of positive and large stock-bond correlations. Until Paul Volcker became chairman of the Federal Reserve Board, monetary policy was mostly accommodating during this period. As shown by e.g. Bekaert et al. (2015), this period was frequently hit by bad supply shocks that push inflation higher at the same time when growth declines. Monetary policy, despite being mostly accommodating during this period, was unable to steer the economy away from low growth and negative real equity returns. At the same time, monetary policy was also unsuccessful at controlling (high) inflation, leading to depressed bond prices and positive stock-bond correlations. The highly anti-inflationary (restrictive) Volcker period was associated with increasing bond yields (bad for bonds) and a contracting economy (bad for equities), leading also to positive stock-bond correlations. Moreover, modern monetary policy has a clear inflation targeting component in its policy rule. As a result, spells of high inflation will be bad for bonds and stocks via an anticipated policy effect as well. See, for example, Park and Ratti (2000), who show that during periods of high inflation and interest rate volatility, expected real stock returns respond more to monetary tightening than at other times. During these periods, monetary policy always tightens in response to a positive shock in inflation.

Our results are consistent with these interpretations, as we find positive stock-bond correlations in the high inflation regime irrespective of monetary policy being in the accommodating or restrictive MP regime.

7 Conclusions and Epilogue

Our main empirical finding that monetary policy stance plays a key role in understanding time-variation and sign switches in stock-bond correlations strongly suggests that theoretical models trying to explain the joint dynamics of stock and bond returns should embed an endogenous central bank. A second key finding of our paper is that stock-bond correlations tend to be more related to global rather than to local macro and MP regimes, indicating that such theoretical models should not narrowly focus on the local macro-economic and MP regime, but instead on the state of the global economy and the degree of coordination between the main central banks across the world. Future work may want to use the model of David and Veronesi (2013) as a good starting point. In their model, inflation shocks may be considered either positive or negative signals of future economic growth depending on investors' current beliefs about the underlying regime. At least one channel for monetary policy to impact stock-bond correlations is that it helps investors in their belief formation of the current regime via the signaling function of its stance (accommodating vs restrictive).

Because our results are generated using data up to December 2013 only, we can revisit the more recent events in an out-of-sample exercise. With interest rates at the zero lower bound for most of this period, it is not trivial to detect changes in monetary policy state over this period using the regime-switching monetary policy rule. One way would be to estimate the MP rule using an estimated shadow rate instead of the observed policy rate. However, Bauer and Rudebusch (2016) show that estimated shadow rates fluctuate widely across estimation methods. Instead, we hypothesize that stock-bond correlations should turn positive when central banks announce a (possible) tightening of MP in the immediate or near future. Measuring the impact of changes in monetary policy on financial markets using an event-type study is, however, challenging. In particular, using the date of official press conference statements as timing of monetary policy communication is tricky for various reasons. First, recent monetary policy communication is characterized by forward guidance aimed at avoiding as much as possible policy surprises. This means MP decisions are typically anticipated quite some time in advance, and are hence also already reflected in asset prices on the day that policy changes are confirmed. Second, MP communication often coincides with macroeconomic news releases, making identification of individual effects problematic. For instance, the Fed's 2016 December rate hike was communicated and anticipated well before that date. The effect was further blurred by the (to many surprising) election of then President-Elect Donald Trump. The anticipation of higher inflation fueled by huge fiscal spending pushed bond yields (returns) higher (lower) but equity returns higher. In this instance, the negative effects of Trump's election on stock-bond correlations dominated the positive effect on correlations of a more likely switch to restrictive MP.

We could nevertheless identify one US monetary policy announcement that clearly came as a surprise to both observers and asset markets: the Taper Tantrum in June 2013. In his June 19, 2013 press conference, Ben Bernanke mentioned that if data on unemployment and inflation were to be consistent with the Committee's forecasts, "*...the Committee currently anticipates that it would be appropriate to moderate the monthly pace of purchases later this year. And if the subsequent data remain broadly aligned with our current expectations for the economy, we would continue to reduce the pace of purchases in measured steps through the first half of next year, ending purchases around midyear*". His intention was to stabilize the market by preparing it for an eventual policy change. However, although he clearly stressed the conditionality based on incoming data and explained during the Q&A that this was not a policy change, markets abruptly changed their view on policy. In only a few days between June 19 and June 25, The S&P500 index lost 3.84%, while at the same time US 10-year Treasury yields jumped higher from 2.18% to 2.61%. The Bloomberg Barclays US Treasury bond index with maturities between 7-10 years posted a negative return of -3.18% over the same period. Interestingly, this policy surprise pushed stock-bond correlations from highly negative levels to deeply positive. Figure 14 shows two measures of the correlation between the returns on the US S&P500 index returns and the returns on 10-year Treasury bonds. The first measure is the DCC estimate using weekly data, while the second measure is a simple 12-week rolling correlation estimate. Correlations between stock and bond returns in the US were clearly negative in the period before June 19, consistent with our fundamental model's estimate in a low inflation, accommodating monetary policy regime. As of the June 19 press conference and the subsequent repricing of the financial markets, stock-bond correlations rapidly increased to levels consistent with our fundamental model's estimate in a low inflation, restrictive (less accommodating) monetary policy regime. As markets started to calm down and understood the conditionality of the statement by Bernanke, stock-bond correlations normalized to the previous regime expected levels.

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A Summary Statistics Stock and Bond Returns

Table A.1: Summary Statistics: Daily Stock and Bond Returns

This Table reports summary statistics for daily stock and bond returns for the 10 countries in our sample.

	US	**Japan**	**Germany**	**UK**	**France**	**Italy**	**Spain**	**Netherlands**	**Belgium**	**Canada**
Start Date	30/06/1961	30/12/1983	31/12/1979	31/12/1979	31/01/1985	29/03/1991	30/11/1990	31/12/1987	30/06/1989	31/12/1984
Obs.	13225	7828	8872	8872	7544	5938	6023	6784	6393	7567
Stocks										
Mean	0.04%	0.02%	0.04%	0.05%	0.05%	0.03%	0.05%	0.04%	0.03%	0.04%
St. Dev.	1.02%	1.25%	1.12%	1.03%	1.22%	1.35%	1.27%	1.15%	1.03%	0.94%
Min.	-19.46%	-14.56%	-11.42%	-12.18%	-9.41%	-8.25%	-8.12%	-8.79%	-7.80%	-10.99%
Max.	11.51%	13.09%	17.42%	9.29%	10.45%	11.08%	12.49%	9.77%	8.59%	9.39%
Skewness	-0.5675	-0.1732	0.0193	-0.3478	-0.1218	-0.0088	0.0530	-0.1693	-0.0106	-0.7037
Kurtosis	18.80	9.06	12.91	8.81	6.01	4.31	5.42	7.10	7.21	14.45
Bonds										
Mean	0.03%	0.02%	0.03%	0.04%	0.03%	0.04%	0.04%	0.03%	0.03%	0.03%
St. Dev.	0.45%	0.32%	0.33%	0.48%	0.37%	0.46%	0.43%	0.31%	0.34%	0.42%
Min.	-3.50%	-4.28%	-2.45%	-6.30%	-2.52%	-3.54%	-2.53%	-1.72%	-2.58%	-2.95%
Max.	4.38%	3.96%	2.89%	3.64%	4.60%	5.99%	6.63%	1.87%	3.39%	4.00%
Skewness	0.2782	-0.6736	-0.0480	-1.5014	0.2560	0.3680	1.0261	-0.2268	-0.0669	-0.0868
Kurtosis	6.46	19.98	4.24	20.44	7.04	14.99	16.54	2.27	6.48	3.63
Correlation	1.33%	-6.75%	-6.74%	3.62%	0.03%	19.08%	8.71%	-19.07%	-4.84%	-6.65%

Table A.2: Summary Statistics: Monthly Stock and Bond Returns

This Table reports summary statistics for the monthly stock and bond returns for the 10 countries in our sample.

	US	**Japan**	**Germany**	**UK**	**France**	**Italy**	**Spain**	**Netherlands**	**Belgium**	**Canada**
Start Date	30/01/1970	28/02/1989	30/01/1970	30/01/1970	30/01/1970	30/04/1991	29/02/1980	30/01/1970	30/01/1970	30/01/1970
Obs.	528	299	528	528	528	273	407	528	528	528
Stocks										528
Mean	0.91%	0.06%	0.81%	1.07%	0.97%	0.65%	1.35%	0.97%	0.97%	0.66%
St. Dev.	4.46%	5.72%	5.67%	5.68%	5.81%	6.46%	6.40%	5.19%	5.16%	4.80%
Min.	-21.22%	-21.05%	-24.93%	-25.93%	-21.82%	-15.37%	-25.27%	-22.29%	-29.72%	-21.79%
Max.	17.79%	16.79%	20.94%	54.49%	23.23%	24.91%	26.95%	22.55%	26.07%	16.13%
Skewness	-0.41	-0.13	-0.48	1.28	-0.12	0.33	-0.16	-0.42	-0.64	-0.52
Kurtosis	1.83	0.87	2.17	15.94	1.11	0.70	1.72	2.17	5.62	2.22
Bonds										
Mean	0.64%	0.33%	0.60%	0.77%	0.74%	0.78%	0.92%	0.62%	0.68%	0.71%
St. Dev.	2.23%	1.58%	1.59%	2.43%	1.80%	2.20%	2.32%	1.67%	1.50%	2.07%
Min.	-9.69%	-6.92%	-5.90%	-9.12%	-11.92%	-7.98%	-7.78%	-5.97%	-4.76%	-6.11%
Max.	11.38%	5.28%	8.37%	12.53%	7.81%	9.61%	9.03%	8.29%	8.98%	11.44%
Skewness	0.38	-0.59	-0.09	0.40	-0.74	0.12	0.03	-0.05	0.11	0.43
Kurtosis	3.03	2.77	1.51	2.69	6.45	2.66	1.32	1.92	2.19	2.45
Correlation	14.48%	-1.12%	6.61%	30.49%	26.04%	21.75%	21.16%	8.12%	21.70%	19.70%

B The DCC-MIDAS Model for Dynamic Stock-Bond Correlations

B.1 Model Description

We use the DCC-MIDAS model of Colacito et al. (2009) to extract the monthly or quarterly component of variances from daily stock and bond returns. This model has been used in a similar context by Baele et al. (2010) and Asgharian et al. (2014). Assume the vector of stock and bond excess returns $r_t = [r_{e,t}, r_{b,t}]'$ follows:

$$r_t \sim i.i.d.\, N(\mu, H_t), \text{ with } H_t = D_t R_t D_t \tag{A.1}$$

where μ is the vector of unconditional means and H_t the bivariate conditional covariance matrix, further decomposed as $H_t = D_t R_t D_t$. D_t is a 2×2 diagonal matrix with the conditional stock and bond return volatilities on the diagonal, and

$$R_t = E_{t-1}\left[\xi_t \xi_t'\right] \tag{A.2}$$

$$\xi_t = D_t^{-1}(r_t - \mu) \tag{A.3}$$

Similar to the DCC model of Engle (2002), this model can be conveniently estimated in two steps. First the parameters governing the stock and bond return volatilities in D_t are estimated. Subsequently, the conditional correlation matrix R_t is estimated on the standardized residuals ξ_t from the first step.

Step 1: A GARCH-MIDAS component model for conditional stock and bond return variances

Following Ghysels et al. (2005) and several subsequent papers, we assume the univariate return $r_{i,t}$ to follow a GARCH-MIDAS process:

$$r_{i,t} = \mu_i + \sqrt{m_{i,t} \times g_{i,t}\xi_{i,t}}\; i = \{e, b\}, \forall t = \tau N_v^i, ..., (\tau+1)N_v^i \tag{A.4}$$

where $g_{i,t}$ and $m_{i,t}$ are the short and long run variance components of the daily returns for asset i. The short run component $g_{i,t}$ varies at the daily frequency t, while the long term component $m_{i,\tau}$- with a time subscript τ- only changes every N_v^i days. The short run variance component of stock and bond returns follows a simple GARCH(1,1) process:

$$g_{i,t} = (1 - \alpha_i - \beta_i) + \alpha_i \frac{(r_{i,t} - \mu_{i,t})^2}{m_{i,\tau}} + \beta_i g_{i,t-1} \tag{A.5}$$

while the long term MIDAS component $m_{i,\tau}$ is a weighted sum of K_v^i lags of realized variances (RV) over a long horizon:

$$m_{i,\tau} = \overline{m_i} + \theta_i \sum_{l=1}^{K_v^i} \varphi_l \left(\omega_v^i\right) RV_{i,\tau-1} \tag{A.6}$$

where $\overline{m}_i$ and θ_i are free parameters and the realized variances (RV) involve N_v^i daily non-overlapping squared returns, namely:

$$RV_{i,t} = \sum_{j=(\tau-1)N_v^i+1}^{\tau N_v^i} (r_{i,j})^2 \tag{A.7}$$

Because most of our macroeconomic data is available at the monthly frequency at best, for the long-term MIDAS component we set N_v^i equal to the effective number of trading days within one month. As a weighting scheme we use a Beta function with decay parameter ω_v^i defined as:

$$\varphi_l \left(\omega_v^i\right) = \frac{\left(1 - \frac{1}{K_v^i}\right)^{\omega_v^i - 1}}{\sum_{j=1}^{K_v^i} \left(1 - \frac{j}{K_v^i}\right)^{\omega_v^i - 1}} \tag{A.8}$$

The weight attached to past realized variances will depend on the two parameters ω_v^i and K_v^i. The latter determines the number of lagged realized variances taken into account. The decay parameter ω_v^i determines the weight attached to those past realized variances. In case of $\omega_v^i = 1$, the past K_v^i will receive an equal weight of $1/K_v^i$. In the likely case of $\omega_v^i > 1$, past realized variances will gradually get less and less weight. The larger ω_v^i, the larger the decay. In our empirical analysis, we allow the decay parameter ω_v^i to differ between stock and bond returns, as well as across countries. The impact on the weights in the weighted average of the realized volatilities is shown in Equation A.8. For $\omega = 1$, each of the 24 realized volatilities receives an equal weight. For $\omega = 2$, the weights decrease linearly. For $\omega > 2$, the weights decrease exponentially for observations further in the past.

Step 2: A DCC-MIDAS component model for conditional stock and bond correlation

In the second step, using the standardized residuals ξ_t obtained in step 1, we compute the matrix Q_t with the following elements:

$$q_{e,b,t} = \overline{\rho}_{e,b,t}(1-a-b) + a\xi_{e,t-1}\xi_{b,t-1} + bq_{e,b,t-1} \tag{A.9}$$

$$\overline{\rho}_{e,b,t} = \sum_{l=1}^{K_c^{eb}} \varphi_l\left(\omega_c^{eb}\right) C_{e,b,t-1}$$

$$C_{e,b,t} = \frac{\sum_{k=t-N_c^{eb}}^{t} \xi_{e,k}\xi_{b,k}}{\sqrt{\sum_{k=t-N_c^{eb}}^{t} \xi_{e,k}^2}\sqrt{\sum_{k=t-N_c^{eb}}^{t} \xi_{b,k}^2}}$$

where we use the same weighting scheme as in Equation (A.8). The long-run correlation component $\overline{\rho}_{e,b,t}$ is a weighted sum of K_c^{eb} past realized correlations, calculated on the N_c^{eb} daily non-overlapping returns over the effective number of trading days within a given month. The conditional correlations between stock and bond returns at the daily frequency is then simply the normalized $q_{e,b,t}$:

$$\rho_{e,b,t} = \frac{q_{e,b,t}}{\sqrt{q_{e,e,t}}\sqrt{q_{b,b,t}}} \tag{A.10}$$

The correlation estimates then populate R_t. In our empirical analysis, we use the monthly long-run correlation component $\overline{\rho}_{e,b,t}$.

B.2 Estimation Results

In our estimations, we set the lag lengths K_v^i $(i = e, b)$, and K_c^{eb} equal to 24 months.[17] Table A-1 of this appendix reports parameter estimates for the bivariate DCC-MIDAS model across all markets. Panels A and B report the estimation results for the conditional bond and equity return variances, respectively. Panel C shows the results for the correlation dynamics. Even with a low-frequency volatility component in place, we still find the high frequency component of volatility to be quite persistent, with sums of α and β in equation A.5 ranging between 0.91 and 0.99. The decay parameters are typically above 2, implying an exponential decay in the weights attached to past realized variances and covariances. Exceptions are the US and Canada, for which the decay parameter for the equity variance is close to 2, implying a linearly decreasing weighting function. Panel C reports the estimation results for the stock and bond return correlation dynamics. We observe a similar persistence in the high-frequency correlation component as we did for variances. The smoothing parameter governing the persistence of the low-frequency correlations differs substantially across countries, but is always above 1, implying that past

[17] We checked the robustness of our results for alternative lag lengths, and found implied correlations to be very similar.

realized correlations get less weight than more recent ones. For completeness, Table A-2 reports parameter estimates for the DCC model based on monthly rather than daily data. Parameter estimates are based on the full sample, but in our main empirical analysis we only use the DCC-implied correlations for the months for which no DCC-MIDAS estimate is available. For a detailed description of the model-implied correlations, we refer to Section 2.3.

Table A-1: DCC-MIDAS Parameter Estimates

This Table reports the estimated parameters of the DCC-MIDAS model with a 24-month look-back for our 10 markets. Panels A and B report estimates for the variance specifications of equities and bonds, respectively. Panel C reports corresponding estimates for the correlation dynamics. For each country, we report the parameter in the first column, and robust standard errors in the second column.

	US		**Japan**		**Germany**		**UK**		**France**		**Italy**		**Spain**		**Netherlands**		**Belgium**		**Canada**	
	Estim.	s.e.	Estim.	s.e.	Estim.	s.e.	Estim.	s.e.	Estim.	s.e.	Estim.	s.e.	Estim.	s.e.	Estim.	s.e.	Estim.	s.e.	Estim.	s.e.
PANEL A: Equity Variance																				
α	0.085	*0.045*	0.140	*0.027*	0.118	*0.019*	0.109	*0.013*	0.106	*0.012*	0.109	*0.014*	0.101	*0.012*	0.093	*0.011*	0.114	*0.014*	0.101	*0.042*
β	0.897	*0.030*	0.810	*0.030*	0.833	*0.015*	0.840	*0.018*	0.847	*0.012*	0.856	*0.012*	0.854	*0.012*	0.879	*0.008*	0.830	*0.016*	0.881	*0.027*
μ	0.062	*0.008*	0.058	*0.013*	0.079	*0.010*	0.076	*0.009*	0.078	*0.012*	0.073	*0.014*	0.097	*0.014*	0.072	*0.010*	0.072	*0.010*	0.065	*0.008*
M	0.409	*0.372*	0.711	*0.188*	0.494	*0.174*	0.396	*0.075*	0.631	*0.134*	0.418	*0.164*	0.463	*0.155*	0.385	*0.097*	0.258	*0.060*	0.602	*0.519*
θ	0.027	*0.017*	0.030	*0.010*	0.027	*0.006*	0.024	*0.005*	0.022	*0.004*	0.034	*0.007*	0.030	*0.006*	0.026	*0.005*	0.029	*0.004*	0.013	*0.009*
ω	1.947	*0.593*	5.403	*1.631*	3.117	*0.616*	5.404	*1.733*	4.272	*0.752*	2.704	*0.774*	4.386	*1.284*	2.682	*0.756*	3.962	*1.147*	1.917	*0.851*
PANEL B: Bond Variance																				
α	0.091	*0.011*	0.069	*0.014*	0.066	*0.008*	0.060	*0.013*	0.056	*0.009*	0.096	*0.016*	0.084	*0.013*	0.053	*0.016*	0.081	*0.015*	0.065	*0.010*
β	0.862	*0.013*	0.910	*0.009*	0.907	*0.007*	0.852	*0.046*	0.926	*0.007*	0.844	*0.019*	0.874	*0.015*	0.937	*0.009*	0.894	*0.011*	0.885	*0.020*
μ	0.016	*0.002*	0.021	*0.003*	0.032	*0.003*	0.031	*0.005*	0.030	*0.004*	0.034	*0.004*	0.038	*0.005*	0.033	*0.003*	0.034	*0.004*	0.030	*0.004*
M	0.001	*0.001*	0.025	*0.013*	0.044	*0.016*	0.021	*0.019*	0.120	*0.036*	0.030	*0.011*	0.042	*0.012*	0.077	*0.048*	0.107	*0.034*	0.064	*0.020*
θ	0.055	*0.004*	0.035	*0.010*	0.027	*0.007*	0.042	*0.007*	0.003	*0.010*	0.038	*0.006*	0.032	*0.006*	0.015	*0.015*	0.003	*0.009*	0.029	*0.006*
ω	3.809	*0.804*	4.077	*1.270*	3.100	*0.912*	3.510	*3.536*	1.868	*0.880*	6.485	*1.735*	5.240	*1.826*	1.095	*0.086*	3.210	*4.247*	6.250	*2.392*
PANEL C: Correlation																				
α	0.064	*0.014*	0.029	*0.005*	0.020	*0.054*	0.031	*0.012*	0.034	*0.005*	0.057	*0.011*	0.065	*0.016*	0.057	*0.010*	0.042	*0.007*	0.040	*0.013*
β	0.827	*0.059*	0.947	*0.009*	0.970	*0.023*	0.940	*0.023*	0.947	*0.006*	0.857	*0.041*	0.786	*0.071*	0.885	*0.023*	0.921	*0.012*	0.906	*0.051*
ω	5.281	*2.509*	1.865	*1.789*	1.275	*33.261*	1.457	*0.556*	1.063	*0.227*	5.616	*1.541*	4.588	*1.532*	2.289	*0.627*	2.158	*1.019*	5.635	*3.615*

Table A-2: DCC Parameter Estimates

This Table reports parameter estimates of DCC model applied to *monthly* stock and bond returns. Panels A and B report estimates for the variance specifications of equities and bonds, respectively. Panel C reports corresponding estimates for the correlation dynamics. For each country, we report the parameter in the first column, and robust standard error in the second column.

	US		**Japan**		**Germany**		**UK**		**France**		**Italy**		**Spain**		**Netherlands**		**Belgium**		**Canada**	
	Estim.	s.e.	Estim.	s.e.	Estim.	s.e.	Estim.	s.e.	Estim.	s.e.	Estim.	s.e.	Estim.	s.e.	Estim.	s.e.	Estim.	s.e.	Estim.	s.e.
PANEL A: Equity Variance																				
ω	0.000	*0.000*	0.001	*0.001*	0.000	*0.000*	0.000	*0.000*	0.000	*0.000*	0.000	*0.000*	0.001	*0.001*	0.000	*0.000*	0.000	*0.000*	0.000	*0.000*
α	0.124	*0.033*	0.130	*0.100*	0.146	*0.052*	0.179	*0.067*	0.170	*0.052*	0.182	*0.093*	0.137	*0.069*	0.088	*0.030*	0.185	*0.063*	0.147	*0.066*
β	0.837	*0.037*	0.606	*0.420*	0.795	*0.080*	0.814	*0.046*	0.701	*0.062*	0.797	*0.084*	0.664	*0.263*	0.797	*0.046*	0.677	*0.055*	0.749	*0.129*
PANEL B: Bond Variance																				
ω	0.000	*0.000*	0.000	*0.000*	0.000	*0.000*	0.000	*0.000*	0.000	*0.000*	0.000	*0.000*	0.000	*0.000*	0.000	*0.000*	0.000	*0.000*	0.000	*0.000*
α	0.092	*0.045*	0.445	*0.189*	0.203	*0.098*	0.054	*0.033*	0.132	*0.047*	0.152	*0.055*	0.075	*0.033*	0.106	*0.073*	0.370	*0.110*	0.131	*0.064*
β	0.855	*0.072*	0.418	*0.120*	0.338	*0.239*	0.942	*0.036*	0.862	*0.055*	0.829	*0.050*	0.916	*0.037*	0.803	*0.188*	0.000	*0.014*	0.827	*0.098*
PANEL C: Correlation																				
α	0.046	*0.037*	0.029	*0.018*	0.025	*0.009*	0.027	*0.015*	0.024	*0.009*	0.008	*0.019*	0.031	*0.017*	0.034	*0.017*	0.030	*0.010*	0.032	*0.019*
β	0.938	*0.061*	0.951	*0.036*	0.970	*0.011*	0.967	*0.018*	0.970	*0.009*	0.967	*0.012*	0.942	*0.018*	0.952	*0.025*	0.957	*0.011*	0.937	*0.043*

C Measuring Output Gap using Unobserved Component Models

C.1 Model Description

Döpke and Changny (2001) provide an overview of the variety of methods used. Broadly speaking they can be classified into four model families. The non-structural or time-series statistical models, direct measures via survey data, theory based structural models and multivariate models. The aim of this paper is clearly not to describe the different methodologies in detail. Instead, we will assess some popular methods.

First, practitioners often rely on the Hodrick-Prescott (Hodrick and Prescott (1997)) filter to estimate potential GDP. This method has the clear advantage of ease of calculation. It is a univariate time-series model and hence requires little information. No theory needs to be specified. However, this methodology has some serious shortcomings.

First, a general shortcoming of univariate methods that attempt to extract the cyclical component and the trend component is that they miss an important point. In fact, Quah (1992) shows that studying the univariate time-series characterizations of a variable leaves unidentified the sources of that variable's fluctuations. Without additional ad-hoc restrictions those characterizations are completely uninformative for the relative importance of the underlying permanent and transitory components. As a result, there are an infinite number of solutions for a permanent and a trend decomposition based on only one time-series. To make the solutions unique, a range of identifying assumptions have been suggested. The Hodrick-Prescott filter, for example, assumes that the expected growth rate of potential GDP is a random walk and that the output gap is serially uncorrelated (Van Norden (1995)).

Second, there are also more general problems with two-sided filters. In the middle of the sample, they are correctly defined. However, at the start end end-point of the sample they become one-sided filters. St-Amant and Van Norden (1997) show that, for the HP filter at the end of the sample, the relative weight of the last observations increases to 20% (for a lambda of 1,600 for quarterly data) compared to 6% in the middle of the sample. As a result, the trend component becomes less stable at end points.

Third, an extension to the traditional Hodrick-Prescott filter is the multivariate HP filter. This model belongs to the family of multivariate models. In fact, computing the trend component of a time series with a HP filter boils down to a minimization problem of two contradictory forces. On the one hand, it minimizes the sum of the squared distances between the original series and the trend component and, on the other hand, it minimizes the sum of the squared changes in the trend component. A multivariate HP filter will add structural information to the univariate case. For example, a typical extension adds information from the Philips curve to the estimation. The Philips curve describes the relationship between inflation and unemployment. By replacing the inflation with the output gap (as approximate inflation gauge), the squared error of this model can be added to the minimization problem. In this way, the resulting trend component will not only minimize the distance with the original series and the changes in the trend, but also the error of the Philips curve model. In this way, more structure is imposed on the trend component. However, this method has also some shortcomings.

First, one has additional parameters to decide on. Besides the smoothing parameter λ, the relative importance of the structural model errors is added.

Second, defining structural models also requires more data. Data availability and information content of the structural models is crucial.

Third, the choice of the structural model(s) can have an important impact on the trend component. Laxton and Tetlow (1992) developed a multivariate HP filter with three structural equations: a Phillips curve specification, Okun's law and a capacity utilization function. Their model improves the GDP estimate compared to the univariate HP filter, but the authors also mention that the confidence bounds around the potential GDP are very wide. In addition, Brouwer (1998) shows that judgment matters. When a structural equation is included or not, the resulting gap can change considerably. So, the estimate of the multivariate HP filter depends on the inclusion of the structural relationships, the information content of these conditioning equations and the relative weight of the components in the loss function.

Another direct measure is the survey data. An important advantage of survey data is that these data are not the result of a model with modeling errors, but that these data are observable. However, the availability of these data is a problem (especially for European countries). For the scope of this research, these data are not sufficiently available.

Finally, the unobservable components method is another statistical way of determining the trend component. By imposing structure on the trend and gap components, one can estimate the unobservable components from the data. This method has been applied frequently and provides reasonable estimates for the output gap. Döpke and Changny (2001) apply a whole range of methods to estimate the output gap in the euro zone. It is striking to see that no two methods tell exactly the same story of the business cycle. Also, despite the clear issues with the HP filter, the correlation of the output gap variable from this method with structural models like SVAR models is 70% over the period 1985-2000. The authors also compute a concordance statistic. The statistic will give a value of 1 if both gap measures have the same sign for a certain time period. It will be zero if both measures have opposite signs. This statistic is particularly interesting for our research since we are only interested in the sign of the gap and not necessarily the size. The unobserved component estimation method has a high concordance of 0.94 with the OECD estimation method. Interestingly, the simple linear trend model also has a high concordance of 0.89 with the OECD estimation.

In this paper, we estimate the output gap based on an unobservable components method. In fact, estimating the unobserved factors implies estimating the parameters of a state-space model. In a state space analysis, the time-series observations are assumed linearly on a state vector that is unobserved and is generated by a stochastic time-varying process (J. Commandeur and Marius (2011)). In general, a linear state-space model with fixed coefficients has the following form:

$$z_t = H\, x_t + D\, u_t + C\, v_t \tag{A.1}$$

$$x_t = \phi\, x_{t-1} + \Gamma\, u_{t-1} + E\, w_{t-1} \tag{A.2}$$

where: z_t is an (tx1) vector of an observable variable, x_t is an (nx1) vector of unobserved state variables, u_t is an (rx1) vector of exogenous variables, v_t and w_t are white noise processes such that: $E[v_t]= E[w_t] = 0$ and $\sigma^2[v_t] = R$ and $\sigma^2[w_t] = Q$. We define a model with four state variables as in Brouwer (1998). Real industrial production (y_t) can be decomposed into a permanent (y_t^p) and a transitory component (g_t), such that

$$y_t \equiv y_t^p + g_t \tag{A.3}$$

The permanent component is assumed to follow a random walk with constant drift:

$$y_t^p = u^y + y_{t-1}^p + \epsilon_t^y \tag{A.4}$$

where μ^y is the drift term and ϵ_t^v is a white-noise error term with $\epsilon_t^y \sim N(0, \sigma_y^2)$. The output gap is assumed to follow an AR(2) process:

$$g_t = \phi_1\, g_{t-1} + \phi_2\, g_{t-2} + \epsilon_t^g \tag{A.5}$$

where $\epsilon_t^g \sim N(0, \sigma_g^2)$. This econometric model can be expressed into state-space formulation and is fed into the Matlab toolbox of Jerez et al. (2011) to extract the trend, cyclical, seasonal and irregular components of the real industrial production for our international sample. The initial estimates of the parameters (μ^y,ϕ_1, ϕ_2, σ_y^2, σ_g^2) come from applying a Hodrick-Prescott filter with a smoothing parameter of 14400.

C.2 Estimation Results

As a quality assessment, we compared our German output gap estimations with the German output gaps computed by Funke (1998).

Figure A.1 shows the cycle component of the log of the real German industrial production expressed as percentage of the log of real industrial production. This component represents the output gap. Since 1958, the German economy has suffered seven distinct slowdowns. A first one occurring in 1958, a second in 1965, one occurring in 1973, one in 1979/1980, one in 1990 and one more recently in 2008 and 2011. These gaps (for the part before 1994) coincide closely with the German output gaps computed by Funke (1998) who used annual data from 1960-1994. Note that the output gaps are not particularly large in Germany. Except for the late '50s and the recent crisis, the gap is rarely larger than 3%.

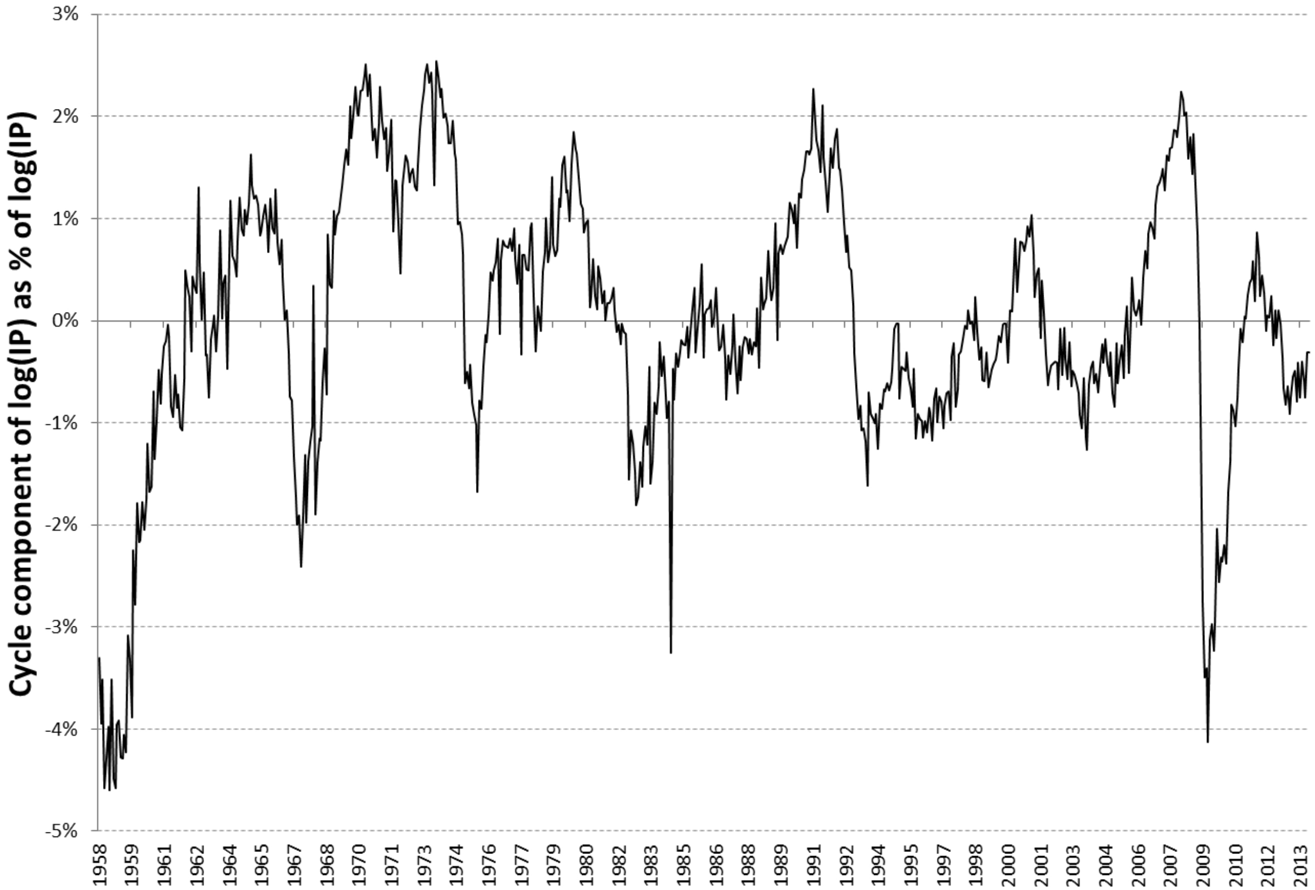
Finally, applying the same methodology to the US real industrial production gives the output gaps as show in Figure A.2. The grey bars show the US recessions (from peak to trough) as described by the NBER. The peaks and troughs of our output gap indicator coincide quite nicely with the NBER dates.

First, in the late 1940's, after World War II, fixed investment dropped in the US and the recession began shortly after President Truman's "Fair Deal" economic reforms which were accompanied by a significant expansion in government spending that was to be financed through an increase in taxes. The recession also followed a period of monetary tightening by the Federal Reserve.

The 1953-1954 recession accompanied the winding down of the Korean War. The US recession of 1958 coincided with a sharp worldwide economic downturn in 1958. This recession has the most negative output gap. The recession in the early sixties was preceded by a tightening of monetary policy in 1959 and the first half of 1960 and was followed by an easing of policy in the second half of 1960. Note that the recessions are characterized by a sudden and sharp drop in the output gaps and that they are short (+/- 10 months) with a fast recovery afterward. The 1969-1970 recession was preceded by a period of unsustainable growth that led to accelerating inflation, which rose from 3.1% in 1967 to 5.3% in 1970. Monetary policy (an aggressive rate increase from 5% in March 1968 to 9.2% in August 1969) and a

Figure A.1: Estimated German Output Gap 1958-2013

This Figure shows the estimated German Output gap by decomposing the log(real Industrial Production) via an Unobserved Components Model



spike in oil prices played an important role in the cause of this recession. With a length of 16 months (from November 1973-March 1975), the 1973-1975 contraction was substantially longer than its predecessors. This long and deep recession was atypical not only because of its length, but also because during this period there was a simultaneous rise in both the inflation rate and the unemployment rate. The supply side 1973 oil shock and the monetary policy tightening in the period '72-'73 drove the economy down.

By 1979, inflation reached a startling 11.3% and in March 1980 soared to 13.5%. Under the recently appointed Chairman Paul Volcker, the Fed chose to act decisively to reduce inflation, even if it led to a reduction in economic activity in the short term. By June 1981, the Federal Reserve rate was at 19.10%. This was the beginning of a deep and prolonged recession from 1981-November 1982. A new oil shock drove up the price of the barrel and contributed to an even deeper recession. This recession also lasted 16 months and the output gap fell to -2.5%. With the benefit of hindsight, after this period of extreme monetary tightening, the average inflation rate and inflation uncertainty was successfully reduced after 1982. After 1982, the average inflation rate dropped from almost 4% to 2.7%. The inflation uncertainty was also much lower. The inflation volatility until 1982 was 3.5% compared to 1.2% for the period after 1982.

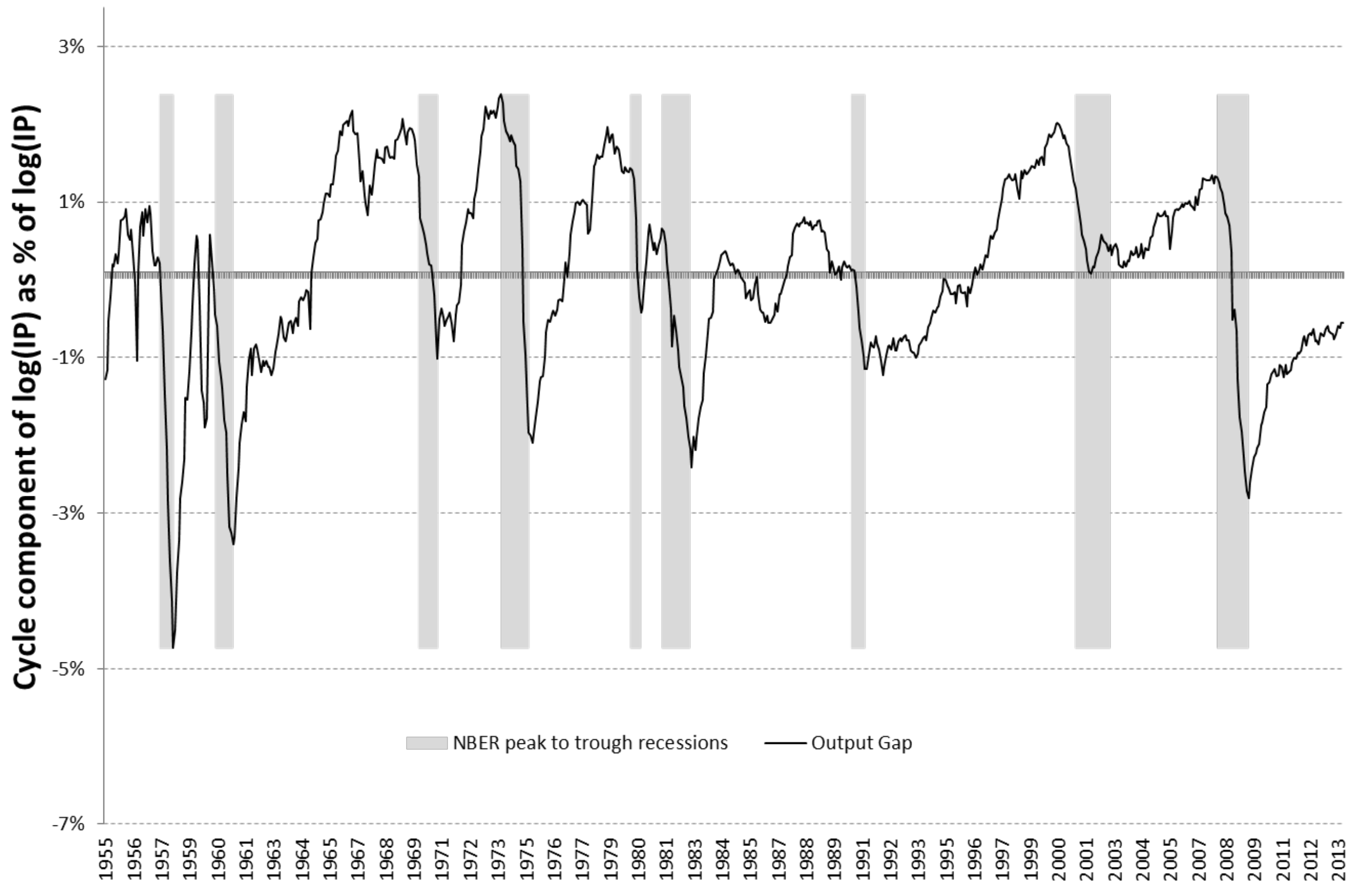
The 1990-91 recession lasted for only 8 months and was not especially deep (the gap fell to -1.3%). Federal reserve hikes rates in the period before the recession in order to fight rising inflation, which reached almost 6% in October 1990. The invasion of Kuwait by Iraq in August 1990, created another oil shock and economic confidence dropped on a global scale. A financial crisis (savings and loans) also hurt economic sentiment.

The 2000-2001 recession is characterized by the bursting of the dot-com bubble. Finally, the most recent crisis started in December 2009 and lasted until June 2009. This is now the longest recession since 1947. The housing market correction and the following sub-prime mortgage crisis affected the global economy. Here also, the Federal Reserve Bank stepped in with a zero-interest rate policy and unconventional monetary stimuli. The above analysis shows that there is a dynamic interaction between economic activity, inflation and central bank policy. Although many crises share many characteristics, no crisis is identical. An important observation is the change in the inflation level and volatility after 1982.

In summary, the detailed cases for Germany and the US confirm that the unobserved components model is successful in identifying realistic output gaps. For Germany, our gap estimates are very similar to the gaps estimated by Funke (1998). For the US, we have shown that our gap definitions are closely related to the recessions as defined by the NBER. Therefore, this methodology is used on our international dataset.

Figure A.2: Estimated US Output Gap 1955-2013

This Figure shows the estimated US Output gap by decomposing the log(real Industrial Production) via an Unobserved Components Model



The NBER US business cycle dates are retrieved from the website of the NBER.

Table 1: 3-State Regime Switching Model for Realized Inflation

This Table reports estimates for a 3-state regime-switching model for realized inflation in 10 developed markets and for global inflation. We allow for both regime switches in the mean and variance. The local inflation rates are the monthly year-on-year % change in the consumer price indices. μ_1, μ_2 and μ_3 represent the state dependent mean in the low, medium and high inflation regime, respectively, and σ_1, σ_2 and σ_3 the corresponding regime dependent volatilities. P_1, P_2 and P_3 represent the staying probabilities of the low, medium, and high inflation regimes, respectively. For each country, we report the estimated parameter and corresponding quasi-ML standard error. CL_1, CL_2 and CL_3 are the expected regime duration (in years) of the low, medium and high inflation regimes, respectively.

	US		Japan		Germany		UK		France		Italy		Spain		Netherlands		Belgium		Canada		Global	
	param	s.e.	param	s.e.	param	s.e.	param	s.e.	param	s.e.	param	s.e.	param	s.e.	param	s.e.	param	s.e.	param	s.e.	param	s.e.
P_1	96.0	8.8	98.2	7.0	98.6	7.5	97.7	43.8	99.2	5.3	99.3	6.2	99.3	6.2	97.7	80.3	97.1	8.6	99.0	5.8	99.2	7.4
P_2	96.0	8.0	94.9	11.5	94.4	12.8	95.1	69.7	96.2	11.2	98.5	8.1	97.3	9.2	95.8	74.2	96.3	9.8	97.7	7.9	98.2	8.3
P_3	97.9	9.5	97.4	11.0	97.6	8.5	98.7	11.8	98.7	0.0	99.4	8.1	99.3	8.9	96.7	10.4	97.9	11.5	99.1	9.6	99.3	9.1
μ_1	1.5	0.1	0.0	0.1	1.4	0.1	1.9	0.0	2.0	0.1	2.2	0.1	3.0	0.1	1.5	0.7	1.3	0.1	1.8	0.1	1.9	0.0
μ_2	3.3	0.1	2.9	0.2	2.8	0.1	4.6	0.8	5.4	0.1	5.4	0.1	7.1	0.2	3.2	0.7	3.2	0.1	4.4	0.1	4.2	0.1
μ_3	7.1	0.3	8.3	0.5	5.3	0.1	12.3	0.7	11.2	0.3	15.2	0.4	16.1	0.4	7.5	0.2	7.7	0.3	9.6	0.2	10.5	0.3
σ_1	0.5	0.0	0.8	0.0	0.7	0.0	0.8	0.0	0.9	0.0	1.0	0.0	1.3	0.0	0.8	0.0	0.7	0.0	0.8	0.0	0.5	0.0
σ_2	0.6	0.0	1.0	0.0	0.4	0.0	0.9	0.0	0.9	0.0	1.0	0.0	1.3	0.0	0.8	0.0	0.7	0.0	0.8	0.0	0.9	0.0
σ_3	3.4	0.0	4.5	0.0	1.1	0.0	5.3	0.0	2.5	0.0	4.1	0.0	3.8	0.0	1.5	0.0	2.6	0.0	1.7	0.0	2.7	0.0
RD_1	2.1		4.6		5.8		3.6		11.1		12.7		11.9		3.6		2.9		8.5		10.7	
RD_2	2.1		1.6		1.5		1.7		2.2		5.4		3.1		2.0		2.3		3.7		4.7	
RD_3	4.0		3.2		3.5		6.6		6.3		13.1		11.5		2.5		4.0		9.8		11.5	

Table 2: 2-State Regime Switching Model for the IP Output Gap

This Table reports estimates for a 2-state regime-switching model for the output gap in 10 developed markets and for a global output gap measure. We allow for both regime switches in the mean and variance. The output gap is the cycle component of the log of the real industrial production as % of log real industrial production. μ_1 and μ_2 represent the state dependent mean in the low and high output gap regime, respectively, and σ_1 and σ_2 the corresponding regime dependent volatilities. P_1 and P_2 represent the staying probabilities of the low and high inflation regimes. For each country, we report the estimated parameter and corresponding quasi-ML standard error. CL_1 and CL_2 are the expected regime duration (in years) of the low and high output gap regimes, respectively.

	US		**Japan**		**Germany**		**UK**		**France**		**Italy**		**Spain**		**Netherlands**		**Belgium**		**Canada**		**Global**	
Start	01/55		01/75		01/58		01/56		06/70		01/55		01/65		04/60		06/61		01/61		01/65	
	param	s.e.	param	s.e.	param	s.e.	param	s.e.	param	s.e.	param	s.e.	param	s.e.	param	s.e.	param	s.e.	param	s.e.	param	s.e.
P_1	0.98	*0.20*	0.96	*0.14*	0.98	*0.11*	0.97	*0.18*	0.98	*0.44*	0.97	*0.27*	0.98	*0.12*	0.95	*0.10*	0.97	*0.13*	0.98	*0.33*	0.98	*0.11*
P_2	0.98	*0.21*	0.98	*0.10*	0.97	*0.19*	0.98	*0.12*	0.98	*0.28*	0.98	*0.15*	0.98	*0.09*	0.97	*0.08*	0.96	*0.16*	0.99	*0.15*	0.99	*0.06*
μ_1	-0.93	*0.20*	-1.12	*0.14*	-0.67	*0.12*	-0.81	*0.13*	-0.56	*0.25*	-1.40	*0.31*	-0.81	*0.08*	-0.63	*0.06*	-0.51	*0.10*	-1.54	*0.38*	-1.18	*0.08*
μ_2	0.95	*0.19*	0.68	*0.08*	1.26	*0.17*	0.56	*0.07*	0.49	*0.14*	0.68	*0.14*	0.57	*0.06*	0.39	*0.05*	0.84	*0.11*	0.68	*0.15*	0.48	*0.04*
σ_1	0.87	*0.00*	1.05	*0.00*	1.03	*0.00*	0.49	*0.00*	0.53	*0.00*	1.00	*0.00*	0.72	*0.00*	0.54	*0.00*	0.55	*0.00*	0.83	*0.00*	0.72	*0.00*
σ_2	0.59	*0.00*	0.62	*0.00*	0.59	*0.00*	0.39	*0.00*	0.48	*0.00*	0.69	*0.00*	0.64	*0.00*	0.56	*0.00*	0.59	*0.00*	0.70	*0.00*	0.58	*0.00*
RD_1	3.8		2.2		5.1		2.7		4.2		2.5		3.6		1.8		2.6		4.4		3.3	
RD_2	3.6		3.4		2.8		3.9		5.3		5.1		5.3		2.7		2.0		11.3		8.7	
$P_{1,U}$	0.51		0.39		0.64		0.41		0.44		0.33		0.41		0.40		0.57		0.28		0.28	

Table 3: Interaction between monthly % changes in CPI and Real Industrial Production

This Table reports the estimated parameters of the bivariate regime switching model for inflation (π) and real industrial production (y) as described in section 3.4.2 where, $\pi_t = \mu_\pi(S_t^\pi) + \xi_{\pi,t}$, $y_t = \mu_y(S_t^y) + \xi_{y,t}$ and $[\xi_{\pi,t}, \xi_{y,t}]^T \sim N(0, \Sigma(S_t^\pi, S_t^y))$. Both S_t^π and S_t^y can take on two states: either inflation (real output) is in the high (h) or in the low (l) regime. μ_h and μ_l represent the mean of real growth and inflation in the high and low state, respectively. σ_h and σ_l represent the standard deviation of real growth and inflation in the high and low state, respectively. ρ_{hh},ρ_{lh},ρ_{hl},ρ_{ll} are the conditional correlations between real growth and inflation with the first subscript indicating the real growth regime and the second subscript indicating the inflation regime. $P_{y_h}, P_{y_l}, P_{\pi_h}, P_{\pi_l}$ are the probabilities of staying in the low or high regime for real growth (y) and inflation (π).

	US		Japan		Germany		UK		France		Italy		Spain		Netherlands		Belgium		Canada		Global	
	Est.	pval.	Est.	pval.	Est.	pval.	Est.	pval.	Est.	pval.	Est.	pval.	Est.	pval.	Est.	pval.	Est.	pval.	Est.	pval.	Est.	pval.
Panel A: Monthly Output Growth																						
μ_h	0.13	*0.00*	0.14	*0.04*	-0.01	*0.81*	-0.21	*0.00*	0.35	*0.88*	-0.12	*0.11*	-0.32	*0.00*	-0.02	*0.81*	-0.04	*0.50*	0.04	*0.68*	-0.10	*0.02*
μ_l	-0.80	*0.00*	-1.38	*0.23*	-0.26	*0.58*	-1.16	*0.00*	-0.24	*0.00*	-0.73	*0.00*	-0.51	*0.12*	-0.46	*0.33*	-0.51	*0.50*	-0.45	*0.22*	-0.68	*0.00*
σ_h	0.55	*0.00*	1.45	*0.00*	1.34	*0.00*	1.00	*0.00*	8.06	*0.00*	1.16	*0.00*	1.46	*0.00*	1.84	*0.00*	1.55	*0.00*	1.03	*0.00*	0.84	*0.00*
σ_l	1.09	*0.00*	4.58	*0.00*	3.67	*0.00*	2.85	*0.00*	1.27	*0.00*	3.03	*0.00*	4.11	*0.00*	4.94	*0.00*	5.23	*0.00*	1.59	*0.00*	1.86	*0.00*
Panel B: Monthly Inflation																						
μ_h	0.57	*0.00*	0.52	*0.00*	0.37	*0.00*	1.31	*0.00*	0.77	*0.00*	1.16	*0.00*	0.98	*0.00*	0.64	*0.00*	0.54	*0.00*	1.66	*0.00*	0.76	*0.00*
μ_l	0.25	*0.00*	0.01	*0.00*	0.07	*0.00*	0.29	*0.00*	0.21	*0.00*	0.28	*0.00*	0.30	*0.00*	0.26	*0.00*	0.19	*0.00*	0.32	*0.00*	0.23	*0.00*
σ_h	0.49	*0.00*	0.80	*0.00*	0.36	*0.00*	0.85	*0.00*	0.32	*0.00*	0.56	*0.00*	0.73	*0.00*	1.30	*0.00*	0.44	*0.00*	0.79	*0.00*	0.35	*0.00*
σ_l	0.18	*0.00*	0.33	*0.00*	0.19	*0.00*	0.39	*0.00*	0.26	*0.00*	0.22	*0.00*	0.48	*0.00*	0.42	*0.00*	0.24	*0.00*	0.41	*0.00*	0.21	*0.00*
Panel C: Conditional Correlation between growth and inflation																						
ρ_{hh}	-8.53	*0.74*	-54.15	*0.00*	-43.04	*0.00*	5.01	*0.90*	-58.15	*0.77*	-9.92	*0.94*	-40.12	*0.00*	-81.13	*0.00*	-17.67	*0.06*	-99.74	*0.00*	-19.89	0.03
ρ_{lh}	-33.12	*0.00*	-54.87	*0.07*	12.10	*0.67*	-52.16	*0.00*	-21.46	*0.27*	-19.69	*0.00*	-27.33	*0.01*	-99.15	*0.00*	-57.41	*0.10*	-18.05	*0.07*	-62.34	0.00
ρ_{hl}	-40.01	*0.00*	-24.81	*0.00*	-8.31	*0.39*	-40.94	*0.00*	20.20	*0.00*	-23.45	*0.00*	-38.86	*0.00*	-14.45	*0.24*	-18.62	*0.00*	-40.57	*0.00*	-18.64	0.03
ρ_{ll}	-15.61	*0.28*	14.65	*0.42*	-49.57	*0.00*	12.74	*0.36*	-25.71	*0.28*	13.99	*0.21*	4.33	*0.77*	-9.56	*0.52*	-8.49	*0.62*	-50.63	*0.00*	17.98	0.13
Panel D: Regime Probabilities																						
$P_{y,h}$	0.973	*0.00*	0.993	*0.00*	0.941	*0.00*	0.966	*0.00*	0.444	*0.73*	0.987	*0.00*	0.926	*0.00*	0.979	*0.35*	0.974	*0.00*	0.959	*0.00*	0.971	*0.00*
$P_{y,l}$	0.908	*0.00*	0.854	*0.00*	0.561	*0.60*	0.788	*0.00*	0.971	*0.00*	0.980	*0.00*	0.781	*0.01*	0.864	*0.56*	0.671	*0.30*	0.854	*0.00*	0.847	*0.00*
$P_{p,h}$	0.914	*0.00*	0.990	*0.00*	0.808	*0.00*	0.878	*0.00*	0.986	*0.00*	0.985	*0.00*	0.993	*0.00*	0.861	*0.04*	0.962	*0.00*	0.002	*0.00*	0.993	*0.00*
$P_{p,l}$	0.976	*0.00*	0.990	*0.00*	0.803	*0.00*	0.979	*0.00*	0.995	*0.03*	0.996	*0.00*	0.995	*0.00*	0.981	*0.00*	0.984	*0.00*	0.995	*0.00*	0.998	*0.00*
Panel D: Regime Duration (in months), *hh/lh/hl/ll*																						
	9/6/20/9		60/6/62/6		4/2/4/2		7/3/18/4		2/23/2/30		35/29/57/42		12/4/13/4		10/3/15/3		6/4/25/7		1/1/22/7		28/6/32/6	

Table 4: Alternative RS Model for Output and Inflation

This Table reports the estimated parameters of the alternative regime-switching model presented in section 3.3. Latent state variables S_t^y and S_t^π govern the time variation in output and inflation volatility (σ_y and σ_π), respectively. The intercepts in the output and inflation equations are allowed to be different across their own volatility regimes. A separate state variable S_t^{cov} determines the covariation (β) between output and inflation shocks. We allow for two states in both inflation and output volatility, i.e.$S_t^y = \{low, high\}$ and $S_t^\pi = \{low, high\}$ and in the output-inflation beta, i.e. .$S_t^{cov} = \{low, high\}$. P_v^y and P_v^π, and Q_v^y and Q_v^π represent the probabilities that output and inflation volatility stay in the low and high regime, respectively, and P_{cov} and Q_{cov} the probability that the output-inflation beta remains in the low and high regime, respectively.

	US		Japan		Germany		UK		Belgium		France		Netherlands		Spain		Italy		Canada		GLOBAL	
	Est.	Pval	Est.	Pval	Est.	Pval	Est.	Pval	Est.	Pval	Est.	Pval	Est.	Pval	Est.	Pval	Est.	Pval	Est.	Pval	Est.	Pval
P_v^y	0.992	0.009	0.989	0.571	0.993	0.000	0.918	0.060	0.993	0.000	0.977	0.493	0.990	0.000	0.993	0.000	0.972	0.000	0.993	0.000	0.971	0.000
Q_v^y	0.909	0.572	0.980	0.609	0.891	0.115	0.870	0.314	0.896	0.514	0.881	0.864	0.881	0.325	0.881	0.548	0.939	0.001	0.881	0.690	0.968	0.000
P_v^π	0.977	0.000	0.993	0.000	0.977	0.352	0.980	0.000	0.980	0.000	0.980	0.000	0.970	0.019	0.946	0.001	0.988	0.000	0.976	0.000	0.975	0.000
Q_v^π	0.926	0.002	0.881	0.006	0.881	0.687	0.881	0.157	0.881	0.002	0.902	0.002	0.881	0.307	0.881	0.055	0.978	0.008	0.883	0.010	0.881	0.001
P_{cov}	0.992	0.000	0.993	0.440	0.985	0.000	0.976	0.000	0.980	0.000	0.991	0.000	0.993	0.000	0.993	0.000	0.993	0.000	0.993	0.000	0.993	0.000
Q_{cov}	0.962	0.000	0.993	0.321	0.953	0.008	0.908	0.001	0.941	0.000	0.979	0.000	0.993	0.036	0.989	0.000	0.983	0.000	0.989	0.000	0.991	0.000
$\alpha_{y,1}$	0.001	0.010	0.002	0.084	0.000	0.894	0.002	0.000	0.001	0.392	0.002	0.002	0.000	0.757	-0.003	0.000	0.001	0.290	0.001	0.377	0.001	0.083
$\alpha_{y,2}$	-0.009	0.000	-0.013	0.225	0.000	0.986	-0.009	0.030	-0.005	0.534	-0.004	0.080	0.000	0.996	-0.004	0.147	-0.007	0.002	-0.008	0.062	-0.007	0.000
$\alpha_{\pi,1}$	0.003	0.000	0.000	0.946	0.002	0.000	0.003	0.000	0.002	0.000	0.002	0.000	0.002	0.000	0.003	0.000	0.003	0.000	0.002	0.000	0.002	0.000
$\alpha_{\pi,2}$	0.007	0.000	0.005	0.119	0.005	0.000	0.010	0.000	0.006	0.000	0.008	0.000	0.005	0.000	0.011	0.000	0.012	0.000	0.007	0.000	0.008	0.000
β_1	-0.088	0.000	-0.019	0.056	-0.029	0.000	-0.028	0.205	-0.019	0.000	-0.012	0.473	-0.025	0.001	-0.048	0.000	0.002	0.791	-0.125	0.000	-0.017	0.505
β_2	-0.864	0.001	-0.348	0.009	-0.314	0.015	-0.306	0.003	-0.589	0.000	-0.154	0.773	-0.679	0.000	-1.050	0.000	-0.072	0.007	-2.052	0.000	-0.100	0.000
σ_y^l	0.562	0.000	1.423	0.000	1.402	0.000	1.041	0.000	1.540	0.000	1.151	0.000	1.901	0.000	1.444	0.000	1.211	0.000	1.016	0.000	0.836	0.000
σ_y^h	1.073	0.000	4.517	0.000	3.587	0.001	3.190	0.000	4.725	0.000	2.624	0.000	4.817	0.000	3.883	0.000	3.137	0.000	1.654	0.015	1.813	0.000
σ_π^l	0.187	0.000	0.321	0.000	0.268	0.000	0.334	0.000	0.251	0.000	0.246	0.000	0.402	0.000	0.489	0.000	0.213	0.000	0.311	0.000	0.202	0.000
σ_π^h	0.380	0.000	0.662	0.301	0.332	0.025	0.635	0.000	0.380	0.036	0.294	0.047	0.468	0.106	0.588	0.117	0.553	0.000	0.366	0.030	0.320	0.000

Table 5: Inflation regimes versus stock bond correlation

This Table reports the estimated parameters of the regression of the (Fisher-transformed) stock-bond correlations $\tilde{\rho}_{SB,c,t}$ for country c (estimated using the DCC-MIDAS model) on the different country-specific inflation regime dummies: $\tilde{\rho}_{SB,c,t} = \sum_{i=1}^{N} \gamma_i \times D_{c,i,t}^{\pi(g)} + \varepsilon_{SB,i,t}^{\pi}$, where $D_{c,i,t}^{\pi}$ equals one when the probability that the process for inflation π in country c or at the global level (g) at time t is in state $i = 1, .., 3$, is larger than 50%. The parameter estimates (γ_i's) capture the average stock-bond correlations across the different inflation regimes. We base inference on Newey-West standard errors (24 lags) to correct for the substantial serial correlation in the dependent variable. Adj. R^2(%) is the regression's adjusted R^2 expressed as %, MAD(%) is the Mean Absolute Difference computed between the fitted and empirically observed correlations (from the MIDAS model), expressed as %. Hit(%) represents the % of observations that the fitted and observed correlations share the same sign. The column "Panel" shows the estimation results of an unbalanced fixed-effects panel regression analysis regressing local stock-bond correlations on the inflation regime dummies. Panel A (B) shows the estimates using local (global) inflation regimes.

	US		**Japan**		**Germany**		**UK**		**France**		**Italy**		**Spain**		**Netherlands**		**Belgium**		**Canada**		**Panel**	
Start Date	07/65		01/88		01/70		01/70		01/70		04/91		02/80		01/70		01/70		01/70			
	Est.	*Pval.*	Est.	*Pval.*	Est.	*Pval.*	Est.	*Pval.*	Est.	*Pval.*	Est.	*Pval.*	Est.	*Pval.*	Est.	*Pval.*	Est.	*Pval.*	Est.	*Pval.*	Est.	*Pval.*
Panel A: Stock-Bond Return Correlation via *Local* Inflation Regime Dummies																						
γ_{Low}(%)	-15.9	0.19	-26.2	0.00	-6.5	0.58	0.8	0.95	8.0	0.47	1.4	0.90	2.8	0.77	-4.6	0.64	8.5	0.40	-5.8	0.49	-0.031	0.39
γ_{Med}(%)	18.1	0.02	23.5	0.12	23.7	0.01	15.6	0.21	26.7	0.00	30.6	0.00	18.5	0.00	2.6	0.79	17.1	0.03	20.9	0.00	0.175	0.00
γ_{High}(%)	19.9	0.00	-	-	31.7	0.00	40.8	0.00	29.2	0.00	-	-	19.2	0.00	16.5	0.00	21.6	0.00	21.0	0.00	0.271	0.00
Adj. R^2(%)	14.5		40.9		23.2		22.7		7.9		10.7		6.8		7.0		3.9		24.6		19.7	
MAD (%)	26.2		27.7		25.5		26.5		30.5		27.1		22.2		26.4		21.7		17.6		24.9	
Hit (%)	77.5		86.5		73.1		74.2		62.5		67		62.7		56.9		67.6		77.8		70.7	
Panel B: Stock-Bond Return Correlation via *Global* Inflation Regime Dummies																						
γ_{Low}(%)	-3.2	0.79	-28.9	0.00	-6.6	0.60	-3.3	0.78	-1.6	0.89	8.6	0.42	4.6	0.61	-9.8	0.37	2.5	0.76	-4.6	0.59	-0.042	0.21
γ_{Med}(%)	23.4	0.00	27.3	0.02	27.0	0.00	29.2	0.00	35.5	0.00	4.4	0.80	11.9	0.05	12.7	0.00	31.4	0.00	19.2	0.00	0.239	0.00
γ_{High}(%)	25.6	0.00	-	-	28.7	0.00	44.4	0.00	28.5	0.00	-	-	20.3	0.00	16.7	0.00	25.4	0.00	20.5	0.00	0.268	0.00
Adj. R^2(%)	14.4		57.5		21.7		33.1		23.0		0.1		3.6		16.2		23.3		20.6		24.4	
MAD (%)	25.3		24.7		24.5		24.8		24.2		28.1		24.3		19.6		22.9		17.0		23.4	
Hit (%)	75.9		95.5		77.1		78.2		75.4		65.9		60.2		66		79		74.4		74.9	

Table 6: Output Gap versus stock bond correlation

This Table reports the estimated parameters of the regression of the (Fisher-transformed) stock-bond correlations $\tilde{\rho}_{SB,c,t}$ for country c (estimated using the DCC-MIDAS model) on the different country-specific output gap regime dummies: $\tilde{\rho}_{SB,c,t} = \sum_{i=1}^{N} \gamma_i \times D_{c,i,t}^{y(g)} + \varepsilon_{SB,i,t}^{y}$, where $D_{c,i,t}^{y}$ equals one when the probability that the process for output gap y in country c or at the global level (g) at time t is in state $i = 1, 2$, is larger than 50%. The parameter estimates (γ_i's) capture the average stock-bond correlations across the different output gap regimes. We base inference on Newey-West standard errors (24 lags) to correct for the substantial serial correlation in the dependent variable. Adj. R^2(%) is the regression's adjusted R^2 expressed as %, MAD(%) is the Mean Absolute Difference computed between the fitted and empirically observed correlations (from the MIDAS model), expressed as %. Hit(%) represents the % of observations that the fitted and observed correlations share the same sign. The column "Panel" shows the estimation results of an unbalanced fixed-effects panel regression analysis regressing local stock-bond correlations on the output gap regime dummies. Panel A (B) shows the estimates using local (global) output gap regimes.

	US		**Japan**		**Germany**		**UK**		**France**		**Italy**		**Spain**		**Netherlands**		**Belgium**		**Canada**		**Panel**	
Start Date	07/65		01/88		01/70		01/70		01/70		04/91		02/80		01/70		01/70		01/70			
	Est.	*Pval.*	Est.	*Pval.*	Est.	*Pval.*	Est.	*Pval.*	Est.	*Pval.*	Est.	*Pval.*	Est.	*Pval.*	Est.	*Pval.*	Est.	*Pval.*	Est.	*Pval.*	Est.	*Pval.*
Panel A: Local Stock-Bond Correlation via *Local* Output Gap Regime Dummies																						
γ_{Low}(%)	14.9	0.20	-28.9	0.00	5.8	0.59	13.5	0.31	29.8	0.00	26.7	0.06	21.8	0.00	-0.9	0.93	13.8	0.03	-4.6	0.70	0.095	0.03
γ_{High}(%)	9.7	0.14	-8.7	0.46	19.9	0.00	19.5	0.02	21.0	0.00	-0.1	1.00	-1.6	0.83	4.3	0.47	18.1	0.02	12.1	0.02	0.089	0.01
Adj. R^2(%)	0.5		10.6		3.4		0.6		3.1		10.8		15.7		0.6		0.6		7.2		6.6	
MAD (%)	28.9		36.7		31		34.3		33.6		30.7		22.6		28.4		23.9		21.4		29.1	
Hit (%)	71.1		21.2		71.2		70.1		67.7		55.7		70.3		60.2		74.4		69.5		65.5	
Panel B: Local Stock-Bond Correlation via *Global* Output Gap Regime Dummies																						
γ_{Low}(%)	-5.6	0.69	-32.1	0.00	-12.4	0.50	-2.6	0.89	16.3	0.10	26.6	0.05	22.4	0.04	-12.4	0.40	8.2	0.38	-6.8	0.59	-0.017	0.72
γ_{High}(%)	18.7	0.00	-11.1	0.25	17.8	0.01	23.1	0.00	26.8	0.00	-0.2	0.99	3.3	0.62	7.2	0.24	17.8	0.00	12.2	0.01	0.129	0.00
Adj. R^2(%)	8.9		9.4		11.7		8.8		3.4		10.8		8.2		7.1		2.2		8.7		10.2	
MAD (%)	28		35.5		29.8		33		30		31.3		25.4		16.1		28.1		19.6		27.6	
Hit (%)	70.1		43.9		72		70.8		68.5		53.1		52.3		73.1		70.1		63.6		65.4	

Table 7: Growth-Inflation regimes versus stock-bond correlations

This Table reports the estimated parameters of the regression of the (Fisher-transformed) stock-bond correlations $\tilde{\rho}_{SB,c,t}$ for country c (estimated using the DCC-MIDAS model) on the different country-specific inflation and output gap regime combination dummies: $\tilde{\rho}_{SB,c,t} = \sum_{i=1}^{N} \gamma_i \times D^{z(g)}_{c,i,t} + \varepsilon^z_{SB,i,t}$, where $D^z_{c,i,t}$ equals one when the probability that the process for inflation-output gap dummy combination z in country c or at the global level (g) at time t is in state $i = 1, ..., 6$, is larger than 50%. The parameter estimates capture the average stock-bond correlations across the different regime combinations. We base inference on Newey-West standard errors (24 lags) to correct for the substantial serial correlation in the dependent variable. R^2 is the regression's adjusted R^2, MAD(%) is the Mean Absolute Difference computed between the fitted and empirically observed correlations (from the MIDAS model), expressed as %. Hit(%) represents the % of observations that the fitted and observed correlations share the same sign. The column "Panel" shows the estimation results of an unbalanced fixed-effects panel regression analysis regressing local stock-bond correlations on the output gap-inflation regime dummy combinations. Panel A (B) shows the estimates using local (global) output gap regimes.

Regimes		US		Japan		Germany		UK		France		Italy		Spain		Netherlands		Belgium		Canada		Panel	
GAP	INFL	Est.	pval.	Est.	pval.	Est.	pval.	Est.	pval.	Est.	pval.	Est.	pval.	Est.	pval.	Est.	pval.	Est.	pval.	Est.	pval.	Est.	pval.
Panel A: *Local* Regime Dummies																							
L	L	-27.9	*0.20*	-28.9	*0.00*	-6.8	*0.60*	-17.2	*0.39*	15.0	*0.40*	27.8	*0.14*	25.1	*0.03*	-4.7	*0.72*	8.4	*0.46*	-25.4	*0.01*	2.16	0.73
L	M	29.6	*0.01*	-	-	40.9	*0.00*	8.6	*0.67*	42.2	*0.00*	23.7	*0.00*	20.6	*0.00*	-3.9	*0.84*	15.0	*0.09*	21.8	*0.00*	20.0	0.00
L	H	14.9	*0.16*	-	-	34.2	*0.00*	42.5	*0.00*	35.6	*0.00*	-	-	14.3	*0.01*	18.8	*0.01*	21.2	*0.00*	29.3	*0.00*	26.9	0.00
H	L	-7.7	*0.54*	-23.6	*0.00*	-4.0	*0.50*	6.8	*0.61*	2.6	*0.83*	-9.6	*0.41*	-10.8	*0.19*	-4.6	*0.66*	8.8	*0.56*	2.7	*0.76*	-3.9	0.26
H	M	7.4	*0.30*	23.5	*0.12*	14.0	*0.26*	23.9	*0.00*	20.3	*0.00*	34.3	*0.00*	17.0	*0.00*	5.4	*0.52*	18.5	*0.07*	20.7	*0.00*	15.9	0.000
H	H	23.9	*0.00*	-	-	30.2	*0.00*	39.6	*0.00*	26.4	*0.00*	-	-	29.8	*0.00*	15.9	*0.00*	22.1	*0.00*	18.7	*0.00*	27.2	0.00
	R^2	0.21		0.42		0.26		0.28		0.11		0.27		0.31		0.08		0.04		0.37		19.9	
	MAD	23.5		18.8		24.8		24.0		26.2		24.9		18.2		23.7		21.0		15.9		24.9	
	Hit Ratio	77.7		86.5		73.1		73.1		70.6		78.0		78.4		64.2		74.4		77.8		70.7	
Panel B: *Global* Regime Dummies																							
L	L	-29.7	0.11	-34.7	0.00	-33.2	0.09	-25.3	0.16	-16.0	0.38	26.6	0.07	23.7	0.10	-27.1	0.09	0.8	0.94	-23.8	0.03	-13.8	0.09
L	M	8.7	0.02	22.4	0.00	50.5	0.00	42.3	0.00	58.0	0.00	26.4	0.00	41.4	0.00	23.0	0.00	53.5	0.00	23.1	0.00	22.2	0.03
L	H	32.8	0.00	-	-	28.7	0.00	44.9	0.00	35.0	0.00	-	-	14.2	0.00	17.7	0.01	20.0	0.00	29.2	0.00	28.5	0.00
H	L	8.8	0.47	-26.0	0.00	5.6	0.66	6.7	0.59	5.0	0.70	-0.3	0.98	-4.1	0.66	-1.9	0.87	3.2	0.75	4.2	0.64	0.03	0.92
H	M	27.8	0.00	27.6	0.03	26.2	0.00	28.8	0.00	34.8	0.00	0.7	0.97	10.7	0.08	12.4	0.01	30.7	0.00	19.1	0.00	23.9	0.00
H	H	23.2	0.00	-	-	28.6	0.00	44.3	0.00	26.3	0.00	-	-	24.9	0.00	16.4	0.00	27.2	0.00	17.5	0.00	26.2	0.00
	R^2	0.27		0.59		0.34		0.42		0.28		0.11		0.17		0.24		0.24		0.33		26.3	
	MAD	22.7		14.5		21.9		19.2		22.5		28.6		19.9		19.4		17.8		16.2		22.6	
	Hit Ratio	78.7		95.5		79.4		78.2		78.8		67.0		71.7		79.9		74.4		77.7		76.7	

Table 8: Monetary Policy Regimes

This Table reports the estimated parameters of the monetary policy rule: $i_t = \alpha + \beta\left(S_t^{MP}\right)\pi_t + \gamma\left(S_t^{MP}\right)y_t + \epsilon_{t,i}, \quad \epsilon_{t,i} \sim N\left(0, \sigma_t^2\left(S_t^V\right)\right)$ where i_t is the nominal observed (country-specific) monetary policy rate. Parameters β and γ govern the reaction of short-term interest rates to inflation (π_t) and the output gap (x_t), respectively, and α is a constant that captures the steady state real interest rate. To distinguish between accommodating and restrictive monetary policy, we condition the reaction of monetary policy to inflation (β) and output (γ) on a latent regime variable S_t^{MP}. Finally, by letting the $\epsilon_{i,t}$'s variance depend on a latent regime variable S_t^V, we additionally distinguish between periods with lower or higher degrees of discretionary monetary policy.

	US		**Japan**		**Germany**		**UK**		**France**		**Italy**		**Spain**		**Netherlands**		**Belgium**		**Canada**		**Global**	
Estimation Results																						
	Est.	*S.E.*	Est.	*S.E.*	Est.	*S.E.*	Est.	*S.E.*	Est.	*S.E.*	Est.	*S.E.*	Est.	*S.E.*	Est.	*S.E.*	Est.	*S.E.*	Est.	*S.E.*	Est.	*S.E.*
P_{mp}	0.965	0.014	0.964	0.012	0.974	0.007	0.968	0.009	0.961	0.013	0.985	0.005	0.987	0.006	0.988	0.008	0.961	0.010	0.979	0.008	0.968	0.009
Q_{mp}	0.964	0.008	0.952	0.030	0.971	0.007	0.952	0.010	0.978	0.006	0.959	0.012	0.988	0.004	0.991	0.005	0.969	0.008	0.973	0.010	0.968	0.011
P_{vol}	0.984	0.005	0.979	0.006	0.978	0.007	0.991	0.003	0.987	0.006	0.988	0.005	0.982	0.005	0.984	0.005	0.989	0.004	0.978	0.028	0.993	0.002
Q_{vol}	0.992	0.004	0.980	0.005	0.983	0.005	0.993	0.004	0.993	0.004	0.993	0.003	0.989	0.005	0.983	0.005	0.993	0.004	0.986	0.016	0.993	0.003
α	1.947	0.109	2.114	0.207	1.189	0.055	2.973	0.079	2.550	0.052	1.311	0.100	3.000	0.190	1.499	0.138	2.255	0.102	2.531	0.141	2.327	0.094
β_1	1.368	0.056	0.947	0.141	1.291	0.049	1.158	0.023	1.245	0.018	1.693	0.025	1.147	0.043	1.348	0.060	1.338	0.049	1.182	0.207	1.000	0.045
β_2	0.594	0.020	0.301	0.078	0.514	0.018	0.396	0.009	0.560	0.014	0.602	0.043	0.229	0.018	0.531	0.063	0.377	0.011	0.571	0.041	0.413	0.012
γ_1	0.666	0.048	0.287	0.157	-1.137	0.151	1.643	0.162	0.430	0.217	0.712	0.217	-0.219	0.154	-0.219	0.090	0.290	0.107	1.230	0.766	0.423	0.051
γ_2	1.004	0.036	0.482	0.040	0.414	0.037	2.121	0.076	0.579	0.058	0.712	0.172	-0.083	0.052	0.491	0.075	0.292	0.061	1.230	0.103	0.775	0.034
σ_1	0.463	0.062	0.311	0.101	0.526	0.025	0.603	0.038	0.355	0.030	0.808	0.068	0.611	0.052	0.460	0.027	0.505	0.060	0.611	0.085	0.364	0.027
σ_2	1.889	0.115	1.308	0.201	2.070	0.089	2.911	0.124	2.089	0.074	4.392	0.228	3.567	0.167	2.535	0.109	2.327	0.082	2.618	0.345	1.746	0.114
Wald Test																						
	W	*pval*	W	*pval*	W	*pval*	W	*pval*	W	*pval*	W	*pval*	W	*pval*	W	*pval*	W	*pval*	W	*pval*	W	*pval*
$\beta_1 = \beta_2$	295.87	0.00	88.53	0.00	318.85	0.00	1310.71	0.00	1285.81	0.00	761.73	0.00	793.17	0.00	496.27	0.00	436.14	0.00	13.20	0.00	260.50	0.00
$\gamma_1 = \gamma_2$	30.82	0.00	1.70	0.19	96.95	0.00	7.05	0.01	0.47	0.49	0.00	1.00	0.67	0.41	41.25	0.00	0.00	0.99	0.00	1.00	38.97	0.00
joint	298.14	0.00	416.45	0.00	353.92	0.00	1961.66	0.00	1435.84	0.00	1485.78	0.00	793.19	0.00	524.54	0.00	536.97	0.00	162.13	0.00	499.79	0.00

Table 9: Monetary Policy regimes versus stock bond correlation: accommodating versus restrictive

This Table reports the estimated parameters of the regression of the (Fisher-transformed) stock-bond correlations $\tilde{\rho}_{SB,c,t}$ for country c (estimated using the DCC-MIDAS model) on the different country-specific monetary policy gap regime dummies: $\tilde{\rho}_{SB,c,t} = \sum_{i=1}^{N} \gamma_i \times D_{c,i,t}^{MP(g)} + \varepsilon_{SB,i,t}^{MP}$, where $D_{c,i,t}^{MP}$ equals one when the probability that the process for monetary policy MP in country c or at the global level (g) at time t is in state $i = 1, 2$, is larger than 50%. The parameter estimates (γ_i's) capture the average stock-bond correlations across the different monetary policy gap regimes. We base inference on Newey-West standard errors (24 lags) to correct for the substantial serial correlation in the dependent variable. Adj. R^2(%) is the regression's adjusted R^2 expressed as %, MAD(%) is the Mean Absolute Difference computed between the fitted and empirically observed correlations (from the MIDAS model), expressed as %. Hit(%) represents the % of observations that the fitted and observed correlations share the same sign. The column "Panel" shows the estimation results of an unbalanced fixed-effects panel regression analysis regressing local stock-bond correlations on the monetary policy gap regime dummies. Panel A (B) shows the estimates using local (global) output gap regimes.

	US		**Japan**		**Germany**		**UK**		**France**		**Italy**		**Spain**		**Netherlands**		**Belgium**		**Canada**		**Panel**	
	Est.	pVal.	Est.	pVal.	Est.	pVal.	Est.	pVal.	Est.	pVal.	Est.	pVal.	Est.	pVal.	Est.	pVal.	Est.	pVal.	Est.	pVal.	Est.	pVal.
Panel A: Local Monetary Policy Regimes																						
γ_{Acc}(%)	-2.3	0.77	-12.0	0.21	-2.3	0.83	-1.0	0.93	-4.3	0.64	-4.2	0.75	-8.4	0.43	-19.4	0.08	3.5	0.64	-2.6	0.73	-4.40	0.04
γ_{Restr}(%)	39.7	0.00	-27.8	0.00	24.4	0.00	36.3	0.00	47.0	0.00	26.8	0.00	22.3	0.00	17.7	0.00	32.1	0.00	20.9	0.00	26.61	0.00
Adj. R^2*(%)*	30.2		5.7		13.0		26.2		45.1		16.3		27.3		29.8		27.3		18.7		25.2	
MAD(%)	23.4		23.8		28.8		25.9		21.7		25.9		18.5		22.0		19.3		19.5		24.9	
Sign(%)	59.8		78.5		64.8		73.9		68.1		69.2		81.8		76.9		74.4		68.6		70.2	
Panel B: Global Monetary Policy Regimes																						
γ_{Acc}(%)	-12.9	0.17	-37.1	0.00	-14.7	0.15	-4.2	0.72	6.3	0.20	-6.0	0.67	-10.8	0.40	-18.6	0.03	-1.0	0.90	-7.1	0.37	-11.4	0.00
γ_{Restr}(%)	31.8	0.00	2.5	0.82	35.2	0.00	37.4	0.00	41.4	0.00	25.9	0.00	19.8	0.00	22.8	0.00	31.2	0.00	22.0	0.00	28.1	0.00
Adj. R^2*(%)*	37.4		42.3		45.5		32.8		53.6		17.7		25.5		45.3		35.1		29.2		27.64	
MAD(%)	23.4		18.8		22.7		24.0		13.9		25.7		18.8		18.7		18.7		18.7		23.1	
Sign(%)	74.4		67.6		80.3		79.2		75.0		73.6		83.5		77.5		74.4		73.7		71.5	

Table 10: Stock-Bond correlations explained by inflation, output gap and monetary policy: An unbalanced panel regression approach

This Table shows the link between stock-bond return correlations and regimes in global and local inflation, output gap and monetary policy regimes. A fixed effects unbalanced panel model is estimated: $\tilde{\rho}_{SB,c,t} = D'_{L_c/G,t}\gamma + \varepsilon_{ct}$, where the γ is assumed to be constant over countries c and over time t and varies per regime and represents the average regime correlation. $D_{L_c,t}$ is a regime dummy indicating the different regime combinations for local inflation, output gap, and monetary policy stance in country c. The global dummies are instead denoted by $D_{G,t}$. We base inference on Newey-West standard errors (24 lags) to correct for the substantial serial correlation in the dependent variable. Panel A (B) shows the γ's using *global* (*local*) regime dummies. Panel C shows the per country MAD which is the Mean Absolute Difference computed between the fitted and empirically observed correlations (from the MIDAS model). Hit ratio represents the % of observations that the fitted and observed correlations share the same sign. the column headed "%" shows the relative importance of the different regimes expressed as a percentage of the sample size. For panel B, this "%" represents the importance of the regimes averaged over the different countries.

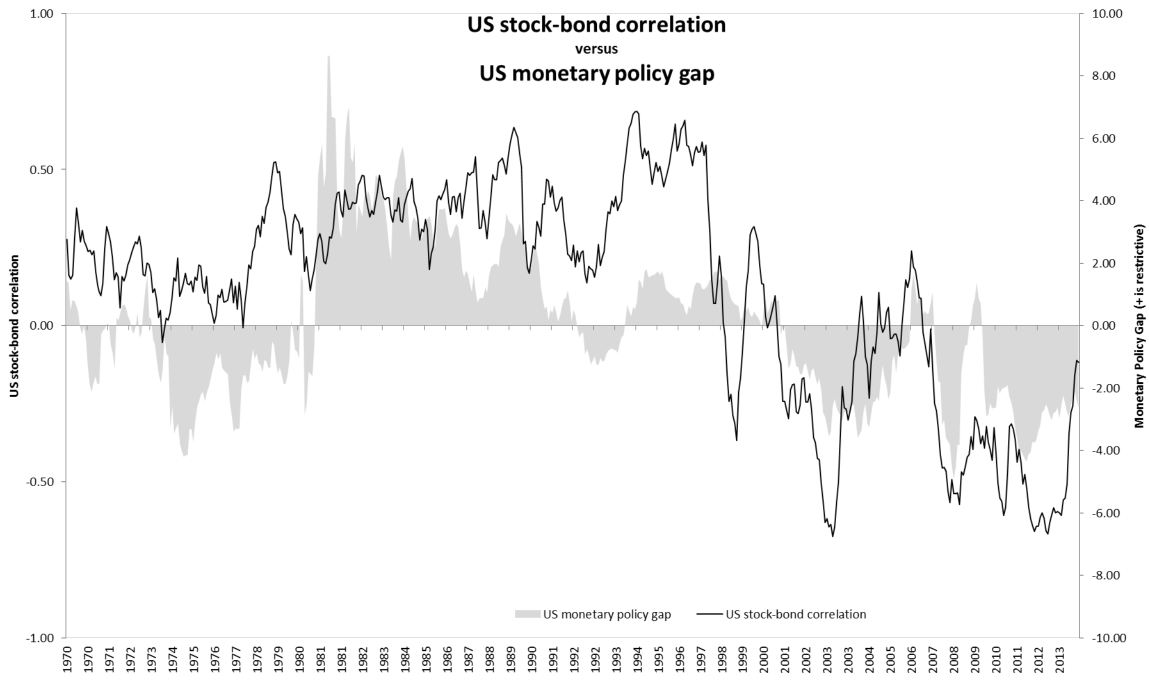
Panel A: Global						Panel B: Local		
Infl	**Gap**	**MP**	γ	**pval.**	%	γ	**pval.**	%
L	L	A	-0.286	0.095	13.1	-0.149	0.068	16.9
		R	0.343	0.056	4.0	0.257	0.089	7.2
	H	A	-0.265	0.015	17.5	-0.164	0.029	19.1
		R	0.245	0.049	19.4	0.169	0.085	10.8
M	L	A	0.000	(omitted)	0.0	-0.119	0.105	2.9
		R	0.222	0.083	1.6	0.350	0.039	6.7
	H	A	-0.019	0.039	4.4	-0.002	0.046	5.6
		R	0.303	0.032	18.3	0.271	0.028	10.8
H	L	A	0.249	0.050	1.9	0.202	0.096	2.8
		R	0.303	0.040	3.7	0.305	0.045	5.5
	H	A	0.245	0.034	10.5	0.256	0.034	8.3
		R	0.293	0.040	5.5	0.321	0.049	3.2
			R^2	0.59		0.38		
			MAD	0.175		0.213		
			Hit ratio	0.889		0.802		

Panel C: Country specific performance

	MAD		Hit ratio	
	Local	Global	Local	Global
US	0.217	0.190	0.778	0.878
JAPAN	0.262	0.252	0.699	0.676
GERMANY	0.232	0.157	0.807	0.962
UK	0.182	0.164	0.964	0.951
FRANCE	0.219	0.158	0.869	0.956
ITALY	0.273	0.289	0.692	0.736
SPAIN	0.201	0.207	0.811	0.835
NETHERLANDS	0.228	0.151	0.769	0.934
BELGIUM	0.183	0.139	0.778	0.902
CANADA	0.172	0.137	0.790	0.896

Figure 1: International Stock-Bond Correlations, Monetary Policy Gap

Panel A: US Stock-Bond Return Correlation and Monetary Policy Gap



Panel B: International Stock-Bond Return Correlations

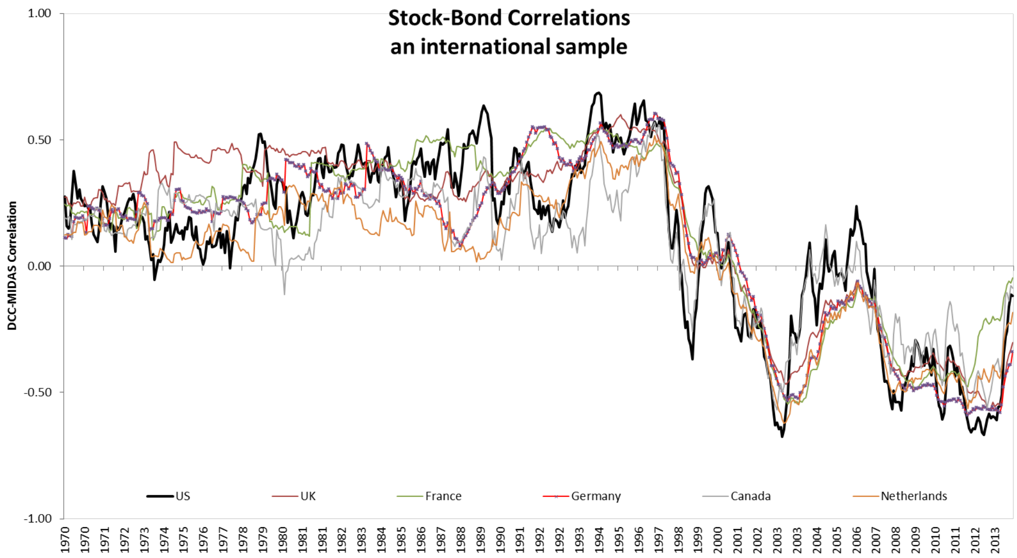


Figure 2: Correlation Estimates for the 10 developed countries

This Figure shows the long-run (monthly) correlation component of the daily DCC-MIDAS model estimated for the 10 developed countries, extended with the monthly dynamic correlations from the DCC model.

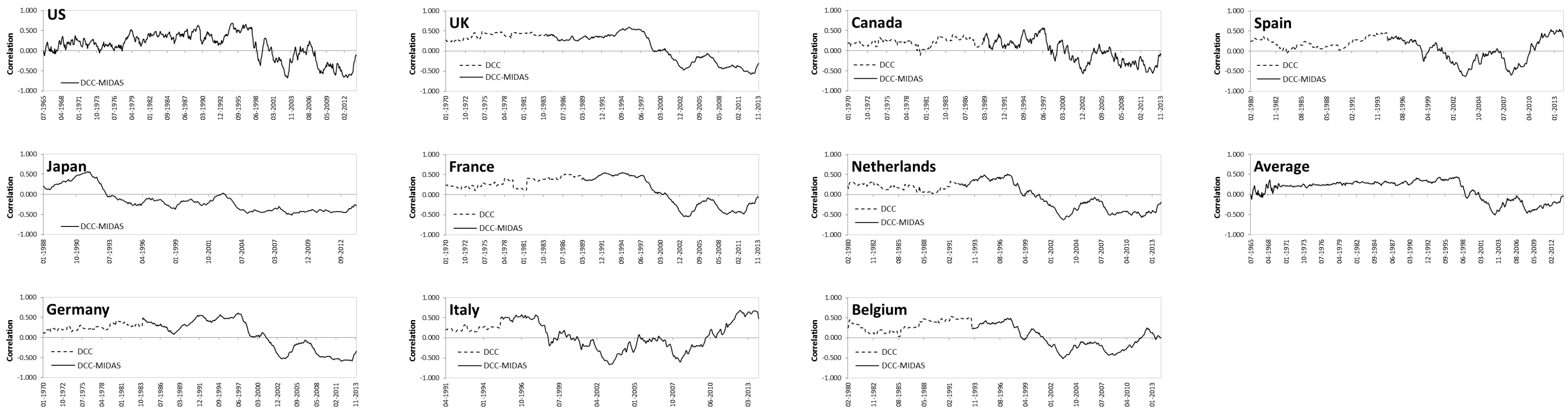


Figure 3: 3-state regime model estimated on realized inflation

This Figure depicts the inflation regimes based on the smoothed regime probabilities of a 3-state regime switching model in the mean and variance as described in Section 3.1 for the 10 developed markets and for global inflation. The local inflation rates are the monthly year-on-year % change in the consumer price indices.

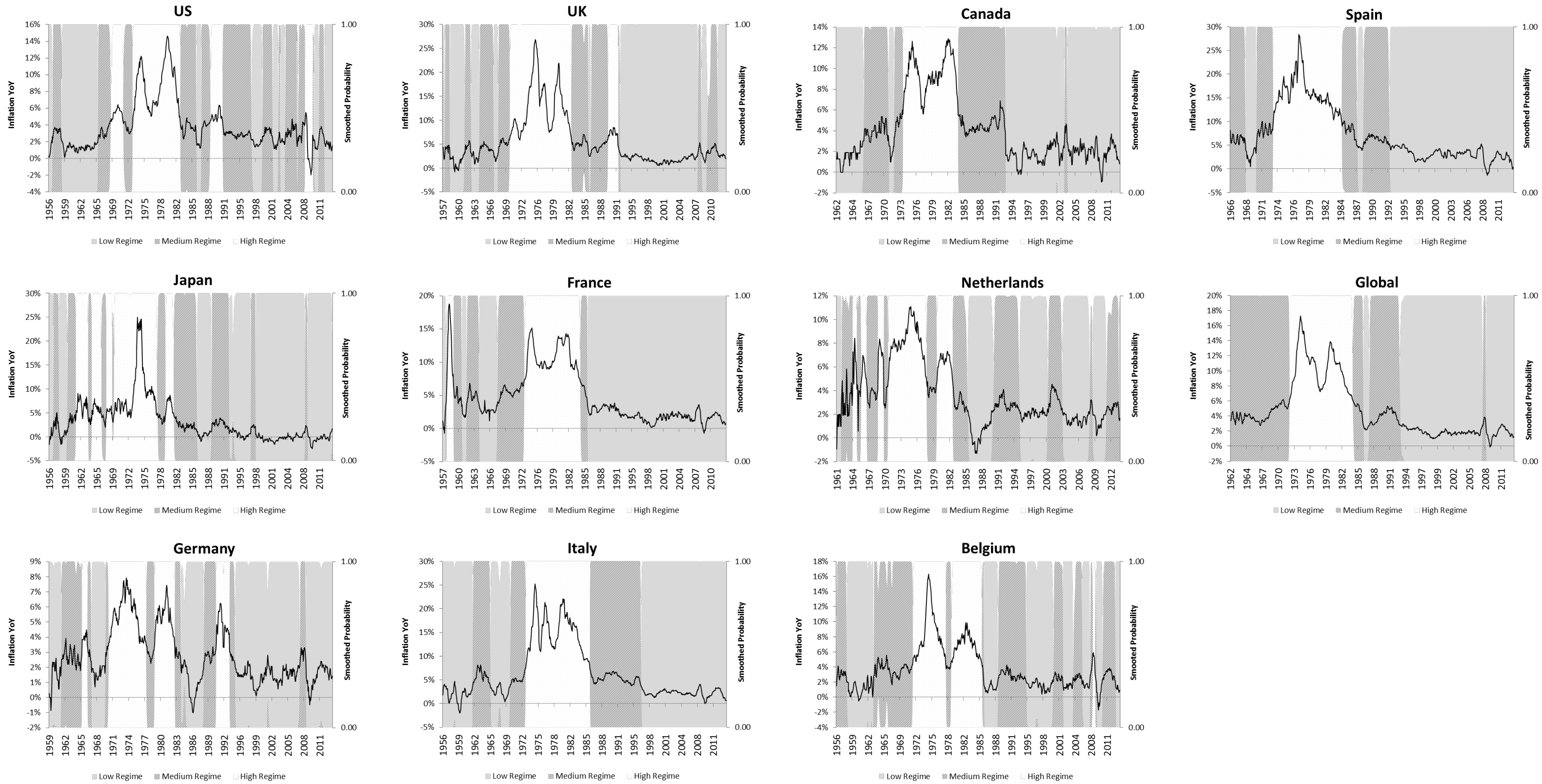


Figure 4: 2-State regime switching model estimated on % output gap

This Figure depicts the output gap regimes based on the smoothed regime probabilities of a 2-state regime switching model in the mean and variance as described in Section 3.1 for the 10 developed markets and for global output gap. The output gap is based on the difference between the actual industrial production and the potential industrial production estimated using an unobserved components model as described in Section C.1

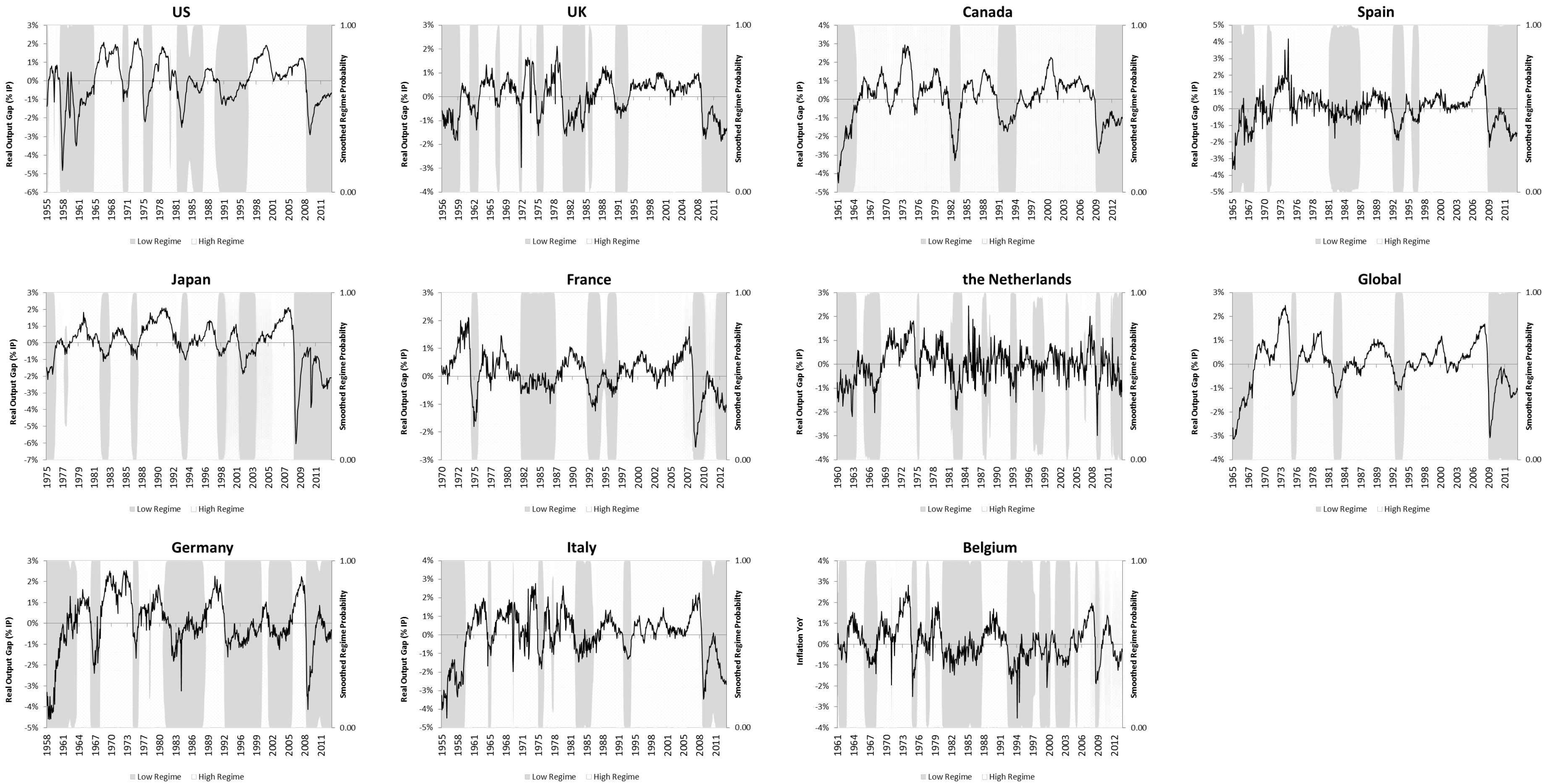


Figure 5: Stock-bond return correlation versus inflation regimes

This Figure shows the monthly implied correlations based on the 3-state inflation regime model dummies and the DCC-MIDAS conditional correlations between stock and bond returns

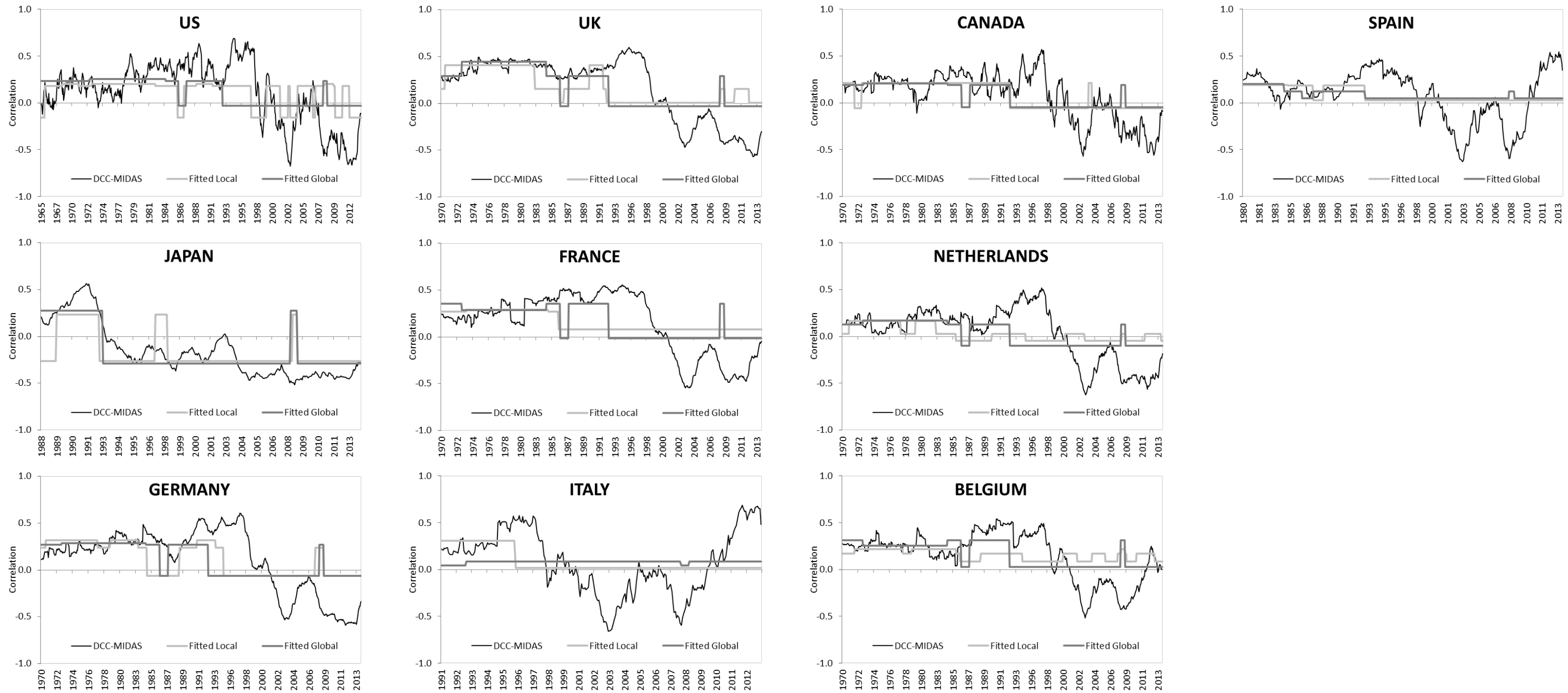


Figure 6: Stock-bond return correlation versus output gap regimes

This Figure shows the monthly implied correlations based on the 2-state output gap regime dummy model and the DCC-MIDAS conditional correlations between stock and bond returns

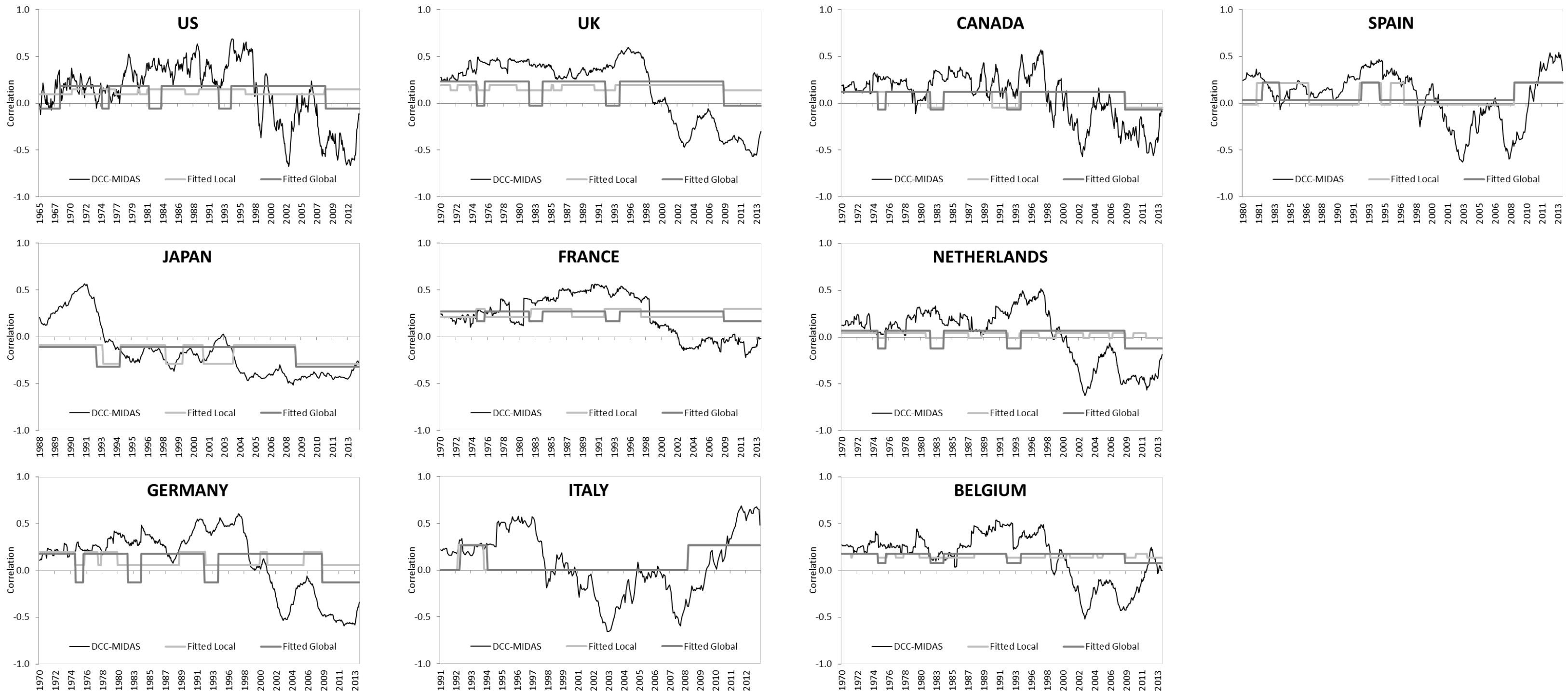


Figure 7: Monetary policy regime: accommodating versus restrictive

This Figure shows the estimated monetary policy regime smoothed transition probabilities of the monetary policy rule: $i_t = \rho i_{t-1} + (1-\rho)\left[\alpha + \beta\left(S_t^{MP}\right)\pi_t + \gamma\left(S_t^{MP}\right)y_t\right] + \epsilon_{t,i}, \quad \epsilon_{t,i} \sim N\left(0, \sigma_t^2\left(S_t^V\right)\right)$ where i_t is the nominal observed (country-specific) monetary policy rate. The parameter ρ captures the degree of lagged dependence in the interest rate. Parameters β and γ govern the reaction of short-term interest rates to inflation (π_t) and the output gap (x_t) , respectively, and α is a constant that captures the steady state real interest rate. To distinguish between accommodating and restrictive monetary policy, we condition the reaction of monetary policy to inflation (β) and output (γ) on a latent regime variable S_t^{MP}. Finally, by letting the $\epsilon'_{i,t}s$ variance depend on a latent regime variable S_t^V, we additionally distinguish between periods with lower or higher degrees of discretionary monetary policy.

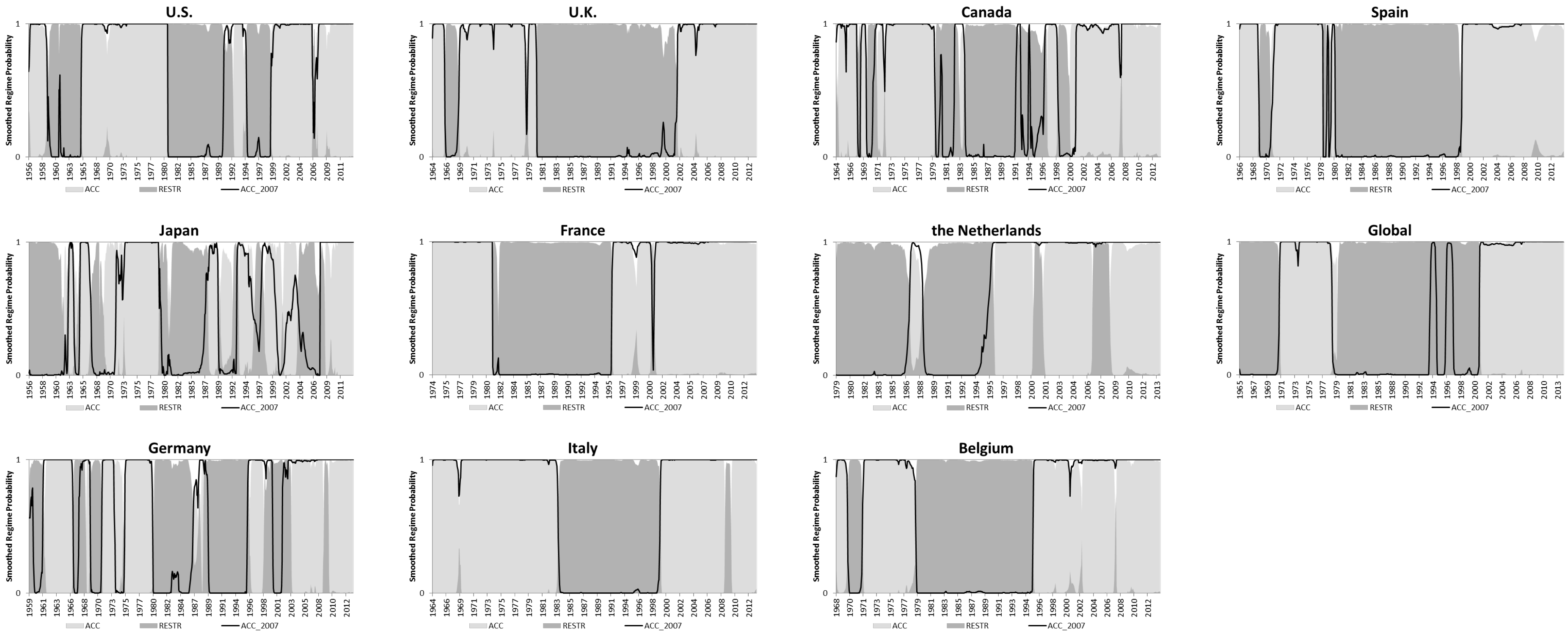


Figure 8: Monetary policy regime: disciplined versus discretionary

This Figure shows the estimated monetary policy regime smoothed transition probabilities of the monetary policy rule: $i_t = \rho i_{t-1} + (1-\rho)\left[\alpha + \beta\left(S_t^{MP}\right)\pi_t + \gamma\left(S_t^{MP}\right)y_t\right] + \epsilon_{t,i}, \quad \epsilon_{t,i} \sim N\left(0, \sigma_t^2\left(S_t^V\right)\right)$ where i_t is the nominal observed (country-specific) monetary policy rate. The parameter ρ captures the degree of lagged dependence in the interest rate. Parameters β and γ govern the reaction of short-term interest rates to inflation (π_t) and the output gap (x_t) , respectively, and α is a constant that captures the steady state real interest rate. To distinguish between accommodating and restrictive monetary policy, we condition the reaction of monetary policy to inflation (β) and output (γ) on a latent regime variable S_t^{MP}. Finally, by letting the $\epsilon'_{i,t}s$ variance depend on a latent regime variable S_t^V, we additionally distinguish between periods with lower or higher degrees of discretionary monetary policy.

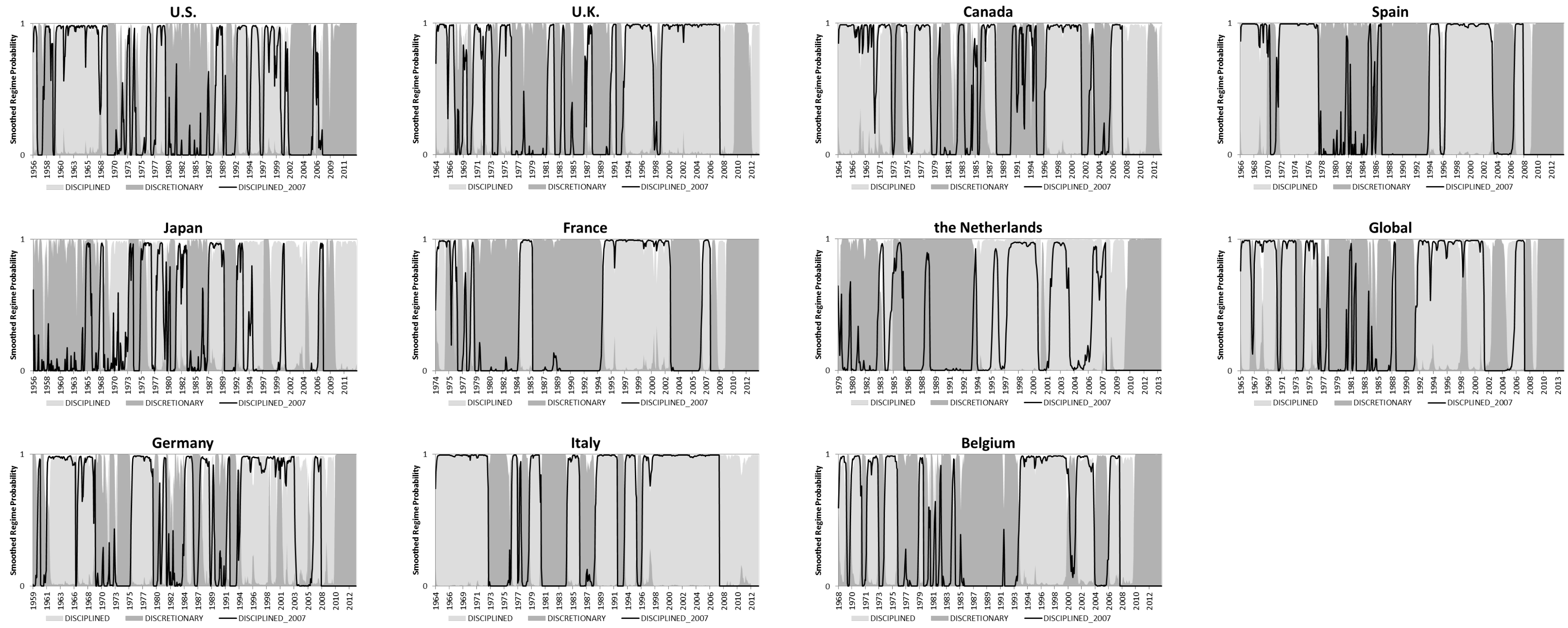


Figure 9: Stock-bond return correlation versus monetary policy stance

This Figure shows the relationship between the DCC-MIDAS stock-bond correlation and the estimated restrictive and accommodating monetary policy regimes based on smoothed transition probabilities of the monetary policy rule: $i_t = \rho i_{t-1} + (1-\rho)\left[\alpha + \beta\left(S_t^{MP}\right)\pi_t + \gamma\left(S_t^{MP}\right)y_t\right] + \epsilon_{t,i}, \quad \epsilon_{t,i} \sim N\left(0, \sigma_t^2\left(S_t^V\right)\right)$ where i_t is the nominal observed (country-specific) monetary policy rate. The parameter ρ captures the degree of lagged dependence in the interest rate. Parameters β and γ govern the reaction of short-term interest rates to inflation (π_t) and the output gap (x_t) , respectively, and α is a constant that captures the steady state real interest rate. To distinguish between accommodating and restrictive monetary policy, we condition the reaction of monetary policy to inflation (β) and output (γ) on a latent regime variable S_t^{MP}. Finally, by letting the $\epsilon'_{i,t}s$ variance depend on a latent regime variable S_t^V, we additionally distinguish between periods with lower or higher degrees of discretionary monetary policy.

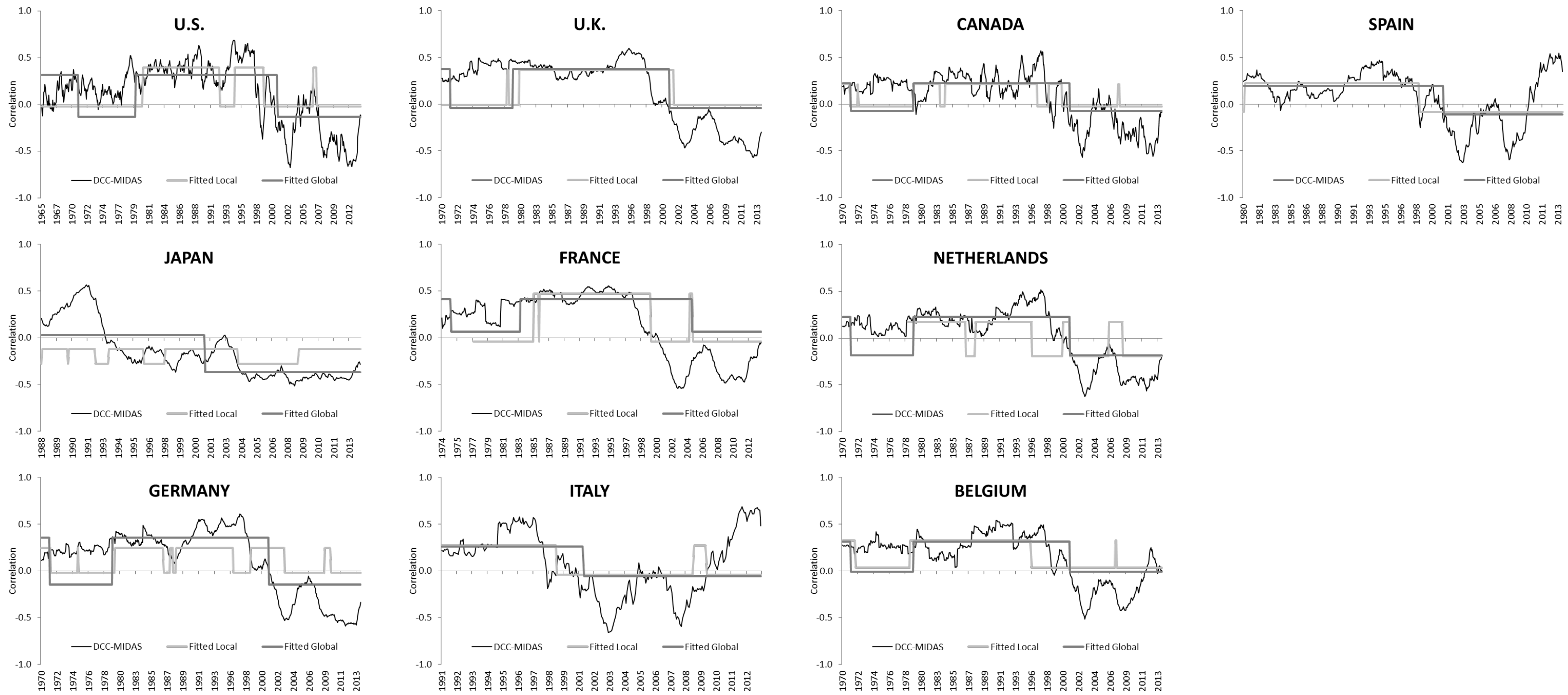


Figure 10: Stock-bond return correlation versus monetary policy style

This Figure shows the relationship between the DCC-MIDAS stock-bond correlation and the estimated disciplined and discretionary monetary policy regimes based on smoothed transition probabilities of the monetary policy rule: $i_t = \rho i_{t-1} + (1-\rho)\left[\alpha + \beta\left(S_t^{MP}\right)\pi_t + \gamma\left(S_t^{MP}\right)y_t\right] + \epsilon_{t,i}, \quad \epsilon_{t,i} \sim N\left(0, \sigma_t^2\left(S_t^V\right)\right)$ where i_t is the nominal observed (country-specific) monetary policy rate. The parameter ρ captures the degree of lagged dependence in the interest rate. Parameters β and γ govern the reaction of short-term interest rates to inflation (π_t) and the output gap (x_t) , respectively, and α is a constant that captures the steady state real interest rate. To distinguish between accommodating and restrictive monetary policy, we condition the reaction of monetary policy to inflation (β) and output (γ) on a latent regime variable S_t^{MP}. Finally, by letting the $\epsilon_{i,t}'s$ variance depend on a latent regime variable S_t^V, we additionally distinguish between periods with lower or higher degrees of discretionary monetary policy.

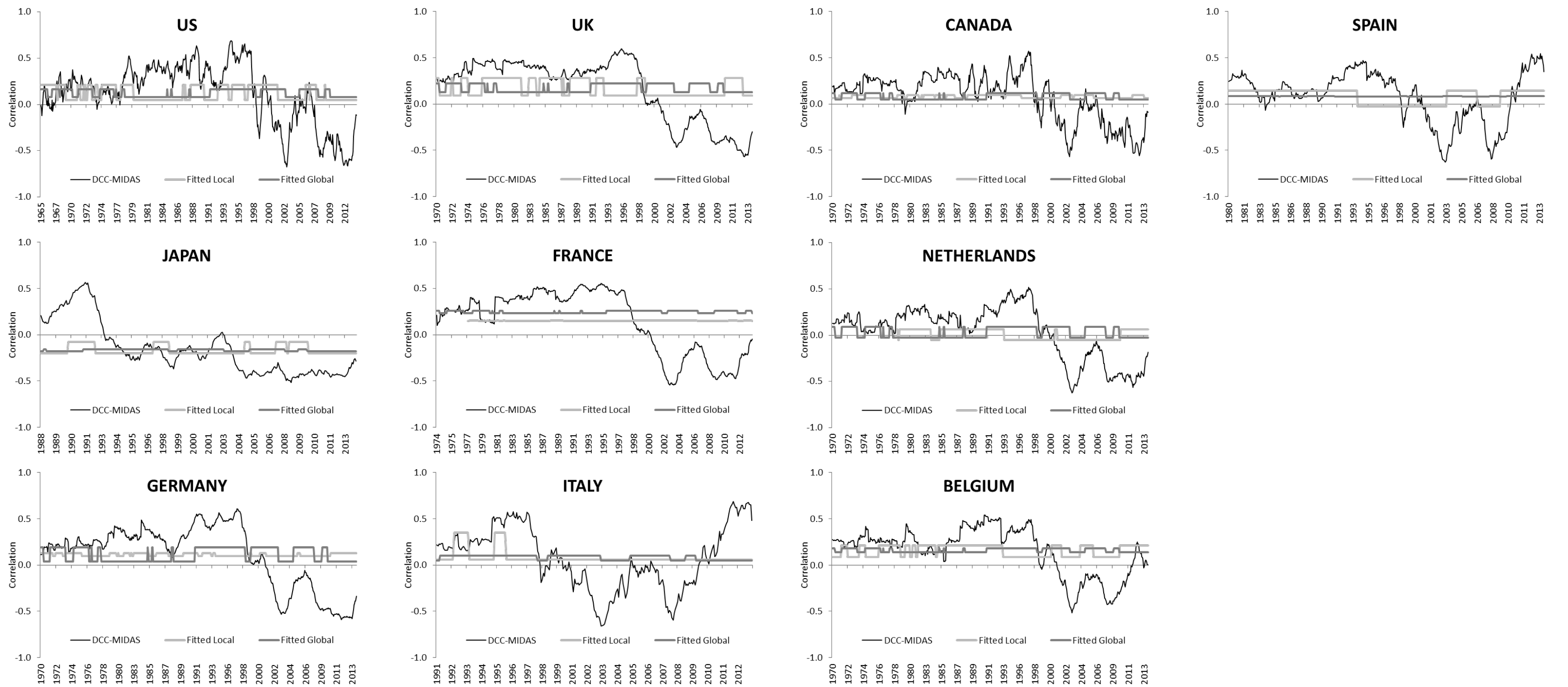


Figure 11: Stock-bond return correlation versus cyclicality of inflation

This Figure shows the monthly implied correlation based on the 2-state model of pro-and countercyclical inflation and the DCC-MIDAS conditional correlations between stock and bond returns

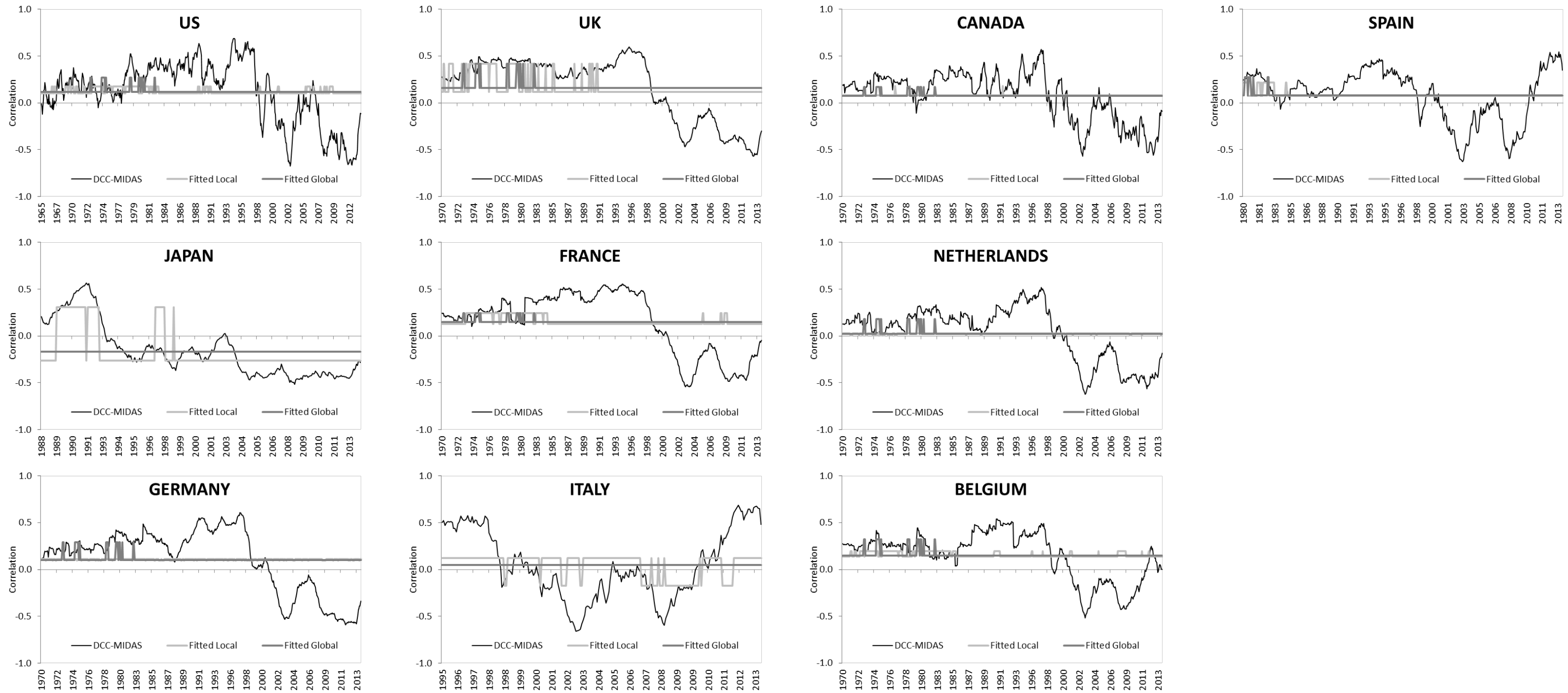


Figure 12: Observed vs fitted stock-bond return correlations: an unbalanced panel regression approach - global and local regimes

This Figure shows the estimated stock-bond correlations using a fixed effects unbalanced panel regression model based on global and local regimes in inflation, output gap and monetary policy

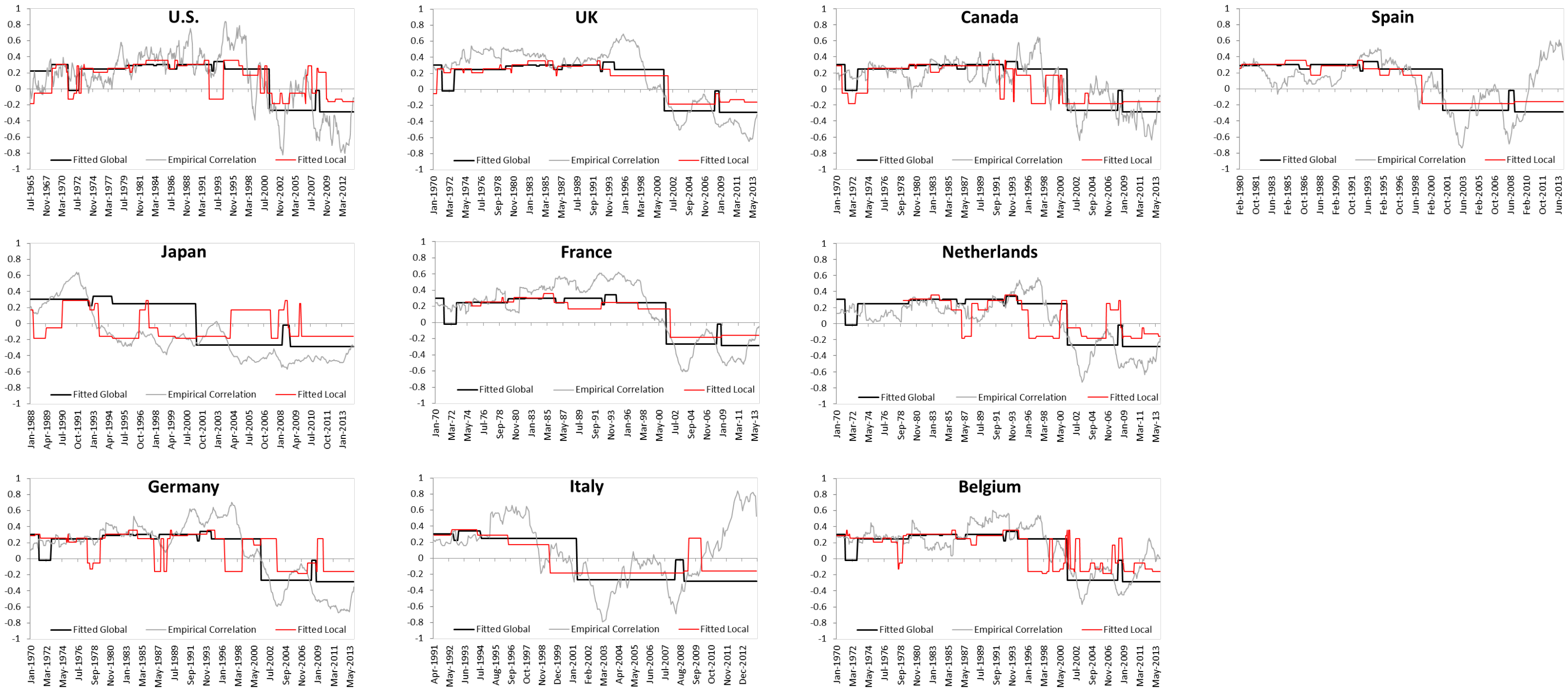
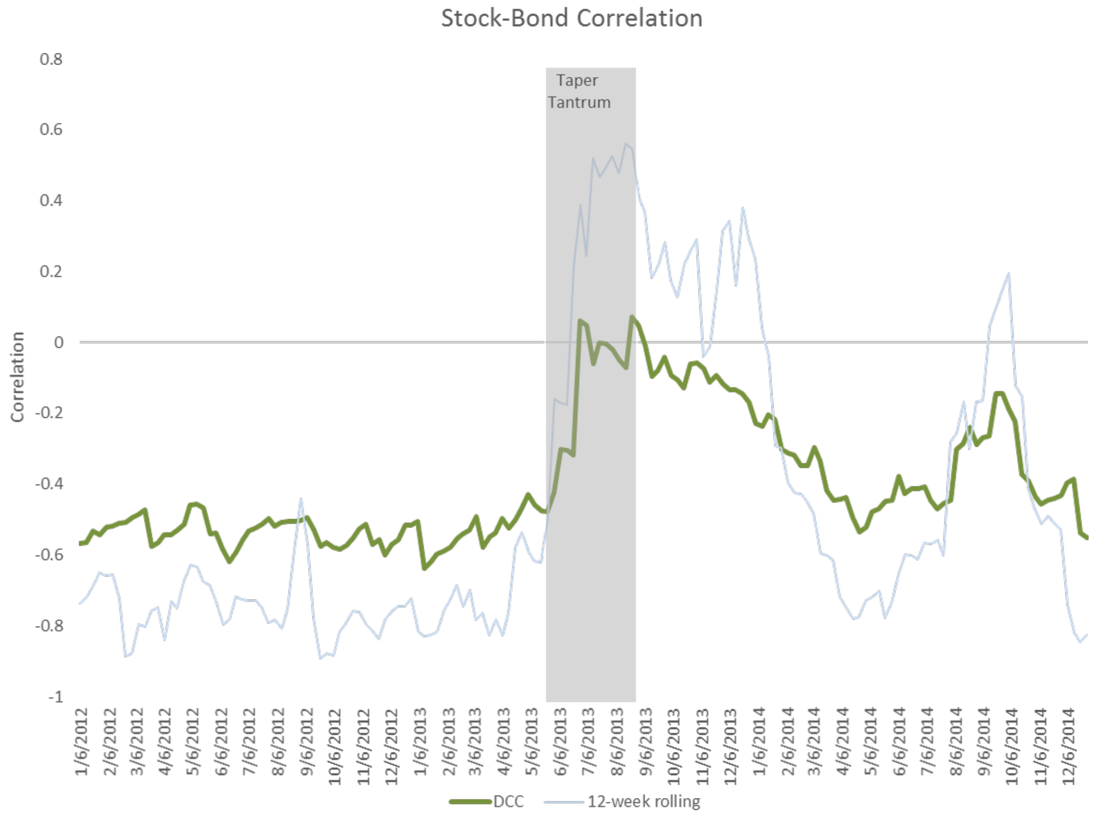


Figure 13: Out-of-sample stock-bond return correlation versus the model's prediction

This Figure compares the DCC-MIDAS stock-bond correlation and model fit using the global inflation, monetary policy and growth regimes to capture the time-variation in the stock-bond correlations during the out-of-sample period from January 2014-March 2017.

Figure 14: Higher frequency impact of monetary policy changes on stock-bond correlations

This Figure shows two measures of the correlation between US stock returns and US 10-year Treasury bond returns based on weekly data. The first measure is the correlation based on a DCC model "DCC", while the second is the correlation based on a 12-week rolling window estimation. The grey area shows the Taper Tantrum period in June 2013.



Additional Tables and Figures

Table 11: Correlation matrix of the local inflation rates

This Table shows the % correlations between the local annual inflation rates

	Belgium	Canada	France	Germany	Italy	Japan	Netherlands	UK	US
Belgium		75	85	74	83	74	79	80	69
Canada			85	56	85	45	53	75	71
France				71	93	69	70	83	84
Germany					67	70	77	70	64
Italy						64	62	82	79
Japan							76	71	60
Netherlands								74	58
UK									80
US									

Figure 15: Effective US Federal Funds rate versus the official target rate

This Figure shows the Effective Federal Funds rate compared to the Official US Federal Reserve Target Rate

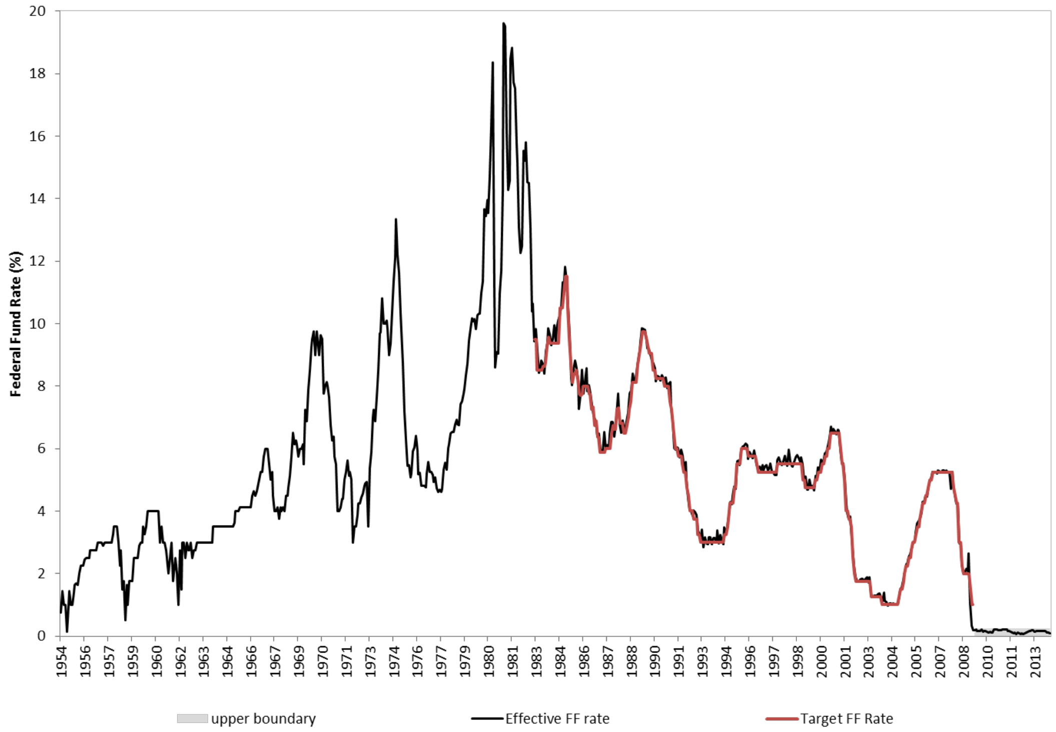


Figure 16: Monetary policy, cyclicality of inflation and stock-bond return correlations

This Figure shows the link between monetary policy, cyclicality of inflation and bond-stock return correlation

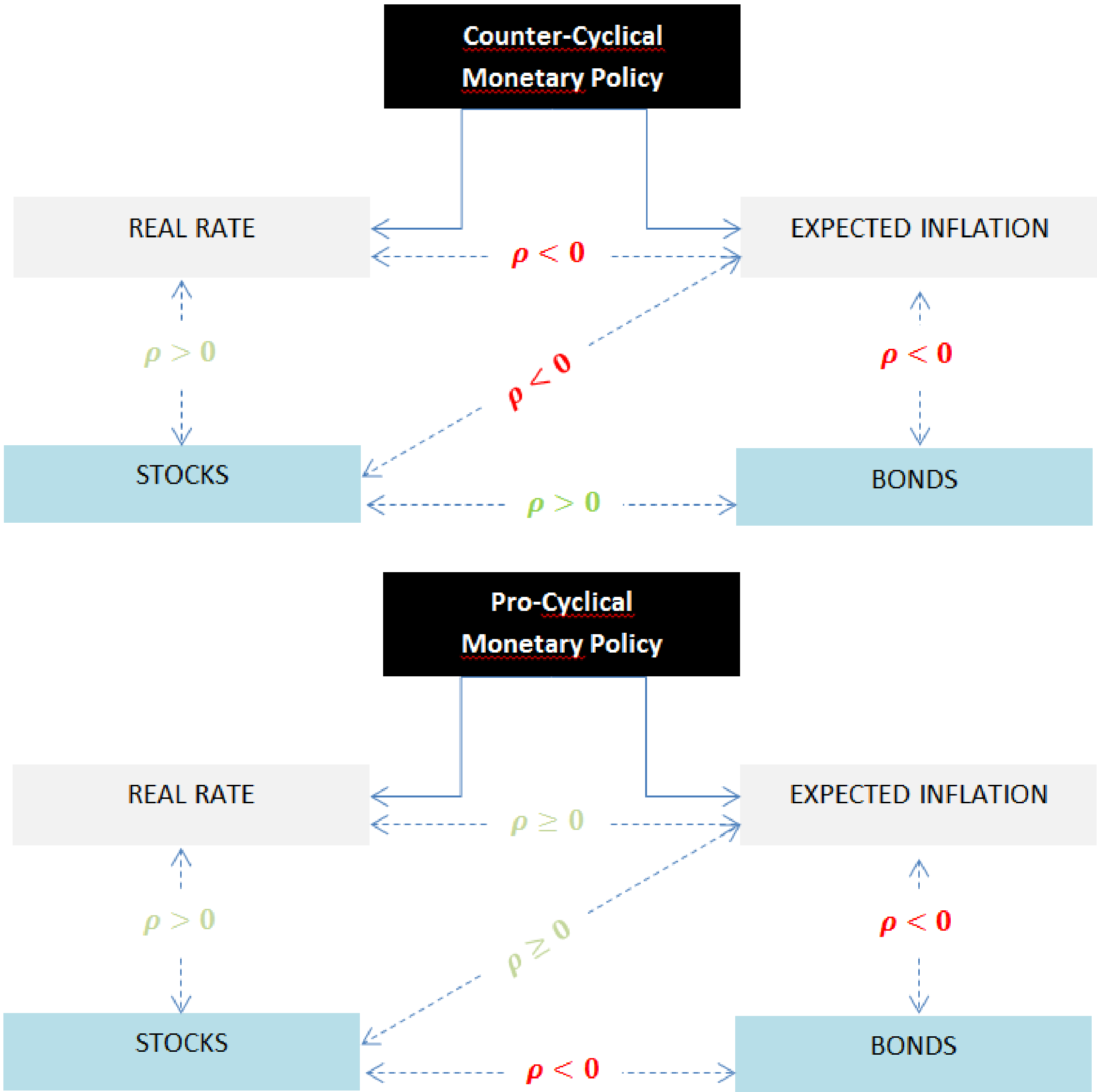


Figure 17: Global inflation rates

This Figure shows monthly year-on-year changes in the international consumer price indexes

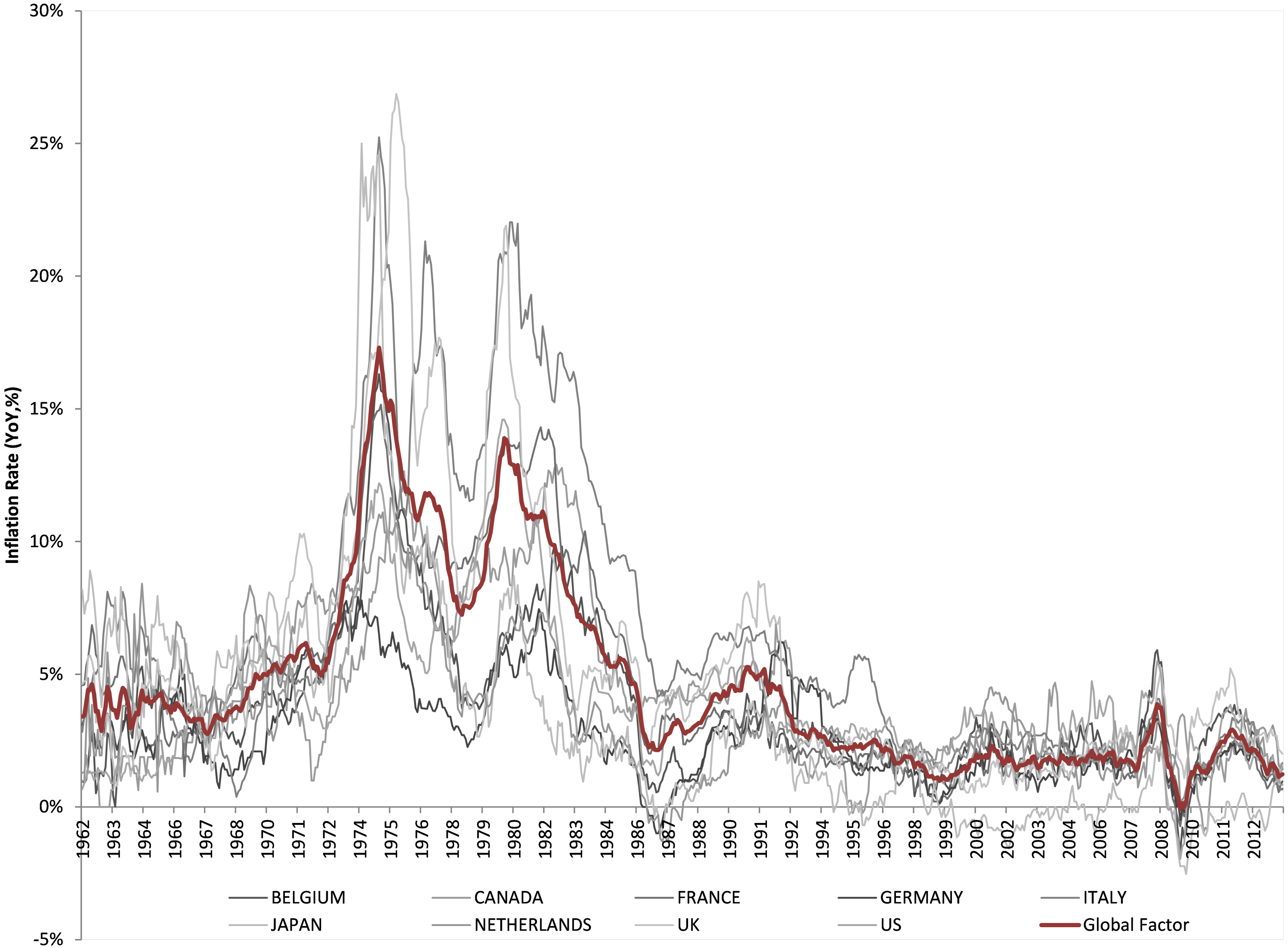


Figure 18: First eigenvector of the inflation rate covariance matrix

This Figure shows the rescaled first eigenvector of the covariance matrix of the international inflation rates

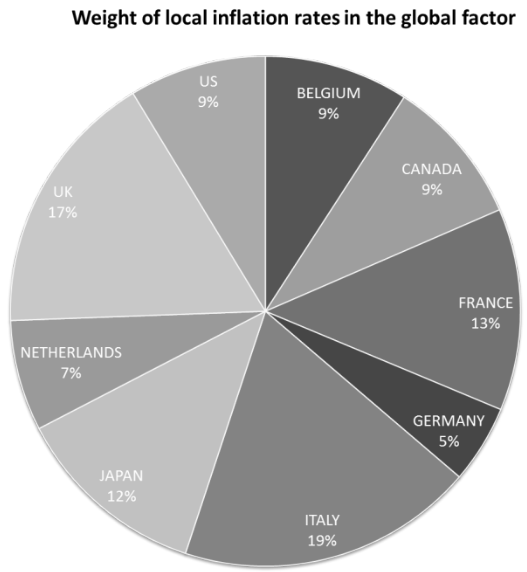


Figure 19: Global output gaps

This Figure shows the output gaps of the countries in our sample and the extracted global output gap