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Globalization and Monetary Policy: An Empirical Analysis

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Abstract

This paper studies the evolution of comovement in monetary policy of the G-7 countries during the period 1980-2009. I estimate a Taylor rule for each country and use the residuals from the Taylor rule to estimate a Bayesian dynamic latent factor model allowing for common and Europe specific components. I quantify the importance of the G-7 factor in explaining the residual of the Taylor rule, and show that the G-7 factor plays a very important role during the period of globalization (1988- 2003). I esimate the time path of the importance of the G-7 factor using rolling sub-samples, and show that both trade-openness and financial integration increase comovement in monetary policy. (JEL classification: F42, E52).

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1 Introduction

Globalization is increasing the links between the world's economies, particularly through trade flows and capital markets. For example, the cumulative increase in the volume of world trade is almost three times larger than that of world output since 1960. More importantly, there has been a striking increase in the volume of international financial flows during the past two decades as these flows have jumped from less than 5% to approximately 20% of GDP of industrialized countries.[1] Does such a dramatic increase in global interdependence mean that international policy coordination is now a necessity for effective policy making?

This question has given rise to a lively debate among academic economists and policymakers.[2] The popular press joined this debate during the recent economic crisis when all major central banks announced coordinated cuts in interest rates to halt the first global recession since the Great Depression. Many pundits were quick to announce that there is little coordination beyond synchronization of the time of announcement.[3] This paper is an empirical investigation into the question: is there any evidence of increased global comovement in monetary policy with the growing importance of global trade and financial links?

In order to answer this question I examine the changes in the nature of monetary policy coordination by employing a Bayesian dynamic latent factor model to estimate a common component in the monetary policy instrument of the G-7 countries. I first estimate a country-by-country Taylor rule allowing for current output gap, inflation stabilization and interest rate smoothing. I estimate a dynamic latent factor model on the residual of the Taylor rule using Bayesian posterior simulation techniques. My two-step empirical strategy allows me to analyze the effect of globalization on monetary policy beyond the effects of globalization on output gap and inflation.[4]

[1] See Kose, Otrok, and Whiteman (2008), Lane and Milesi-Ferretti (2007) for reference.

[2] See Brooks, Frobes, Imbs, and Mody (2003), Taylor (2008), Bernanke (2007), and Rogoff (2006) for example.

[3] See Dougherty and Andrews (2008, NY Times), Buiter (2008, Financial Times).

[4] Monetary policy has the stated objective of output and inflation stabilization. As long as global factors affect output and inflation processes of domestic economies, naturally monetary policy would be influenced

In the dynamic factor model, I allow for a G-7 factor that affects all the countries in my sample and a Europe factor that affects only the European countries. The European countries have the same central bank for almost one- third of my sample period. Their short term interest rates are naturally more coordinated over this period. I incorporate the Europe factor to allow for this effect.

Both the G-7 factor and the Europe factor are very well- identified in the estimation. I calculate variance decomposition that characterizes the fraction of variance of the residual of the Taylor rule that is attributable to the G-7 factor, and consider this fraction as the relevant measure of importance of global coordination in monetary policy. The G-7 factor explains a significant fraction (on average 18% over the entire sample) of variation in monetary policy.[5]

I provide a systematic examination of the evolution of monetary policy coordination over different periods. In particular, I use two approaches to analyze the evolution of global coordination. First, I consider the period from 1980 to the present as being composed of three different sub-periods and estimate factor models for each sub-period. The first sub-period, 1980-1987, witnessed a set of common shocks associated with sharp fluctuations in oil prices and severely contractionary monetary policy in major industrial economies. The second period, 1988-2003, represents the globalization period that witnessed dramatic increases in the volume of cross-border trade in goods and assets. The third sub-period, 2004-2009, coincides with a brief period of globalization followed by a period of significant asset price volatility, global recession and trade-collapse. These demarcations are useful for differentiating the impact of common shocks from that of globalization on the degree of coordination in monetary policy. The globalization period is associated with a higher degree of global coordination compared to the common shocks and crisis period. Second, I evaluate the time variation in the degree of coordination by estimating factor models using rolling sub-periods. While both approaches lead to broadly similar findings, they provide a more complete characterization of the evolution of global coordination in monetary policy.

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by such global factors. See section 3.2.1 for further discussion on the choice of empirical strategy.

[5] Kose, Otrok, and Whiteman (2008) report similar magnitudes for variation explained by the G- 7 factor for real macroeconomic aggregates.

Importance of the G-7 factor varies significantly across countries and over time. I analyze the effect of globalization, both trade and financial integration, on the time path of global coordination in monetary policy. Trade integration is found to be very important in increasing global coordination for all countries and regions. Financial integration also increases the importance of the G-7 factor in North America. I also analyze contributions of asset price volatility and real effective exchange rate volatility on global coordination. I check robustness of the regression results allowing for possible dependence of globalization and volatility on monetary policy synchronization in a VAR framework.

I also explore alternative interpretations of monetary policy synchronization. Most importantly, countries may synchronize their reactions to inflation and output gap fluctuations. I show evidence of increasing similarity in how central banks of G-7 countries respond to inflation over the sample period. Allowing for synchronized Taylor rules, I show that the G-7 factor plays an even higher role in explaining monetary policy of the G-7 countries.

I discuss the related literature in section 2. I briefly describe the data and the methodology in section 3, relegating the details of the estimation strategy in the appendix. Section 4 presents the estimation results. Section 5 concludes.

2 Related Literature

The existing literature on international dimensions of monetary policy is mainly theoretical and *normative* in nature. For example, Ball (1999), Benigno and Benigno (2006), Corsetti and Pesenti (2004), and Sutherland (2004) build a two country dynamic, stochastic, general equilibrium model and analyze an open economy *optimal* monetary policy problem. Ball (1999) argues that exchange rates should play a role in optimal monetary policy in the open economy in a highly globalized market. Sutherland (2004) concludes that financial market integration leads to a higher gain from global coordination in monetary policy. Benigno and Benigno (2006) argue that optimal monetary policy rules should allow for global effects only through the effect of globalization on domestic output gap and inflation. Corsetti and Pesenti

(2004) show that optimal monetary policy in an open economy Nash equilibrium reduces exchange rate volatility and the gains from international cooperation depend on the exchange rate pass-through. In a related branch of literature, Rogoff (2006) and Taylor (2008) advise policymakers on how to conduct monetary policy in a global economy. These papers also address normative questions like should central banks pay any attention to exchange rate or asset price volatility in a globalized market or should global excess capacity play a role in optimal monetary policy.

This paper, on the contrary, is a *positive* and empirical analysis on monetary policy in the open economy. The questions that I address are whether global factors affect *observed* monetary policy, specifically whether the effect of global factors extend beyond effects on domestic output gap and inflation and whether globalization and volatility affect evolution of the global factor in monetary policy.

This paper is closely related to the empirical literature on global business cycle, particularly Kose, Otrok, and Whiteman (2003, 2008). Kose, Otrok, and Whiteman (2003) employ Bayesian dynamic latent factors and identify global business cycle as a global factor in macroeconomic aggregates of various countries. In a related paper, Kose, Otrok, and Whiteman (2008) analyze the evolution of global business cycle in the G-7 countries by studying the variance explained by the G-7 factor in macroeconomic aggregates using different sub-periods. They conclude that the G-7 factor was most important in the common shocks period, 1973-1986, followed by the globalization period, 1987-2003, and was least important during the Bretton-Woods fixed exchange rate regime, 1960-1972. Stock and Watson (2005) employ a factor-structural VAR model to analyze the importance of international factors in explaining business cycles in the G-7 countries and conclude that comovement has fallen in the globalization period of 1986-2002 compared to the common shocks period in 1960-1985. In this paper I find that global coordination in monetary policy was at least as high in the globalization period (1988-2004) as in the common shocks period (1980-1987). As in Kose, Otrok, and Whiteman (2008), I also obtain a time path of the importance of the G-7 factor for each country by estimating the dynamic factor model using the rolling sub-samples.

Then, I systematically explore the determinants of the importance of the G-7 factor in a manner similar to Imbs (2004) who analyzes the importance of trade openness and financial integration on business cycle synchronization.

A related branch of literature studies the evolution of global inflation, namely whether global factors affect the domestic inflation process. Important papers in this literature are Bianchi and Civelli (2009), Borio and Filardo (2007), and Ihrig, Kamin, Lindner and Marquez (2007). This literature reaches a mixed conclusion regarding effects of globalization on domestic inflation. Bianchi and Civelli (2009), and Borio and Filardo (2007) find evidence in favor of the globalization hypothesis, while Ihrig, Kamin, Lindner and Marquez (2007) find no conclusive evidence in favor of this hypothesis.

Methodologically, this paper is related to the literature on estimation using Bayesian posterior simulation methods (Geweke (1996, 1997), and Kim and Nelson (1999)), particularly Bayesian estimation of dynamic factor models (Justiniano (2004), Otrok and Whiteman (1998), and Kauffmann (2000)). I use Gibbs sampling to estimate the dynamic factor model. Kim and Nelson (1999) illustrate the implementation of Gibbs sampler for static factor models. Kauffmann (2000) and Justiniano (2004) provide details of the estimation when dynamics in factor loadings are introduced.

3 Data and Methodology

3.1 Data

I use quarterly data from the G-7 countries for the period 1980-2009. All quarterly data are seasonally adjusted. I use 3 -month Treasury bill rate as the measure of monetary policy instrument. This short-term nominal interest measure is the standard measure of monetary policy instrument in the literature (see for example, Bianchi and Civelli (2009)).

The real GDP data are first passed through a Hodrick-Prescott filter which defines the potential output for any country. Following Hodrick and Prescott (1997), I set the parameter of the filter to 1600 for the quarterly data. I then compute the output gap for country c as the percentage deviation of the real GDP from the potential,

$$x_{c,\,t} = \frac{\text{real GDP}_{c,\,t}}{\text{potential output}_{c,\,t}} - 1,$$

where $x_{c,\,t}$ stands for output gap of country c at time t. I use quarter to quarter % change in CPI as the measure of inflation. I collect the interest rate, real GDP and CPI data from the International Financial Statistics (IFS) database of IMF.

Following Imbs (2004) and Bianchi and Civelli (2009), I use volume of exports and imports to GDP ratio as the measure of trade-openness. I follow Lane and Milesi-Ferretti (2007) in constructing a measure of financial integration of a country as the ratio of external assets and liabilities to GDP. I collect the exports and imports data from the IFS database of IMF, and I use external assets and liabilities data from Lane and Milesi-Ferretti (2007). The external assets and liabilities data are available only at an annual frequency, and are converted to quarterly data using quadratic interpolation. For robustness checks, I also construct a within-G-7 measure of trade-openness. I use the NBER bilateral trade data from Feenstra et. al (2005). The billateral trade flows data are available at a yearly frequency for the period 1960 to 2000. For each year and for any G-7 country in my sample, I construct a measure of exports to and imports from the rest of the G-7 countries. I convert the yearly data to quarterly frequency using quadratic interpolation, and use this data to construct a measure of within-G-7 trade-openness.[6]

I also use data on real effective exchange rate volatility and stock market volatility. I collect the real effective exchange rate data from the IFS, and the stock market index data from the Global Financial Database (GFD). A broad stock index is chosen to reflect economy-wide asset price volatility. For example, I use S & P 500 Total Return Index for the US.[7]

[6] No such bilateral international financial flows data is publicly available. However, Lane and Milesi-Ferretti (2007) report that most of the world financial flows take place within the advanced industrial economies, particularly the G- 7.

[7] For the rest of the countries I use UK FTSE All Share Return Index, Canada S & P TSX 300 Total Return Index, France SBF-250 Total Return Index, Germany CDAX Total Return Index, Italy BCI Global Return Index, and Japan Nikko All-Japan Return Index.

Monthly stock index data are converted to quarterly frequency using arithmetic averaging. Following Rogoff (2006), I measure volatility as 3-month rolling standard deviation of the month-to-month log change of the corresponding variable.

3.2 Methodology

3.2.1 Empirical Strategy

For each country I estimate a Taylor rule using standard OLS regressions. I allow for an interest-rate smoothing objective of the central bank in addition to output and inflation stabilization objectives in the Taylor rule. The estimating equation is

$$i_{c,\,t} = \alpha_c + \beta_c \pi_{c,\,t} + \gamma_c x_{c,\,t} + \delta_c i_{c,\,t-1} + \epsilon_{c,\,t}, \tag{1}$$

where $i_{c,\,t}$ is monetary policy rate for country c at time t, $\pi_{c,\,t}$ is CPI inflation and $x_{c,\,t}$ is output gap. I estimate a dynamic factor model on the panel of residuals from the Taylor rule. The dynamic factor model is given by

$$\epsilon_{c,\,t} = B_0^c F_t + B_1^c F_{t-1} + .. + B_P^c F_{t-P} + \xi_{c,\,t} = B^c(L) F_t, \tag{2}$$

where F_t is a vector of 2 factors, B_k^c , $k = 1 : P$, is a 1×2 vector of factor loadings for country c at lag k, and $B^c(L)$ is a P-th degree lag polynomial for country c. The factor loadings reflect the degree to which variation in $\epsilon_{c,\,t}$ can be explained by each factor. The first factor (F_t^{G7}) is a G-7 factor affecting all the countries in the sample, the second factor is a Europe (F_t^{EUROPE}) factor affecting only the three European countries. Thus, the assumption in the factor model is that the deviation of the monetary policy from the standard Taylor rule for the G-7 countries can be explained by a common G-7 factor and a Europe factor common to the European countries. The unexplained idiosyncratic errors, $\xi_{c,\,t}$, are assumed to be normally distributed, but possibly serially correlated. They follow Q-order autoregressions,

$$\xi_{c,\,t} = \varphi_0^c \xi_{c,\,t-1} + \varphi_1^c \xi_{c,\,t-2} + .. + \varphi_Q^c \xi_{c,\,t-Q} + \eta_{c,\,t} = \varphi_Q^c(L) \xi_{c,\,t-1}, \tag{3}$$

where φ_j^c , $j = 1 : Q$ are autocorrelation coefficients, and $\varphi_Q^c(L)$ is a lag polynomial of order Q. Notice that all the innovations, $\eta_{c,\, t}$, and the factors are assumed to be zero mean, contemporaneously uncorrelated normal random variables,

$$\begin{aligned} \eta_{c,\, t} &\sim N(0, \sigma_c^2), \\ F_t &\sim N(0, \Sigma). \end{aligned} \tag{4}$$

Thus, Σ is a diagonal matrix with variance of the factors, $\sigma^2_{F_t^{G7}}$ and $\sigma^2_{F_t^{EUROPE}}$, as the diagonal entries. However, the factors affect the relevant variable, $\epsilon_{c,\, t}$, with P lags.[8] Also, the idiosyncratic errors are orthogonal to the factors. The time paths of the factors $\{F_t\}$, the factor loadings B_k^c, the autocorrelation coefficients φ_j^c, the error variances σ_c^2, and the factor variances $\sigma^2_{F_t^{G7}}$ and $\sigma^2_{F_t^{EUROPE}}$ are jointly estimated. Importance of the G-7 factor is measured as

$$IMPG7_c = \frac{\sum_{k=1}^{P} B_k^c(1,1)^2 * var(F_t^{G7})}{var(\epsilon_{c,\, t})}, \tag{5}$$

where $var(.)$ is the measured variance of the relevant variable.

It is imperative to understand the economic logic behind fitting the dynamic factor model on the residual from the Taylor rule. It is well-documented that global factors affect domestic output and inflation and to the extent that monetary policy aims at output and inflation stabilization, monetary policy is affected by global factors. The question that I address here is whether central banks synchronize their policy reactions beyond the influence of global factors on domestic output and inflation. The optimal monetary policy literature

[8] An alternative assumption would be that the factors affect $\epsilon_{c,\, t}$ only contemporaneously, but the factors have autoregressive representation. While these two assumptions are equivalent theoretically, the assumption made in this paper, lags in factor loadings and no autoregression in factors, allows for simpler estimation technique following Justiniano (2004). Kose, Otrok and Whiteman (2003, 2008) employ the alternative assumption. It would be tempting to combine dynamics in the factor loadings with autoregressions in the factors themselves, resulting in generalized factor models. This approach, however, can result in difficulties in the estimation due the problem of common roots in ARMA models. See, for example, Quah and Sargent (1993).

(for example, Benigno and Benigno (2006) and Corsetti and Pesenti (2004)) unanimously argues that monetary policy should take into account global factors when those factors affect domestic output and inflation. The debate there is whether monetary policy should take into account global factors beyond their effects on output and inflation in the face of rapid and dramatic increases in globalization. Thus, the positive approach pursued here parallels the approach in the normative literature.

3.2.2 Estimation Strategy

Estimation of the dynamic factor model requires further identification and normalization assumptions. Identification denotes exclusion restrictions with the aim of interpreting the factors as representing shocks of different nature. Here, the identification assumption is that the Europe factor, F_t^{EUROPE}, does not affect the non- European countries. This is meant to capture the fact that the three European countries in the sample, France, Germany and Italy, have a common central bank. Hence,

$$B_k^c(1,2) = 0,$$

for c= USA, Canada, UK, and Japan, and for all k. Following Justiniano (2004) and Kose, Otrok, and Whiteman (2007), I normalize the contemporaneous factor loading of the US for the G-7 factor and the contemporaneous factor loading of France for the Europe factor to unity,

$$B_0^{US}(1,1) = 1,\ B_0^{FRANCE}(1,2) = 1.$$

This assumption helps us identify the scales and signs of the factors separately.[9]

Because the factors are unobservable, special methods must be employed to estimate the model. I employ Bayesian posterior simulation techniques to estimate the dynamic

[9] The choice of countries is essentially arbitrary. In any particular ordering of the countries, one can normalize contemporaneous factor loading for the first country to fix the scale of the G- 7 factor, and can normalize contemporaneous factor loading for the first European country to fix the scale of the Europe factor. See Justiniano (2004) for further discussion on normalization assumptions.

latent factor model. The estimation procedure builds on the following key observation: if the factors were observable, under a conjugate prior the models (2)- (4) would be a simple set of regressions with Gaussian autoregressive errors; that simple structure can in turn be used to determine the conditional normal distribution of the factors given the data and the parameters of the model. Then it is straightforward to generate random samples from this conditional distribution, and such samples can be employed as stand-ins for the unobserved factors. Because the full set of conditional distributions is known– parameters given data and factors, factors given data and parameters– it is possible to generate random samples from the joint posterior distribution for the unknown parameters and the unobserved factors using a Markov Chain Monte Carlo procedure. In particular, given arbitrary starting values of $(\{F_t\}_0, \Sigma_0, \{B_k^c\}_0, \{\varphi_j^c\}_0, \{\sigma_c^2\}_0)$, in iteration 1 I draw the factors $\{F_t\}_1$, conditional on $(\Sigma_0, \{B_k^c\}_0, \{\varphi_j^c\}_0, \{\sigma_c^2\}_0)$; then draw the factor variance Σ_1, conditional on $(\{F_t\}_1, \{B_k^c\}_0, \{\varphi_j^c\}_0, \{\sigma_c^2\}_0)$; then draw the factor loadings $\{B_k^c\}_1$, conditional on $(\{F_t\}_1, \Sigma_1, \{\varphi_j^c\}_0, \{\sigma_c^2\}_0)$; then draw the AR coefficients $\{\varphi_j^c\}_1$, conditional on $(\{F_t\}_1, \Sigma_1, \{B_k^c\}_1, \{\sigma_c^2\}_0)$; and finally, draw the error variances $\{\sigma_c^2\}_1$, conditional on $(\{F_t\}_1, \Sigma_1, \{B_k^c\}_1, \{\varphi_j^c\}_1)$. The process is iterated a large number of times. This sequential sampling of the full set of conditional distributions is known as Gibbs sampling.[10] Under regularity conditions satisfied here, the Markov chain so produced converges, and yields a sample from the joint posterior distribution of the parameters and the unobserved factors, conditioned on the data. I provide additional details of the Gibbs sampling procedure in the appendix.

In my implementation, the lag in factor loadings (P) and the length of idiosyncratic autoregressive polynomial (Q) are both 1. I follow Kose, Otrok, and Whiteman (2008) to specify the prior distributions. The prior on all the factor loading coefficients and the autoregressive parameters is N(0, 1). The prior assumption on the factor loadings reflect the expectation that on average the factors do not affect the residuals from the monetary policy rule. The prior on the error variances and the factor variances is Inverted Gamma (6, 0.001), which is very diffuse. A diffuse prior allows for considerable uncertainty regarding

[10]See Kim and Nelson (1999) and Geweke (1996, 1997) for reference.

the parameter of interest.[11]

4 Results

First, I present the estimation results for the full sample period 1981:1-2009:4. Figure 1 displays the median of the posterior distribution of the G-7 factor, along with the 5% and 95% quantile bands. The G-7 factor is estimated quite precisely as is evident from the narrowness of the bands.

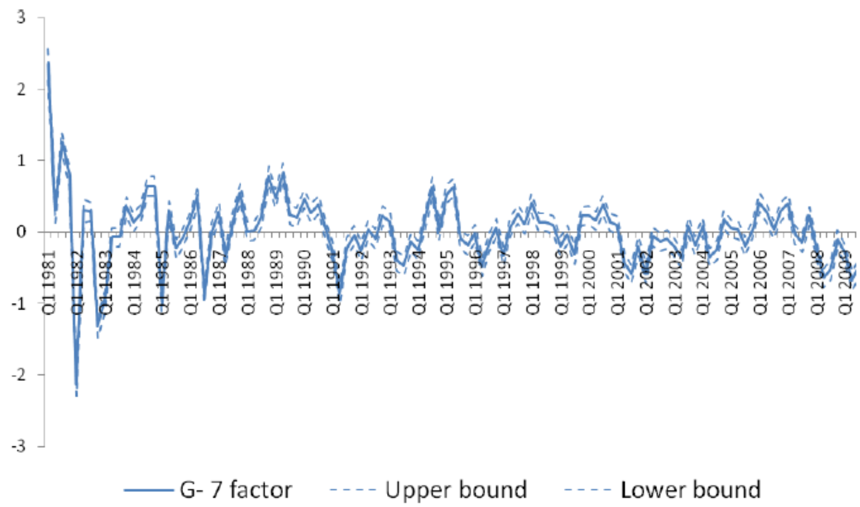

Figure 1: Estimated G-7 factor.

More importantly, the G-7 factor is able to capture the general trend of monetary policy in the G-7 countries. In Figure 2 I plot the G-7 factor (the solid line) along with the average Treasury bill rate of the G-7 countries (the dash-dot line) and the US Treasury bill rate (the dashed line). All the series are normalized to unity at the beginning of the period in 1981:1. The G-7 factor tracks the development of the Treasury bill rates quite well.[12]

[11] Despite such a loose prior, the variance parameters are well-identified in the data, as Table 4 and Table 5 in the appendix demonstrate.

[12] Correlation between average G-7 interest rate and the G-7 factor is .25, and correlation between US Treasury bill rate and the G-7 factor is .34. The correlations are quite high considering that the G-7 factor is estimated using residuals from the standard Taylor rule.

For example, contractionary monetary policy of the early 1980's, expansionary monetary policy after the dot- com bubble in 2001 for a prolonged period and the world-wide cut in interest rates during the recent crisis in 2007-2009 period are well captured by the G-7 factor. Rogoff (2006) argues that central banks should take into account extreme asset price volatility, even though at normal times it is better not to pay much attention to stock market fluctuations. Thus, it is worth emphasizing that even after I purge the response of monetary policy instruments to output gap and inflation, the G-7 factor still displays a declining trend during the recent crisis period marked by extreme volatility in the global asset markets.[13]

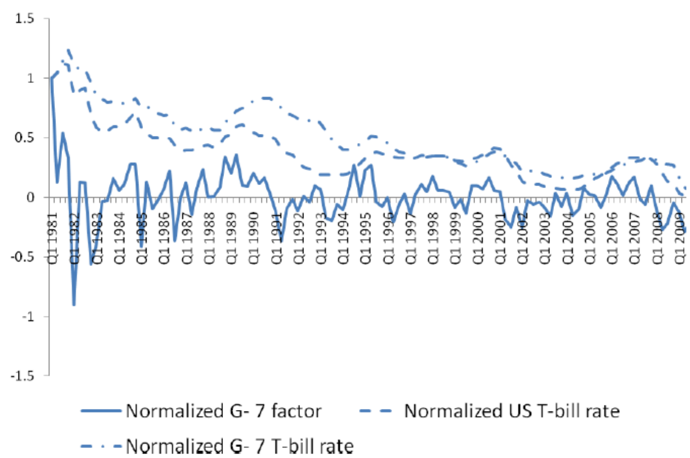

Figure 2: The G-7 factor and Treasury bill rates of the US and the G-7 countries.

In the appendix I present the estimated Europe factor and the rest of the parameters (factor loadings, autoregressive parameters, and factor and error variances) along with relevant error bands. In Figure 3 I present the estimated G-7 factor (the solid line) and the estimated Europe factor (the dashed line). While the Europe factor and the G-7 factor display some comovements, there is significant variation in the time paths of the two factors in every decade. This justifies incorporating two different factors to explain the regional and the G-7 wide comovements in monetary policy.

[13]See Roubini and Mihm (2010) for a discussion on stock market volatility during the 2007- 2009 crisis.

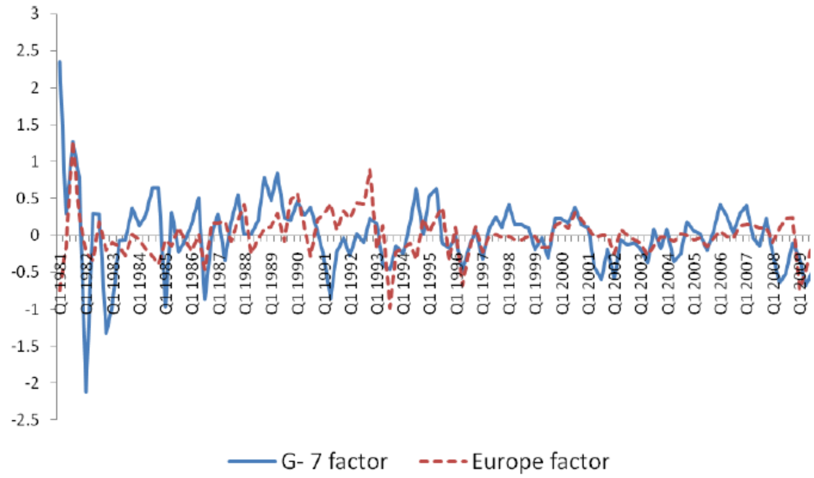

Figure 3: G-7 factor and Europe factor.

I estimate the variance decomposition as described in (5) to measure the contribution of the G-7 factor in explaining the residual of the Taylor rule. Figure 4 displays the variation explained by the G-7 factor over the entire sample. The estimated contribution is approximately 20% for the US, UK, Germany, France and Italy, and is above 35% for Canada. Japan appears to be an outlier with very little contribution from the G-7 factor. While contribution of the G-7 factor varies significantly across time for the rest of the countries, Japan is little affected by the G-7 factor in any sub-sample. This may reflect that events specific to Japan, a period of strong growth in the 1980's followed by the collapse of Japanese asset price bubble and a prolonged recession, have influenced Japanese monetary policy significantly more than the global shocks. Japan also stands out from the rest of the G-7 countries in terms of global business cycle.[14]

[14] See for example, Kose, Otrok, and Whiteman (2008) and Doyle and Faust (2005) for evidence that the global factors affected little of real economic activity in Japan over this sample period.

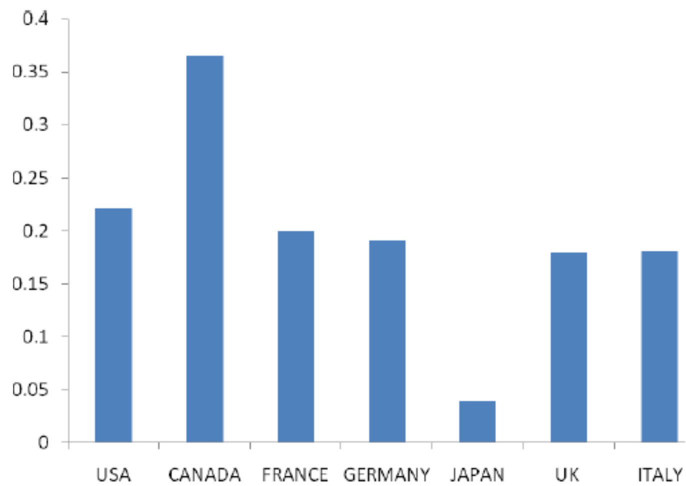

Figure 4: Variation explained by the G-7 factor, 1981-2009.

Do we observe an increased importance of the G-7 factor with increase in globalization? To analyze this key question, one needs to distinguish periods in which the countries experience common shocks from periods in which the countries become more integrated through global trade and financial linkages. I divide the sample period into three sub-samples: the oil-price shock and contractionary monetary policy period (1980-1987), the globalization period (1988-2003), and the housing bubble and crisis period (2004-2009), and estimate the dynamic factor model ((2)- (4)) separately for each sub-sample. Kose, Otrok, and Whiteman (2008) also consider the 1980-1987 period as a period in which the industrialized countries experienced common shocks in the oil prices, and followed overtly contractionary monetary policy. They also estimate their dynamic factor model using real variables separately for this period to distinguish this period as a time of global shocks. Roubini and Mihm (2010) elaborate that the US housing bubble started building in 2004, reached it's peak in 2005-2006, and collapsed in 2007 ushering in global stock market turmoil and recession. On the other hand, the period 1988-2003 is associated with unprecedented increases in global linkages in goods and asset markets. Over this period, average trade openness of G-7 countries increase by 50% from .3 to .45, while the average financial integration measure increase by 150%. Thus, my breakdown of the sample period into the three sub-samples essentially allows me to separately analyze a common shock period, followed by a period of rapid globalization, and another common shock period.

From the estimated parameters and factors from each sub-sample I compute the country- specific contribution of the G-7 factor in different sub-samples. In Figure 5, I display the contribution of the G-7 factor in different sub-samples on average for the G-7 countries and for the US.

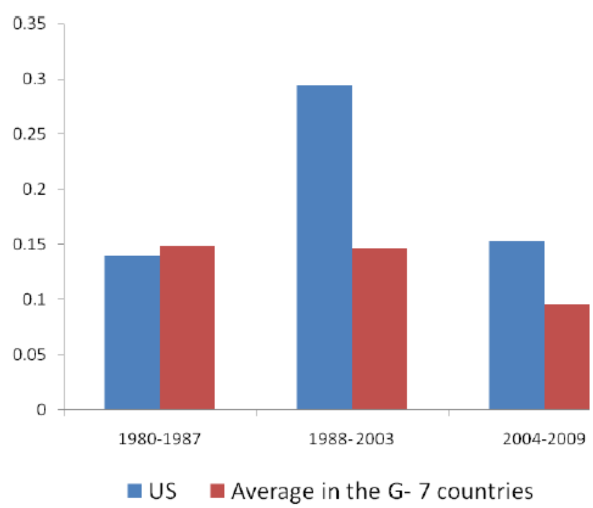

Figure 5: Variation explained by the G-7 factor, different sub-samples.

On average, the G-7 factor explains approximately 14% both in the early common shock period and in the globalization period, and less (9%) in the recent crisis period. For the US, the G-7 factor explains a significantly higher % of variation in the globalization period, compared to either the common shock period or the crisis period. This result is different from the global business cycle literature. Both Kose, Otrok, and Whiteman (2008) and Stock and Watson (2005) analyze the global business cycle for the G-7 countries. They find that the contribution of the G-7 factor was higher in the common shocks period of the early 1980's. Thus, globalization increases global coordination in monetary policy even more than real comovement in macroeconomic aggregates.

To explore this result further I estimate the factor models using 7-year rolling sub-periods incremented by a quarter. In other words, I roll the start and end dates forward by a quarter for each sub-period after each estimation. Figure 6 reports the variation explained by the G-7 factor in the two North American countries. In Figure 6, the solid line corresponds to the US, and the dashed line displays the case for Canada. Figure 7 reports the variation explained by the G-7 factor in the three European countries. In Figure 7, the solid line represents France, the dashed line stands for Germany, and the dash-dot line corresponds to Italy.

Figure 6: Variation explained by the G-7 factor in North America, using rolling sub-sample.

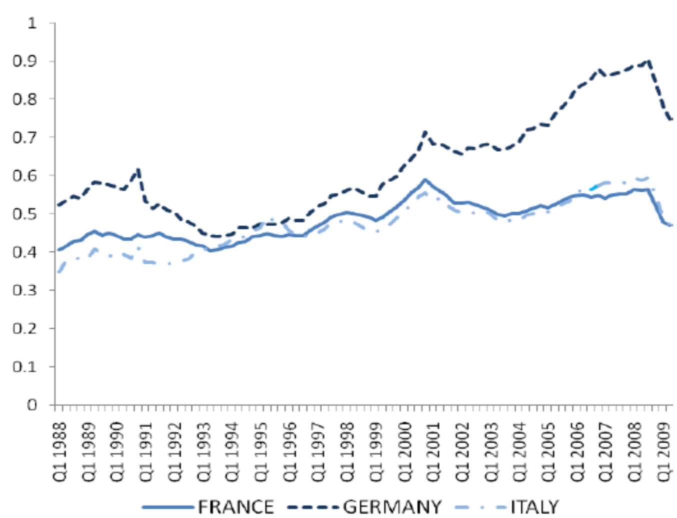

Figure 7: Variation explained by the G-7 factor in the European countries, rolling sub-samples.

The estimation results obtained from rolling sub- samples reveal a finer nature of time variation in the importance of the G-7 factor. In the first half of the 1990's, included in my globalization sub-sample (1988-2003), the G-7 factor is less important than the common shocks period in the early 1980's. However, the degree of global coordination increases rapidly beginning the late 1990's. The recent crisis period actually shows a trend of slight decline in the variation explained by the G-7 factor. The three European countries display very similar time path of the importance of the G-7 factor throughout the sample.

Estimation using rolling sub- samples allows me to explore systematically determinants of the importance of the G-7 factor over time and across countries. I estimate the following regression equation,

$$\begin{aligned} IMPG7_{c,\,t} &= \theta_c + \lambda_1 trade\_int_{c,\,t} + \lambda_2 fin\_int_{c,\,t} + \lambda_3 REER\_vol_{c,\,t} \\ &\quad + \lambda_4 stock\_vol_{c,\,t} + \nu_{c,\,t}, \end{aligned} \tag{6}$$

where $IMPG7_{c,\,t}$ is the importance of the G-7 factor for country c in a sub-sample of 7 years ending at time t, $trade\_int_{c,\,t}$ is a measure of trade integration for country c in a sub-sample of 7 years ending at time t, $fin\_int_{c,\,t}$ is a measure of financial integration for country c in a sub-sample of 7 years ending at time t, $REER\_vol_{c,\,t}$ is a measure of real effective exchange rate volatility for country c in a sub-sample of 7 years ending at time t, and $stock\_vol_{c,\,t}$ is a measure of stock market volatility for country c in a sub-sample of 7 years ending at time t. Here, θ_c is a country specific fixed effect, and $\nu_{c,\,t}$ is idiosyncratic error. The integration and volatility measures for a sub-sample are obtained as arithmetic average of quarterly integration and volatility measures for that sub-sample. The main question of this paper is to assess effects of globalization, namely trade and financial integration, on the importance of the G-7 factor. I include the volatility measures in the regression since whether asset price and exchange rate volatility affect global coordination in monetary policy is a pertinent question in the literature. For example, Taylor (2008) argues that central banks should not attempt to stabilize asset prices or exchange rates while Corsetti and Pesenti (2004) argue that reducing exchange rate volatility should be a part of optimal monetary policy rule in the open economy.

	G- 7	North America	Europe	G- 7	North America	Europe
trade_int	0.291	0.549	0.556			
	(4.03)**	(2.49)*	(5.05)**			
trade_int_G- 7				1.435	8.41	20.111
				(5.03)**	(6.54)**	(9.17)**
fin_int	0.009	0.249	0.005	0.02	2.233	0.057
	(-1.38)	(4.71)**	(-0.65)	(-1.3)	(7.04)**	(2.48)*
REER_vol	-102.308	-1,237.92	-189.242	-93.512	563.133	376.173
	(-2.38)*	(-3.72)**	(-5.38)**	(-2.48)*	(-0.7)	(2.52)*
stock_vol	-8.25	129.095	2.986	16.514	424.711	-615.386
	(-1.47)	(2.66)**	(-0.68)	(3.27)**	(-0.64)	(-0.5)
Observations	560	160	240	364	104	156
R-squared	0.54	0.54	0.45	0.75	0.79	0.79
Value of t statistics in parentheses						
* significant at 5%; ** significant at 1%						

Table 1: Regression results to analyze determinants of the importance of the G-7 factor.

The regression results are presented in Table 1. The column headings refer to regression results using data from the corresponding set of countries. In all cases trade-integration significantly increases the variation explained by the G-7 factor. I check the robustness of this result using trade-openness measure within G-7 countries, denoted as trade_int_G-7. Financial integration increases the variation explained by the G-7 factor only for North America. The results strongly support the globalization hypothesis, namely countries increasingly coordinate their domestic policies, in this case monetary policies, in an increasingly globalized world. Real effective exchange rate volatility reduces the importance of the G-7 factor, while stock volatility increases its importance in North America.

However, it is relatively difficult to give causal interpretation to the contemporaneous correlations observed in Table 1. Globalization may also be the result of coordinated policies across countries. Similarly, it is possible that central banks coordinate to reduce exchange rate volatility and hence the correlation observed in the regression actually implies a reverse causation. Or, central banks make correlated mistakes (since the relevant variable in the factor model is the residual from the Taylor rule) which exacerbates asset price volatility. To allow for these possibilities of reverse causation, I estimate a reduced form

VAR model on $(trade\_int_{c,\,t},\ fin\_int_{c,\,t},\ REER\_vol_{c,\,t},\ stock\_vol_{c,\,t},\ IMPG7_{c,\,t})$. Any particular ordering of the variables in a VAR reflect the assumption that a variable contemporaneously affects the variables below it in the ordering, and affects all the variables with a lag. For example, in this particular ordering monetary policy synchronization, as measured by $IMPG7_{c,\,t}$, affects both globalization variables and volatility variables only with a lag. In Figure 8, I report the impulse response of the synchronization measure to trade-openness from the VAR estimated with three lags for each variable. In Figure 9, I report the impulse response of the synchronization measure to financial integration from the same VAR. The dotted lines correspond to the 5% and 95% error bands, and the solid line represents the median impulse response. In both cases, the responses are positive and significant for at least first 10 periods, and then converge to zero. I have checked robustness of the results by estimating the VAR with different lags and by changing the order of the variables. While the magnitudes of the responses vary, the positive and significant nature of the responses remain unchanged. Thus, it is safe to interpret these results as central banks increasing coordination in their monetary policies in the face of rapid and dramatic globalization.

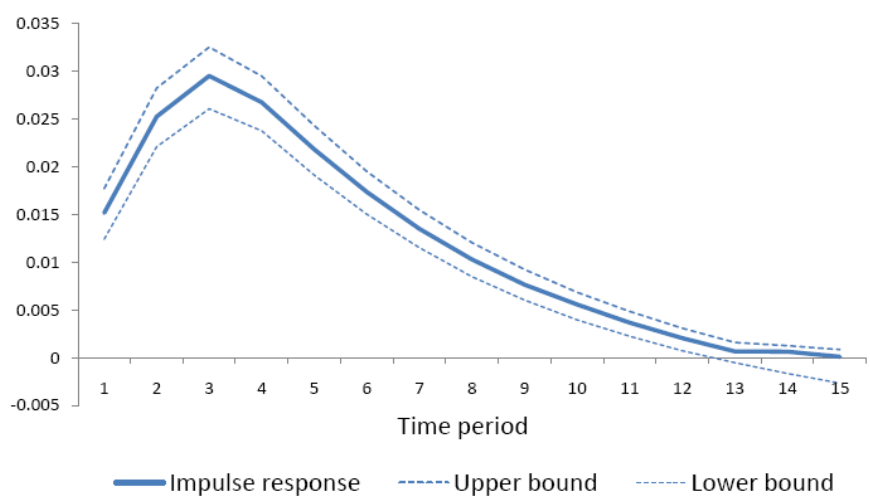

Figure 8: Impulse response of monetary policy synchronization to trade-openness.

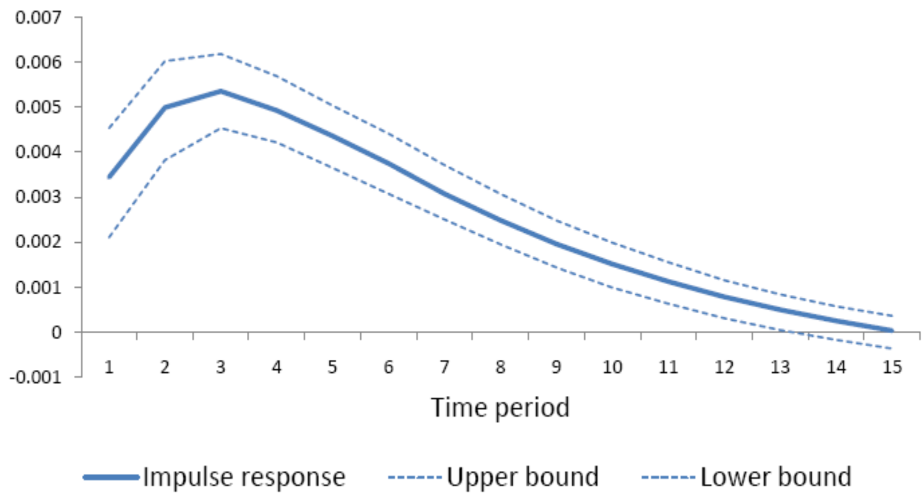

Figure 9: Impulse response of monetary policy synchronization to financial integration.

So far, I have considered a particular empirical interpretation of monetary policy synchronization. It is important to acknowledge that there can be different ways of capturing such synchronization. For example, central banks may choose to synchronize their systematic reaction to output gap and inflation fluctuations. This can be captured by Taylor rules that become increasingly similar over time with increases in globalization. I estimate a separate Taylor rule (1) for each of the G-7 countries using my rolling sub-samples. For any coefficient in the Taylor rule, I construct variance across the G-7 countries over that corresponding sub-sample. In Figure 10, I plot the time path of the variance of the inflation and the output gap coefficients of the Taylor rule. The solid line corresponds to the variance of the inflation coefficient (the inflation coefficient is denoted by β in equation (1)), and the dashed line corresponds to the variance of the output gap coefficient (the output gap coefficient is denoted by γ in equation (1)). Evidently, the G-7 countries are increasing responding in a similar manner to inflation, as represented by a steady decline in the variance of the inflation coefficient of the Taylor rules of the G-7 countries. The variance of the output gap coefficient also shows a declining trend towards the end of the sample period, even though not quite as evident as the inflation coefficient. This evidence points towards increasing similarity in systematic responses to inflation and output gap of the central banks of the G-7 countries.

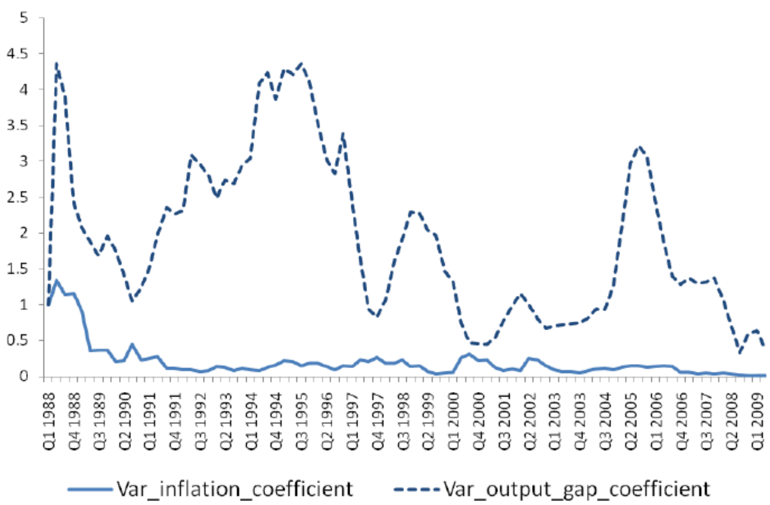

Figure 10: Time path of the variance of the inflation and the output gap coefficients, using rolling sub-samples.

What is the implication for the importance of the G-7 factor , if I allow for monetary policy synchronization in the Taylor rules themselves? I estimate a common Taylor rule for all the countries, and use the residual from this common rule to estimate the dynamic factor model consisting of equations (2) to (4). In Figure 11, I show the variance explained by the G-7 factor using residuals from the common Taylor rule. Comparing with Figure 4 which reports the variance explained by the G-7 factor using residuals from country specific Taylor rules, the importance of the G-7 factor has increased substantially for all the countries except Japan. On average, the G-7 factor explains 30% of the residual variation in monetary policy instruments when common Taylor rules are used to calculate the residual, as opposed to 18% when country specific Taylor rules are used. I checked robustness of this result in various ways. First, I allow only a common inflation coefficient across countries instead of a Taylor rule with all common coefficients. Second, I allow a Taylor rule that is common among the European countries, and allow rest of the countries to have their country-specific Taylor rules. The results remain fairly unchanged. In my rolling sub-sample estimations, I also use country-specific Taylor rules for all countries except for the European countries starting 1999, the year in which the common central bank across Europe was established, and check the regression results for (6). As before, both trade-openness and financial integration increase the importance of the G-7 factor significantly.

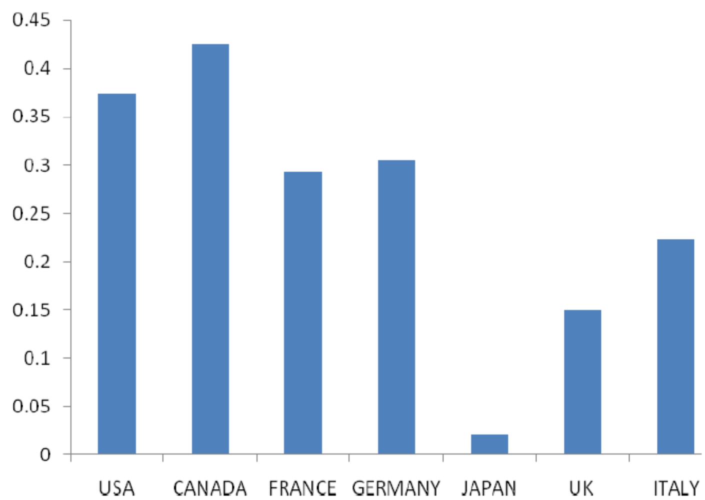

Figure 11: Variance explained by the G-7 factor using a common Taylor rule, 1981-2009.

Thus, there is robust and conclusive evidence that increasing global linkages in both goods and asset markets increase synchronization in monetary policy. I interpret this as central banks increasingly coordinating their policy reactions. However, it is important to acknowledge that an increase in the importance of the G-7 factor may also reflect increasing similarity in monetary policy implementation with increases in globalization.

5 Summary and Conclusion

I study changes in the nature of coordination in monetary policy among the G-7 countries over time by estimating common dynamic components in monetary policy. In particular, I employ a Bayesian dynamic latent factor model and decompose the residual from the Taylor rule into a G-7 factor, a Europe factor, and idiosyncratic components.

I first show that the G-7 factor is very well-identified and tracks the evolution of monetary policy in the G-7 countries. I document that the G-7 factor is able to explain a sizable variation in monetary policy that was left unexplained by the Taylor rule. The G-7 factor, in particular, assumes an important role during the period of rapid globalization beginning in late 1990's. I also estimate the dynamic factor model using rolling sub-samples and analyze the effect of trade integration and financial integration on global comovement in monetary policy. Both goods and asset market integration is shown to increase comovement in monetary policy, with trade openness playing a very important role.

The period of globalization coincides with an increased importance of the emerging countries in the world economy. Do we observe an increased comovement of monetary policy incorporating the emerging countries in the analysis? What is the cross-section pattern of importance of the global factor comparing emerging and advanced economies? I would like to answer these questions in a future extension incorporating the G-20 countries. Also, channels through which trade-openness influences global coordination in monetary policy demand further scrutiny.

6 Appendix

6.1 Estimation Strategy: Gibbs Sampling

In this section I discuss the estimation strategy of the dynamic factor model in detail. The dynamic factor model consisting of equations (2) to (4) can be written in stacked form, by stacking observations across series for a given period of time, such that, for any t equation (2) becomes

$$\epsilon_t = B\overline{F}_t + \overline{\xi}_t, \tag{7}$$

where ϵ_t corresponds to the stacked column vector of ϵ_t^{US}, ϵ_t^{CANADA}, ϵ_t^{FRANCE}, $\epsilon_t^{GERMANY}$, ϵ_t^{JAPAN}, ϵ_t^{UK}, and ϵ_t^{ITALY}. The stacked matrix of factor loadings,

$$B = (B_0\ B_1\ ...\ B_P)$$

is of dimension 7 X 2(P+1), and it is made up of the submatrices B_k which at lag k, for k=1, .., P are given by

$$B'_{s[7X2]} = [B_k^{US\prime}\ B_k^{CANADA\prime}\ ..\ B_k^{ITALY\prime}] \tag{8}$$

such that for any c B_k^c is a 1X2 vector of factor loadings. The vector of contemporaneous and lagged factors correspond to

$$\overline{F}_{t[2(P+1)X1]} = (F_t'\ F_{t-1}'\ ..\ F_{t-P}').$$

Also, equation (3) can be written in stacked form as

$$\overline{\xi}_t = \Phi\overline{\xi}_{t-1} + \overline{\eta}_t, \tag{9}$$

with $\overline{\xi}_t$ corresponds to the stacked column vector of ξ_t^c, Φ is a square matric of dimension 7 and $\overline{\eta}_t$ is a column vector obtained by stacking η_t^c. The dynamic factor model stacked by series is given by equations (7) and (9). Note that the assumption in (4) implies that the variance covariance matrix of innovations $\overline{\eta}_t$ is a diagonal matrix Σ_η with c-th diagonal entry being σ_c^2.

Let $\Gamma = \{B,\, \Sigma_\eta, \Sigma,\, \Phi\}$ represent the hyperparameters of the stacked model given by equations (7) and (9). In addition, $\epsilon^T = \{\epsilon_{1,}\ \ .., \epsilon_T\}$ denotes the full realization of the data and similarly $F^T = \{F_{1,}\ \ .., F_T\}$ stands for the history of the factors.

Bayesian inference is based on the posterior distribution, denoted by Π, of the hyperparameters and factors conditional on the data, $\Pi(F^T, \Gamma|\epsilon^T)$. Let $\varpi(.)$ represent a prior distribution, $L(\epsilon^T|\Gamma)$ the likelihood, and finally (at a slight abuse of notation) $\Gamma_{-\gamma}$ the set of hyperparameters obtained by excluding the block of parameters Γ_γ from Γ. Notice that there are four parameter blocks present in the dynamic factor model, $\{B,\, \Sigma_\eta, \Sigma,\, \Phi\}$, and also the latent factors F^T are estimated.

The premise behind Gibbs sampling is that even if $\Pi(F^T, \Gamma|\epsilon^T)$ is intractable to analyze, the conditional densities of the parameter blocks may have standard forms under suitable conjugate priors. These conditional distributions can therefore be sampled iteratively to obtain an accurate approximation of the joint posterior and marginal ordinates of interest, which are referred to as target densities.

At any given iteration, therefore, the Gibbs algorithm obtains a sample from the full contional distribution of each parameter block (conditional on ll other hyperparameters, factors, and data). Newly generated values are used in the next iteration to sample once again from these conditional distributions and represent a sample from the joint posterior density. Repeating this process several times the simulated draws are used to characterize the target densities.

Before proceeding to detailed discussion of the sampling technique, I adopt two notational simplifications. First, the dependence of all conditional densities on ϵ^T is implicit and I ommit it from the notation. Second, in discussing the steps involved in the Gibbs sampler, the conditional ordinates are written without reference to the superscript g which indicates the current iteration of the chain. Only at the beginning and at the end of each step, the iteration superscript is introduced to clarify to which iteration do the differing conditioning elements belong to.

Suppose that the sampler has completed iteration $g-1$, producing a set of conditional draws given by $\{F^{T,g-1}, \Gamma^{g-1}\}$. At the current iteration g, a new set of simulated values for factors and hyperparameters $\{F^{T,g}, \Gamma^{g}\}$ is obtained with the following five steps.

In step 1, I draw the factors $F^{T,g}$, conditional on Γ^{g-1}. Conditional on Γ, a new sample of the whole history of unobservable factors, F^T, can be infered using the Kalman filter. The model is first cast in the state space form. Equation (2) is written as

$$\epsilon_{c,\ t}(1 - \varphi^c_Q(L)) = \epsilon^*_{c,\ t} = H^c(L)F_t + \eta^c_t,$$

where $H^c(L)$ is a 1X 2 vetor of lag polynomial and is given by $B^c(L)(1 - \varphi^c_Q(L))$, and it is therefor of the order P+Q. The measurement equation follows, therefore, from stacking the observations by series

$$\epsilon^*_t = (H_0\ H_1, .., \ H_{P+Q})\overline{F}_t + \overline{\eta}_t. \tag{10}$$

Similarly, stacking lagged values of the factors I obtain the transition equation of the state space representation

$$\overline{F}_{t+1} = G\overline{F}_t + M\zeta_{t+1}, \tag{11}$$

with

$$\zeta'_{t+1[2*(1+P+Q)X1]} = (F'_{t+1},\ 0')$$

and G is a square matrix of order 2(1+P+Q) and is given by

$$G = \begin{bmatrix} 0_{2X2} & 0_{2X2(P+Q)} \\ I_{2(P+Q)} & 0_{2X2} \end{bmatrix}.$$

Here I is identity matrix. M is also a square matrix of order 2(1+P+Q) and is given by

$$\begin{bmatrix} I_K & 0 \\ 0 & 0 \end{bmatrix}.$$

Conditional on Γ, a full history of stacked factors is inferred by initializing the Kalman filter with a draw from the unconditional distribution of the factors and applying the standard prediction and updating formulas of the forward Kalman filter. The formulas for sampling with a singular M matrix as is the case here, and further details can be found in Kim and

Nelson (1999). At iteration g therefore, a new history of factors, $F^{T,g}$, is generated by drawing F_t^g recursively backward from the posterior distribution of $\Pi(F_t^g |\ F_{t+1}^g, \Gamma^{g-1})$.

At second step, I draw the facto variance Σ^g, conditional on $F^{T,g}$. Conditional on the simulated factors, for each factor the conjugate prior for the factor variances, $\varpi(\sigma_f^2|F^T)$, f= G- 7 and Europe, is given by an inverse gamma distribution with d_f^0 degrees of freedom and scale parameter v_f^0, written as $IG(\frac{d_f^0}{2}, \frac{v_f^0}{2})$. The posetrior density is given by

$$\Pi(\sigma_f^2|F^T) = IG(\frac{d_f^1}{2}, \frac{v_f^1}{2}),$$

where $d_f^1 = d_f^1 + T - P$, and $v_f^1 = v_f^1 + (F_f^T)' F_f^T$. Here, F_f^T stands for the history of factor f. Therefore, at iteration g, conditional on $F^{T,g}$ a new Σ^g is drawn.

At third step, I draw the factor loading B^g, conditional on $\{F^{T,g}, \Sigma^g, \Phi^{g-1}, \Sigma_\eta^{g-1}\}$. To sample the factor loadings, multiply equation (2) by the lag-polynomials and define a set of factors

$$F_{c,t}^* = (1 - \varphi_Q^c(L))F_t.$$

Now I can rewrite equation (2) as

$$\epsilon^*{}_{c,t} = (B_0\ B_1, .., B_P)\overline{F}^*_{c,t} + \eta_{c,t}. \tag{12}$$

Inference on factor loadings in equation (12) follows the analysis of a linear regression equations with Gaussian innovations and known variance. The analysis can be done equation by equation under the assumption of orthogonality of the idiosyncratic disturbences. With a prior density for the loadings, $\varpi(B^c|\Gamma_{-B^c}, F^T)$, given by a normal conjugate prior $N(\mu_{B^c}^0, \Sigma_{B^c}^0)$, the likelihood and prior are combined to obtain a posterior distribution, which is also normal $N(\mu_{B^c}^1, \Sigma_{B^c}^1)$. The posterior mean and variance are obtained from standard formulas (see, for example, Justiniano (2004)). Consequently, at iteration g, the factor loadings $B^{c,g}$ are sampled from $\Pi(B^{c,g}|F^{T,g}, \Sigma^g, \Phi^{g-1}, \Sigma_\eta^{g-1})$ equation by equation.

At the fourth step, I draw the AR coefficients in the idiosyncratic disturbences, Φ^g, conditional on $\{F^{T,g}, \Sigma^g, B^g, \Sigma_\eta^{g-1}\}$. For each of the lag polynomials $\varphi_Q^c(L)$, conditional on a sample of factors and loadings, the idiosyncratic disturbences are constructed as the residuals in equation (2). With the sample idiosyncratic errors, inference on the coefficients of

$\varphi_Q^c(L)$, in (3) follows once again the standard analysis of a linear regression with Gaussian innovations. In this case, with a $N(\mu^0_{\varphi^c}, \Sigma^0_{\varphi^c})$ prior, the conditional posterior density is a multivariate normal $N(\mu^1_{\varphi^c}, \Sigma^1_{\varphi^c})_{I[\varphi_Q^c(L)]}$ where $I[\varphi_Q^c(L)]$ is used to indicate that all roots of the lag polynomial $[1-\varphi_Q^c(L)]$ are outside the unit circle. Therefore, at iteration g, the AR coefficients Φ^g are obtained by sampling with rejection from a normal density, conditional on $\{F^{T,g}, \Sigma^g, B^g, \Sigma_\eta^{g-1}\}$. Whenever the roots of $\varphi_Q^c(L)$ are on or inside the unit circle, all draws from step 2 onwards are discarded and new draws generated until the condition for the roots is satisfied.

At the fifth and final step, I draw the variance covariance matrix Σ_η^g, conditional on $\{F^{T,g}, \Sigma^g, B^g, \Phi^g\}$. With Φ drawn in the previous step, the innovation of the idiosyncratic disturbence, η^c, is constructed as the residual in equation (3). Following the same procedure as in step 2, with an inverse gamma prior for σ_c^2, $IG(\frac{d_c^0}{2}, \frac{v_c^0}{2})$, the variance of eacch country's innovation is sampled from the posterior density $IG(\frac{d_c^1}{2}, \frac{v_c^1}{2})$ with

$$d_c^1 = d_c^0 + T_{\eta^c},$$

where T_{η^c} is the dimension of η^c, and

$$v_c^1 = v_c^0 + (\eta^{c,T})'\eta^{c,T}.$$

Having completed steps 1 throuh 5, the Gibbs sampler generates new draws $\{F^{T,g}, \Gamma^g\}$, from the conditional posterior distributions, which are then used in iteration $g+1$ to obtain a new sample $\{F^{T,g+1}, \Gamma^{g+1}\}$ by repeating these five steps. This process is run for a total of $G \times h + D$ iterations which results in a sample of $G \times h + D$ draws of the hyperparameters and factors. Following Kim and Nelson (1999), I discard the intil number of D draws to remove any dependence on intial conditions and to ensure that the Gibbs sampler has converged. In addition, usually only one in h draws is retained such that inference is based on a sample of size G. This is meant to reduce autocorrelation in the draws. I typically choose $G \times h + D$ to be 1000000, D to be 200000 and h equal to 10 following standard practice (for example, se Otrok and Whiteman (1998)). The median of the posterior draws are used as point estimates of the relevant parameter and factor, and error bands are calculated.

6.2 Estimation Results

In this section, I present additional estimation results for the full- sample (1981: 1 - 2009: 4). I present the estimated Europe factor in Figure 12. The solid line represents the median of the posterior distribution and the dotted lines stand for the 5% and 95% quantile bands.

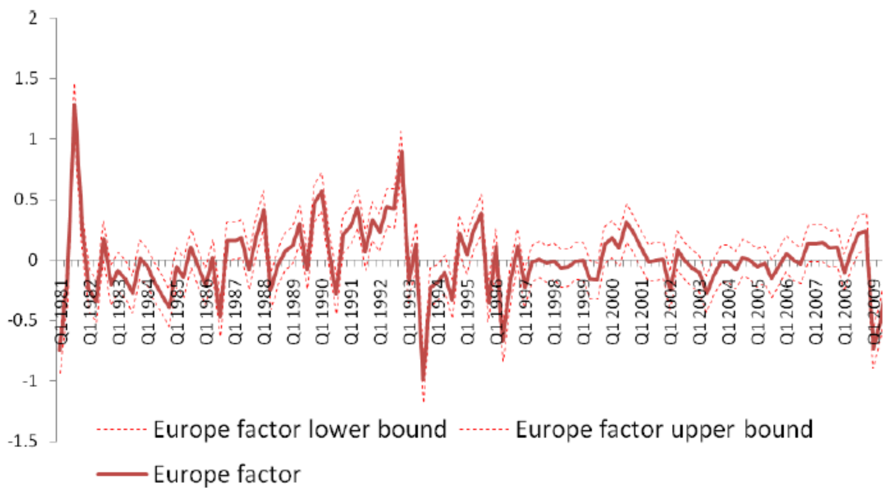

Figure 12: Estimated Europe factor.

Table 2 presents the estimated factor loadings along with the error bands. The estimated parameters correspond to the median of the posterior distribution.

Country	G-7	Europe	G-7 , 1st lag	Europe, 1st lag
USA	1	0	0.0138	0
			(-0.04, 0.07)	
CANADA	1.029	0	0.294	0
	(.96,1.09)		(0.23,0.35)	
FRANCE	0.448	1	0.166	0.125
	(0.38,0.50)		(0.11,0.21)	(0.05,0.19)
GERMANY	0.333	0.255	0.119	0.198
	(0.29,0.37)	(0.19,0.31	(0.08,0.16)	(0.14,0.25)
JAPAN	0.129	0	0.032	0
	(0.09,0.16)		(-0.003,0.06)	
UK	0.331	0	0.148	0
	(0.26,0.39)		(0.09,0.20)	
ITALY	0.168	0.591	0.192	0.222
	(0.11,0.22)	(0.49,0.68	(0.14,0.24)	(0.15,0.29)
5% and 95% bands are in parenthesis.				

Table 2: Estimated factor loadings, full sample.

Most of the factor loading parameters are precisely estimated. Table 3 presents the estimated autoregressive coefficients; Table 4 presents the estimated error variances and Table 5 presents the estimated factor variances.

Country	Median	5% and 95% bands
USA	0.176	(0.116, 0.227)
CANADA	0.019	(-0.035, 0.07)
FRANCE	0.032	(-0.017, 0.081)
GERMANY	0.266	(0.212, 0.32)
JAPAN	0.016	(-0.035, 0.062)
UK	0.036	(-0.006, 0.077)
ITALY	0.19	(0.145, 0.232)

Table 3: Estimated autoregressive parameters, full sample.

Country	Median	5% and 95% bands
USA	0.327	(0.303, 0.352)
CANADA	0.431	(0.398, 0.463)
FRANCE	0.355	(0.328, 0.383)
GERMANY	0.242	(0.228, 0.256)
JAPAN	0.232	(0.219, 0.245)
UK	0.652	(0.614, 0.688)
ITALY	0.445	(0.415, 0.475)

Table 4: Estimated error variances, full sample.

Factor	Median	5% and 95% bands
G- 7	0.489	(0.448, 0.531)
Europe	0.258	(0.234, 0.283)

Table 5: Estimated factor variances, full sample.

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