Forecasting macro-financial variables and evaluating monetary policy effectiveness through an International Data-Rich Environment Autoregressive Model*

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Abstract

We propose a new data-rich environment model of the yield curve, the macroeconomy, monetary policies and effective exchange rates for a panel of 11 countries: the iDREAM. The endogenous variables are observable (short- and long-term interest rates, exchange rates) and latent factors (economic activity, inflation, monetary policy). Local economies are modelled in a FAVECM with weakly exogenous variables and then linked by means of a connectedness matrix estimated with a network approach. We use our framework to evaluate Conventional and Unconventional monetary policies and to do forecasts. We also investigate the effects of helicopter money on the economy. We find that our framework is effective in forecasting long-term interest rates and economic activity; moreover, we find that Unconventional Monetary policies are effective in sustaining domestic business cycles and that the global economy is more resilient to spillover effects originating in the Euro Area than in the US.

JEL classification: C33; C38; C51; C53; C54; C55; E43; E44; E47; E52

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1 Introduction

The term structure of interest rates, the macroeconomy and monetary policies are closely related. On the one hand, long-term bond yields are risk-adjusted averages of expected short-term rates, which are in turn monetary policy instruments directly controlled by central banks. On the other hand, central banks take their monetary policy decisions on the basis of a large information set of past, contemporaneous and expected macrofinancial indicators concerning economic activity, employment, inflation, financial conditions, etc. Therefore, the yield curve, macrofinancial factors and monetary policies need to be jointly modeled in a unified framework.

In a seminal paper, Ang and Piazzesi (2003) find that macroeconomic factors are useful in forecasting interest rates; following this findings, a vast literature has explored different approaches to modeling the yield curve and the macroeconomy (Moench (2008)). However, a common drawback of most of these contributions is that they tend to exploit small datasets of indicators in models that do not explicitly take into account international macrofinancial linkages.

In this paper we address both limitations of the existing literature by proposing a new econometric framework to model the yield curve, the iDREAM (international Data Rich Environment Autoregressive Model). Our goal is to provide an effective tool to forecast global short-term and long-term interest rates, which should also be solidly grounded in economic theory and capture real and financial linkages at the international level. Therefore, we extend the existing empirical literature along several dimensions. First, following Moench (2008), we extract macrofinancial drivers of the yield curve from large panels of economic time series by means of factor analysis, and model the joint dynamics of the yield curve and the macroeconomy in a Factor-Augmented Vector Error Correction model (FAVECM). Second, we explicitly model international linkages in a unified, consistent model, following an infinite-dimensional VAR (IVAR) approach (Chudik and Pesaran (2011)).

In practice, our approach contains the following ingredients. First, the endogenous variables of the system are described by unobservable (latent) factors as well as observable indicators on interest rates, real effective exchange rates and the oil price. We include in the model a monetary policy latent factor, which should descrive the central banks's monetary policy stance when the policy rate approaches the *zero-lower bound* (ZLB) and is no more available as a policy tool to stabilize the economy. Second, the adjacency matrix describing the international interconnectedness of countries is estimated in a network approach. Third, at the local level, each Small Open Economy is modelled in a FAVECM framework with weakly exogenous variables. Fourth, the international solution of the model is obtained in the standard GVAR-IVAR fashion (see Pesaran, Schuermann, and Weiner (2004) and Chudik and Pesaran (2011)). The model is evaluated in terms of its forecast accuracy of short-term and long-term government bond yields against some alternative benchmarks, namely the random walk, the autoregressive model and the Global VAR in its standard form as outlined by Dees, Mauro, et al. (2007).

The iDREAM is also suitable for economic policy evaluation, as for example monetary policies. The ZLB on nominal interest rates limited the scope for monetary easing throught cuts to the policy rate in many countries. Hence, international central banks adopted a wide spectrum of non conventional measures, in line with the Bernanke and Reinhart (2004) normative prescriptions, according to which at the ZLB central banks should: a) shape expectations on future path of the policy rate (i.e. the *forward guidance*); b) increase the size of the balance sheet (i.e. implement *asset purchase programs*); c) change the composition of the balance sheet (i.e. affect the relative supply of assets). Non-standard measures gave rise to a vast literature on the empirical effects of such unconventional measures, which seems to confirm the ability of uncoventional policy measures to sustain output growth and reduce unemployment and long-term yields, but with decreasing marginal effects (see for example Chen et al. (2015) and Panizza and Wyplosz (2016)).

We apply our econometric framework to a panel of 11 international countries. To anticipate some of the key results, in terms of the performance analysis of the model, our approach seems effective in forecasting the business cycle, monetary policy and long-term interest rates, while the model underperforms the benchmarks (random walk and autoregresive models) for the US short-term rate. This is not surprising, since the out-of-sample evaluation period corresponds to the ZLB on the Fed Funds rate. Our approach also outperforms a standard GVAR model in forecasting interest rates, which motivates our choice to include latent factors in the vector of endogenous variables and to estimate the weight matrix in a network connectedness framework.

Regarding monetary policy effects, our goal is to explore a wider range of non standard measures, like for example helicopter money (where, following the intuition of Milton Friedman and the recent Bernanke (2016) definition, helicopter money is an expansionary fiscal policy - an increase in public spending or a tax cut - financed by a permanent increase in the money stock, under the expectation that such an intervention will not be repeated in the future).

According to our estimates, Unconventional Monetary Policies are generally more effective in stimulating domestic economic growth and inflation and seem preferable in pursuing central banks' targets compared to conventional monetary policies; however, this result may be biased by the relative importance of the post crisis period in the estimation sample. Among different policy measures, the US economy seems more resilient to monetary policies originating in the Euro Area, while the opposite is not generally true. Finally, concerning helicopter money, we find that it is generally less effective in stimulating inflation in both areas, while it seems preferable as a stimulus to economic activity in the Euro Area.

The paper is organised as follows. Section 2 presents the iDREAM approach: in particular, latent factors extraction, local-country models and weight matrix estimation. A detailed description of our approach in identifying monetary policy shocks is also presented in this section. Section 3 introduces the dataset used for estimation and describes our procedure to extract latent macroeconomic factors. Section 4 presents the estimation results: country-specific models specification, weak exogeneity tests and detailed evidence on the stability of the model. In Section 5 our identification strategy for estimating monetary policy shocks is presented and compared to other approaches in the literature. We then compare impulse-responses to US and Euro Area monetary policy shocks. Section 6 evaluates forecasting performance of the model. Section 7 offers some concluding remarks.

2 The methodology

2.1 Econometric framework

Vector-Autoregressions (VAR) are a useful tool for forecasting purposes and economic policy evaluation (structural analysis: see Sims (1980)). However, VARs have a well-known limitation in the so-called "curse of dimensionality": even small systems with few endogenous variables and a parsimonious lag structure incur in a substantial proliferation in the number of parameters to be estimated. For this reason, standard VARs are not applicable to our problem, i.e. modelling global interest rates and macrofinancial spillovers, even for a small number of countries.

Three approaches have been applied in the empirical literature to overcome the curse-of-dimensionality issue: a) data shrinkage (e.g. factor-models; see for example Stock and Watson (2002)); b) parameter shrinkage (e.g. Large Scale Bayesian VARs and regularization methods; see Banbura, Giannone, and Reichlin (2010)); c) Global VARs (GVAR), i.e. large systems linking small-scale, small-open-economy (SOE) local models in an international model by means of a weight matrix, often derived from international trade or financial flows; see for example Pesaran, Schuermann, and Weiner (2004).

In this paper we propose a novel econometric approach to deal with large information sets in terms of both cross-sectional units and endogenous variables. Our approach combines all the mentioned solutions to the curse-of-dimensionality issue in a unified framework.

iDREAM belongs to the class of infinite dimensional VAR (IVAR; see Chudik and Pesaran (2011)); IVARs are a generalization of the GVAR approach, since they identify the conditions under which the GVAR is applicable to arbitrarily large cross-sections of countries. Moreover, our IVAR is estimated in a data-rich environment, which is the natural information set for central bankers (see Bernanke, Boivin, and Eliasz (2005)), i.e., we allow latent factors extracted from large panels of indicators, as well as observables to be included as endogenous variables in the system.

To illustrate the point of the IVAR approach, start with the following representation of a VAR:

$$x_{i,t} = \underbrace{\sum_{j \in n_i} \phi_{i,j}^{n_i} x_{j,t-1}}_{neighbours} + \underbrace{\sum_{j \in d_i} \phi_{i,j}^{d_i} x_{j,t-1}}_{non-neighbours} + u_{i,t}.$$

We can assume that every unit i has strong links with other neighbouring units (for example, adjacent countries), and negligible connections to non-neighbour units. This is equivalent to assume that the coefficients for non-neighbour countries tend to zero as the number N of units tends to infinity, such that

$$\left|\phi_{i,j}^{d_i}\right| \leq \frac{K}{N}, K < \infty.$$

At the same time, non-neighbouring units can have a significant aggregate impact on $x_{i,t}$, such that

$$\lim_{N \to \infty} \sum_{j=1}^{N} \left|\phi_{i,j}^{d_i}\right| < K$$

which is the case when units in the system are strongly cross-sectional dependent.

To construct the iDREAM we proceed as follows.

First, the endogenous variables of the system are described by unobservable (latent) factors as well as observable indicators. A large body of empirical literature shows that forecasting models for intererest rates specified on latent factors perform better than those specified on observed variables (see Moench (2008) and Favero, Niu, and Sala (2012)). Hence, we estimate national macroeconomic factors from a large dataset of indicators following the procedure of Stock and Watson (2002). Second, the adjacency matrix describing the international network of countries is supposed to be unknown (i.e. it is not derived from observed data like, for example, trade flows) and it is estimated in a network connectedness framework. Third, at the local level, each SOE is modeled in a FAVECM framework with weakly exogenous variables. Fourth, the international solution of the model is obtained in the standard GVAR fashion (see Pesaran, Schuermann, and Weiner (2004)).

More formally, for each SOE, x_{it} is the vector of endogenous variables specific to country i:

$$x_{i,t} = \left(cic^{'}_{i,t}, inf^{'}_{i,t}, mpl^{'}_{i,t}, tb3^{'}_{i,t}, y10^{'}_{i,t}, rfx^{'}_{i,t}\right)^{\prime}$$

for $i \neq$ United States, and

$$x_{US,t} = (cic^{'}_{US,t}, inf^{'}_{US,t}, mpl^{'}_{US,t}, tb3^{'}_{US,t}, y10^{'}_{US,t}, rfx^{'}_{US,t}, oil^{\prime}_{t})^{\prime}$$

for United States, where cic is a measure of a country's business cycle, inf is the inflation factor, mpl is a factor describing the monetary policy stance, $tb3$ is the 3-month government interest rate, $y10$ is the 10-year government bond interest rate, rfx is the annual growth of the real effective exchange rate, oil is the annual growth rate of oil price. The inclusion of oil price in the vector of endogenous variables for the United States accounts for the dominant role of the country on the world economy and international financial markets.

Stacking local endogenous variables in the vector

$$x_t = \left(x^{\prime}_{1,t}, x^{\prime}_{2,t}, ..., x^{\prime}_{N,t}\right)^{\prime}$$

we can define the vector of country i-specific foreign variables as:

$$x^*_{i,t} = \sum_{j=0}^{N} \tilde{w}_{i,j} x_{j,t},$$

i.e. the vector $x^*_{i,t}$ contains weighted averages of the endogenous variables of other countries. Each SOE is then modeled as a local Factor-Augmented Vector Autoregressive model with exogenous variables that can be generally written as

$$\Phi_i(L, p_i) x_{i,t} = a_{i,0} + \Lambda_i(L, p_i) x^*_{i,t} + u_{i,t} \quad i = 0, ..., N \quad \text{and} \quad t = 1, ..., T \tag{1}$$

or

$$A_i(L, p_i, q_i) z_{i,t} = \varphi_{i,t} \quad i = 0, ..., N \quad \text{and} \quad t = 1, ..., T \tag{2}$$

where

$$A_i(L, p_i, q_i) = \left[\Phi_i(L, p_i), -\Lambda_i(L, p_i) \right], z_{i,t} = \begin{pmatrix} x_{i,t} \\ x^*_{i,t} \end{pmatrix}$$

and

$$\Phi_i(L, p_i) = \sum_{j=0}^{p_i} \Phi_{i,j} L^j$$

We can express the vector $z_{i,t}$ as $z_{i,t} = \tilde{W}_i x_t$, where $\tilde{W}_i$ is a $(k \times k^*)$ link matrix, k is the number of country-i endogenous variables and k^* is the number of foreign variables. Then

$$A_i(L, p) \tilde{W}_i x_t = \varphi_{i,t}$$

or equivalently

$$G(L,p)x_t = \varphi_t \quad t = 1, ..., T \tag{3}$$

where $p = \max(p_i, q_i), i = 1, ..., N$ and

$$G(L,p) = \begin{pmatrix} A_0(L,p)\tilde{W}_0 \\ A_1(L,p)\tilde{W}_1 \\ \vdots \\ A_N(L,p)\tilde{W}_N \end{pmatrix}, \varphi_t = \begin{pmatrix} \varphi_{0,t} \\ \varphi_{1,t} \\ \vdots \\ \varphi_{N,t} \end{pmatrix}.$$

The weights $\tilde{w}_{i,j}$ are estimated following a network approach, as in Diebold and Yilmaz (2015). A network $\mathbf{N} = [n_{i,j}]$ can be defined as a collection of N nodes and L links. In the case of our IVAR, the network is directed (i.e. $\mathbf{N}$ is non-symmetric) and weighted (i.e. $n_{i,j} \in [0,1]$, where $n_{i,j} > 0$ when the nodes i and j are connected and $n_{i,j} = 0$ if the nodes are not connected). According to Diebold and Yilmaz (2015), connectedness can be estimated as the share of forecast error variation in a node (variable/country) due to a shock arising in another node. The estimation of network connectedness is based on a VAR approach specified on different theoretical vehicles of macrofinancial linkages, i.e. the business cycles, monetary policies, inflation, the yield curve and exchange rates. Connectivity is explored along all these possible linkages; that is, an adjacency matrix is derived from the estimation of the VAR on a vector of first difference of endogenous variables given by $\Delta y_t = (\Delta y_{1,j,t}, \Delta y_{2,j,t}, ..., \Delta y_{N,j,t})'$ for each separate $j = cic, inf, ..., rfx$. The VAR is then specified as

$$\Delta y_t = A_0 + A_1 \Delta y_{t-1} + ... + A_p \Delta y_{t-p} + e_t, e_t \sim N(0, \Sigma)$$

and it is estimated in a Large Bayesian framework (see Banbura, Giannone, and Reichlin (2010)), shrinking the coefficients with a Minnesota-type prior distribution, which is equivalent to shrinking the dynamics of the system towards a random walk for integrated variables or a white noise for stationary variables.

In the network analysis jargon, the adjacency matrix is obtained by estimating the Generalized Forecast Error Variance Decomposition (Pesaran and Shin (1998)) with a forecast horizon $H = 4$ on the Large Bayesian VAR.The elements $n_{i,j}$ of the adjacency matrix are then given by

$$n_{i,j} = \frac{\sigma_{j,j}^{-1} \sum_{h=0}^{H} (e_i' A_h \Sigma e_j)^2}{\sum_{h=0}^{H} (e_i' A_h \Sigma A_h' e_i)}$$

where e_j is a selection vector with the j-th element equal to 1 and zeros elesewhere.

Final weights are then derived ignoring negligible connections, i.e. elements of the adjacency matrix which are below a given threshold; that is $\tilde{w}_{i,j} = n_{i,j}$ if $n_{i,j} \geq \tau$, $\tilde{w}_{i,j} = 0$ otherwise.

2.2 Identification strategy

For the purpose of the analysis of domestic and spillover effects of monetary policies, we follow the approach of Eickmeier and Ng (2015). The approach consists of two-steps. First, we identify structural monetary policy shocks at the local level; second, we evaluate international effects in a non-structural way. The local structural identification is based on sign restrictions (Uhlig (2005)), whereas the response of different variables for foreign countries is based on Generalized Impulse Response Functions (Pesaran and Shin (1998)), which are useful in the context of large VAR systems as they are invariant to the ordering of endogenous variables.

Consider for example the structural representation of a FAVARX(1,1) for the US (which is assumed to be country 0):

$$P_0 x_{0,t} = \pi_0 x_{0,t-1} + \rho_{0,1} x_{0,t}^* + \rho_{0,2} x_{0,t-1}^* + \epsilon_{0,t}$$

The Cholesky orthogonalization P exactly identifies P_0 and allows the computation of structural impulse responses. In our identification strategy, the sign restrictions identification procedure is based on the selection of the rotations $P_0 = PK$ of the Choleski factor P that satisfies the restrictions on the sign of the effects of structural monetary policy shocks at the local level, where $K = Q'$ and Q is the QR decomposition of a matrix sampled from a multivariate standard normal.

Now consider the international solution of the IVAR:

$$Gx_t = Hx_{t-1} + ... + u_t$$

and define

$$P_G^0 = \begin{pmatrix} P_0 & 0 & 0 & 0 \\ 0 & I & 0 & 0 \\ & & \ddots & \\ 0 & 0 & 0 & I \end{pmatrix}.$$

Then if we premultiply the IVAR by P_G^0 we get

$$P_G^0 Gx_t = P_G^0 Hx_{t-1} + ... + \epsilon_t$$

where $\epsilon_t = (\epsilon'_{0,t}, u'_{1,t}, ..., u'_{N,t})'$ and $\Sigma_\epsilon = Cov(\epsilon_t)$.

It can be shown (see Dees, Holly, et al. (2007)) that the contemporaneous international effects of a local (US) structural monetary policy shock is given by

$$\psi(0, x : \epsilon_0) = \frac{(P_G^0 G)^{-1} \Sigma_\epsilon e_i}{\sqrt{e_i' \Sigma_\epsilon e_i}},$$

where e_i is a selection vector applied to x_t. Effects at longer horizons can then be obtained recursively as in the standard fashion.

3 Data

Our approach relies on estimating country-specific latent factors on partitions of the full dataset on the business cycle, inflation and monetary policy. In particular, given a data matrix $X_{i,j,t}$ specific to country i, category j of dimension $T \times N_{i,j}$ we estimate a single factor $F_{i,j,t}$, using the EM approach (see Appendix A in Stock and Watson (2002)) to deal with missing values. The main advantage of data partitioning is having a homogenous interpretation of latent factors across countries that would not be feasible by estimating factors from an unique country-specific dataset. On the other side the cost of partitioning is the loss of information that originates from omitting interactions between variables across different categories. Still, the extent of this loss is questionable. While in theory having more data is always better, in practice this is true only when the data are homogeneous. Boivin and Ng (2006) show that using more series to extract factors does not necessary yield better forecasting performances.[1]

Table 1: Countries in the iDREAM model

	Euro Area	**Rest of Western Europe**	**Emerging**
USA	Germany	Switzerland	China
Japan	France		Russia
UK	Italy		Brazil
	Spain		

The iDREAM model presented in this paper covers 11 countries that are listed in Table 1. The countries included in this paper account for 55% of World GDP in 2016. A detailed description of the variables entering in the estimation of each factor is presented in Tables B1-B3 in the Appendix. Among the variables used to estimate the business cycle factor, there are industrial production, PMI, orders, confidence indicators, capacity utilization rate, employment, GDP components and other series. For most of these variables we also included sectorial indicators. For the inflation factor, we used different components of the consumer price index, producer price index, GDP deflator, wages and house prices. For the monetary policy factor, we included monetary aggregates, loans to the private

[1] In their application, they show that ad-hoc selection of 40 series entering in the factors leads to slightly better forecasting performances compared to using all data (147 series).

sector (households and non financial corporations), central bank assets. The choice of the variables entering monetary policy factors deserves further comment since it is a novel contribution of our paper. This monetary policy factor has been included in the model as one of the driving forces of global macrofinacial comovements. Nevertheless this factor does not only capture monetary policy stance, since private lending data are also included in the estimation. Therefore we could define this factor as a credit condition index that strongly depends on the stance of monetary policy and on the trasmission mechanism of these policies to the financial sector and finally to the real economy. It is important to stress that the sample size of the series underlying each factor differs across countries. In particular for US, Germany and Italy we included more disaggregated data resulting in a larger sample size to get better estimates for countries that are the focus of our analysis. In total 521 time series have been used to estimate 33 latent factors, ranging from 80 series for Germany to 33 for Russia. We adopted a principle of homogeneity by picking the same variables for each country to avoid differences in factor estimation deriving from data of different sources/interpretation, but this was not always possible.

Data have been transformed before extracting latent factors. The principle adopted when transforming a series has been to mimic the behaviour of annual growth rates of benchmark series in a category. As an example, for the business cycle we considered the annual growth rate of total employment in the manufacturing sector because it should convey similar information to annual growth rate of industrial production. For the same reason we did not transform PMI manufacturing index. A summary of different trasformations is presented in Table B4. We coded trasformations[2] in the following way. Given Z_t the original time series and $\tilde{Z}_t$ the trasformed variable

- Trasf. 0: $\tilde{Z}_t = Z_t$
- Trasf. 1: $\tilde{Z}_t = Z_t - Z_{t-12}$
- Trasf. 2: $\tilde{Z}_t = \log(Z_t) - \log(Z_{t-12})$

[2] We took the annual difference of confidence indicators and surveys when the index does not refer to the recent past.

After data trasformation, each series is standardized and a unique factor is extracted[3] for a specific country category as in Stock and Watson (2002).

We interpret each factor by running univariate regressions between the factor and each contributing time series. We select the time series with the largest R^2 from this set of regressions and, when necessary, we invert the sign of the factor to impose positive correlation between the factor and the most correlated time series.

Real effective exchange rates have been calculated from Consumer Price Indices and are included in each country model as annual growth rates. Regarding government bond yields: short-term yields have a 3-month maturity, while long-term yields are 10 year Constant Maturity Par Yields.[4] Oil corresponds to the growth rate of Brent. Our data source is Datastream Thomson Reuters. The model has been estimated on monthly observations from January 2000 to October 2016. In Table B5 in the Appendix we present summary statistics of the endogenous variables of our model where we omit latent factor since they are standardized.

In Figure A3 we present the endogenous variables of the US model. We associate each latent factor to a specific variable using the R^2 criterion specified above. Business cycle is closely linked to the growth rate of industrial production, while the inflation factor is mostly correlated to the annual change of the Consumer Price Index. Monetary policy, is instead closely associated to the growth rate of M0.

The interpretation of latent factors across countries does not differ significantly when we consider business cycle or inflation. The most correlated variable for inflation is always the annual growth rate of the Consumer Price Index (or one of his components), while, for the

[3]Some differences compared to Stock and Watson (2002) are worth to emphasize. Due to the large persistence of the series and relative small size of the dataset for some country/category, quarterly variables' fitting performance from EM algorithm was in some case very small. To deal with this issue, we proceeded by temporally disaggregation of quarterly series to monthly frequency using the Denton-Cholette interpolation method (Denton (1971)).

[4]To achieve a balanced panel with respect other countries, we extended backward with an ARDL(2,2) all interest rate time series not available before January 2000. In particular, we derived Chinese interbank rate 3-month and 10-year government interest rates, provided starting from respectively January and June 2002, conditional to Chinese 3-month interbank interest rate provided by OCSE and the China Special Time Deposit rate. Moreover, we extended backward the Brazilian 10-year interest rates, not available before January 2006, conditional to Brazilian 3-month government interest rate and the EMBI Global Diversified Brazil yield.

business cycle, industrial production is the most correlated variable in 7 out of 11 countries. Instead the interpretation of monetary policy is more diverse across countries and the comovement between this factor and the underlying variables is low when compared to the other factors. In particular monetary policy is mostly correlated to private lending growth rate in Italy, Spain, UK and Brazil, while monetary aggregates are usually the most correlated variables in the other countries. Large correlation with private lending could be sinthomatic of an impaired transmission mechanism of monetary policy in these countries.

In Tables B6 in the Appendix we report the ADF test statistic on the level of endogenous variables entering the iDREAM. According to this test, a large majority of variables of the model are I(1). In particular for interest rates, business cycle and monetary policy we accept the null hypothesis of unit root in at least 9 countries out of 11. Instead there is strong evidence that the annual growth rate of real effective exchange rates and oil are I(0). Regarding inflation, the evidence is more mixed.[5] These results support our modelling strategy of estimating a local-country FAVECM.

4 Estimation

4.1 Weight Matrix

Previous IVAR or GVAR applications used trade or financial weights to construct foreign variables, choosing a fixed or time-varying weight matrix. In our study, we adopted a new approach to quantify the interconnection between our variables of interest using a Large BVAR model. We apply this estimation method to each category of endogenous variables. For each weight matrix we run an iterated estimation of our model counting the number of stable iterations along the sample time horizon to choose the most performing one. We

[5] ADF test has been performed by allowing a trend component, while the number of lags has been selected using AIC. Results are robust when using BIC to perform lag selection. If we allow for a drift component, the unit root hypothesis on business cycle looks less robust but conclusions regarding the other variables do not change. First differences of endogenous variables are stationary (not reported).

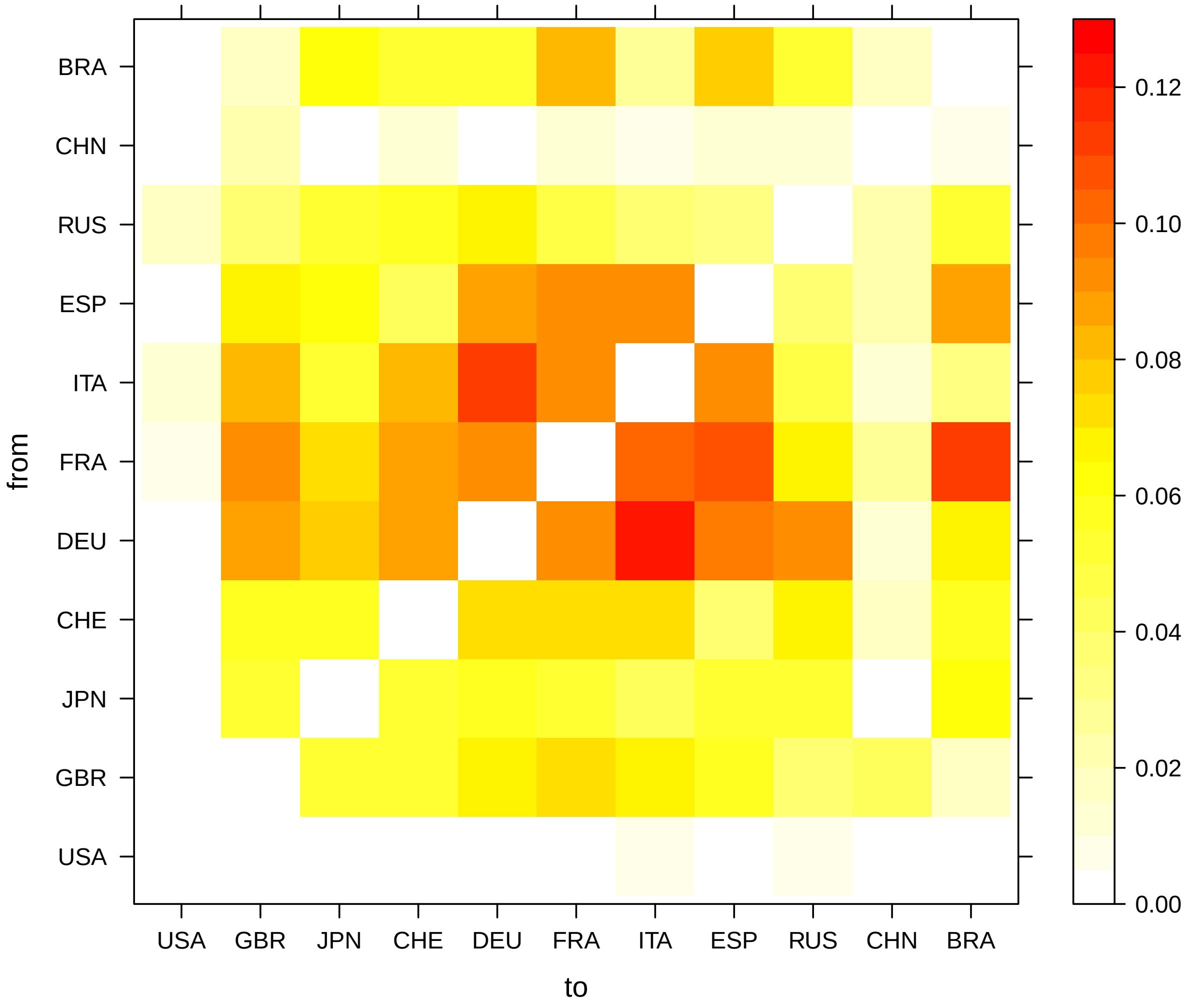
find that the business cycle weight matrix is the most performing (see the Section 6 for further details) and for this reason we use it for all the analysis presented in the paper. As shown in Figure 1 each colored square inside the adjacency matrix represents the interconnection between two different countries (the white squares are interconnection below a certain threshold and consequently are restricted to 0). Looking at the results it is immediately evident that there are strong interconnections among the European countries and, in general, among the developed countries. Another important information that emerges from the adjacency matrix is the robust interconnection among the Emerging countries. Nevertheless, the nearly null interconnection from and to the US is quite surprising, because the weights of US trade is generally sizeable. This could be related to our approach to estimate the weight matrix. Indeed, we compute the interconnection between two countries with the generalized forecast error variance decomposition, so if the residuals of an equation are small, i.e. the model entirely fits the endogenous variable, the decomposition will be a sum of negligible errors and there will be no shock connected with the forecast error.

4.2 Model Specification and stability checks

Once the variables to be included in the local FAVECM(p_i, q_i) models are specified, we estimate all models determining the rank of their cointegrating space, avoiding any kind of restrictions on cointegrating vectors, and selecting the order of lags based on the Bayesian Information Criterion (BIC), allowing different values for lags of endogenous and weakly exogenous variables. Starting from a maximum number of 4 lags for both type of variables and using the BIC we find the same lag specification for all the country models, with an order of 2 for endogenous variables and 1 for the weakly exogenous (Table B7).

We compute the rank of cointegration for each country-specific model considering both Johansen's trace and the maximum eingenvalue statistic for cointegrated models with weakly exogenous regressors, considering a restricted intercept and no trend as deterministic component (labeled as case "II"). In order to maximize the tradeoff between stability and

Figure 1: Adjacency matrix estimated on business cycle



specification of the model, cointegration rank is chosen from the minimum rank supplied by trace and maximum eigenvalues statistic (at 95% critical value level). Among the country-specific models we find between 1 and 3 cointegrating relations, without any particular difference between developed and emerging or core and risky countries.

In order to verify the weak exogeneity of country-specific foreign variables with respect to the long-run coefficients of the FAVECM(p_i, q_i) we use the weak exogeneity test following Johansen (1992) and Harbo et al. (1998), which involves a test of the joint significance of the estimated error correction terms in auxiliary equations for the country-specific foreign variables. As presented in Table B8, we find that the weak exogeneity assumption is rejected at the 5% significance level in only 8 cases out of 67, especially for the business cycle and Price Index of developed countries. Following the theory, we had to threat these variables as endogenous in the respective local models, but to preserve an homogeneous specification for all countries we considered those variables as weakly exogenous regressors.

Given the R^2 of each country-specific FAVECM(p_i, q_i) in Table (B9) we claim that our specification is able to capture the path of all endogenous variables with a decent goodness of fit. On average we obtain better result on the business cycle and the inflation factor, while real effective exchange rates has a lower goodness of fit. The government bond yields have a heterogeneous pattern among developed and emerging countries, probably due to recent and unsynchronized conventional and unconventional monetary policy measures adopted by local central banks and different macroeconomic shocks affecting the domestic economies.

Finally, we check the stability and dynamics of the model running a persistence profile analysis (Pesaran and Shin (1996) and Dees, Holly, et al. (2007)) on the moving average representation of the global solution. The persistence profiles, by definition, refer to the time profiles of the effects of system (or variable-specific) shocks on the cointegrating relations and allow examining the speed at which the long-run relations converge to their equilibrium states. In the presence of a stable model the persistence profiles starting from a value of unity at the time of impact converge to zero as the time horizon goes to infinity, as shown in Figure A1 in the Appendix where all persistence profiles are well behaved, quickly converging to zero. We find another proof of model's stability from eigenvalues of the global solution: the decreasing path of the largest eigenvalues in absolute value suggests that our estimated model is stable (Figure A2 in the Appendix).[6]

5 Empirical Application: Monetary policy shocks

Following the financial crisis, central banks aggressively cut policy rates to stimulate domestic demand. To continue the necessary policy stimulus, central banks started implementing unconventional monetary policies. According to Bernanke and Reinhart

[6] In our model we have exactly 52 eigenvalues equal to 1 in absolute value (number of variables minus the number of cointegrating relations).

Table 2: Identification of monetary policy shocks using sign restriction: previous contributions

		m3	**y10**	**y**	π	**cr**	**Ass**	**Vix**	**R**	**lr**
Baumeister et al. (2010)	sign	0	-	+	+					
	months	0-24	0	0	0					
Peersman (2011)	sign	0		0	0	+				-
	months	ND		ND	ND	ND				ND
Gambacorta et al. (2014)	sign			0	0		+	-		
	months			0-1	0-1		0-1	0-1		
Chen et al. (2015)	sign	-		+	+				+	
	months	0-6		0-6	0-6				0-2	
Schenkelberg et al. (2011)	sign			0	+		+			
	months			0	1-12		0-12			

Note: m3 = policy rate / interbank rate / shadow rate, y10 = 10-year government bond yields, y = output, π = inflation, cr = credit, Ass = Total Assets Central Bank/Reserves, Vix = vix, R = stock market returns, lr = lending rates.

(2004), when the zero lower bound (ZLB) is reached, central banks should: a) shape expectations on the future path of monetary policy (i.e. forward guidance); b) increase the size of their balance sheet (i.e. QE); c) change the composition of the balance sheet (by affecting the relative supply of securities). Unconventional monetary policy (UMP) actions by central banks have led to a growing literature on their impact. Many papers focused on the effectiveness of these policies on macroeconomic variables. Panizza and Wyplosz (2016) showed that UMPs, identified by a reduction of the shadow rate[7] have decreasing marginal effects on output and inflation. Wu and Xia (2016) show that US expansionary monetary policies, measured by a decrease in the shadow rate, have been effective in reducing unemployment since 2009. According to Chen et al. (2015), QE has been more effective in the US with broader spillover effects on other countries compared to the Euro Area. Another strand of literature focused on the effects of these policies on financial markets and on the price of securites, using event study analysis. Joyce et al. (2011) showed that the Bank of England's asset purchases were effective in reducing long-term yields and sustaining asset prices through a portfolio balance channel. Gagnon et al. (2011) show that the Federal Reserve's asset purchases led to economically meaningful and long-lasting reductions in longer-term interest rates on a range of securities, including securities that

[7]The shadow rate, unlike the short-term interest rate, is not bounded below by 0 percent, and the level of the rate reflects the impact of unconventional monetary policies on the short end of the yield curve

were not included in the purchase programs, mostly by means of a compression of risk premia.

In this section we investigate domestic and spillover effects of conventional and unconvenional monetary policies originating in the US and in the Euro Area using of impulse response analysis. We contribute to the literature by using the monetary policy factor as a key variable in identifing UMPs. Furthermore, to our knowledge, we are the first to investigate the effects of helicopter money, a policy option that has never been implemented so far, but has recently been debated by scholars and policy makers.

To estimate the effects of monetary policies we use Generalized Impulse Response functions (Pesaran and Shin (1998)) for Conventional monetary policy (CMP, interest rate cut) and sign restrictions (Uhlig (2005)) for Unconventional Monetary Policies (UMPs). In particular, we identify shocks at the country-level in the following way. We structurally identify UMPs shocks by choosing a rotation of the Cholesky trasformation of the variance-covariance matrix of the errors that is closest to the median of impulse responses that satisfy sign restrictions as in Fry and Pagan (2011). Shocks are then trasmitted to the global economy by means of Generalized Impulse Response functions as in Dees, Mauro, et al. (2007) and Chen et al. (2015), Regarding CMP and UMPs originating in the Euro Area, we proceede by aggregating shocks originating from each European country in our dataset. In particular, since the Euro Area (EA) is not included in the model, we identify monetary policy shocks for Germany, France, Italy and Spain and we aggregated the responses by weighting each of them according to the National Central Banks' contributions to the European Central Bank (ECB)'s capital, the so called *capital key.*[8]

5.1 Identification of Quantitative Easing

Table 2 summarizes previous contributions on the identification of Quantitative Easing policies using sign restrictions. Following Baumeister and Benati (2010), Chen et al.

[8]In implementing QE, ECB buys sovereign bonds of each country that arise from the application of the ECB capital key. We use National Central Bank contributions updated at January 2015.

(2015) and Schenkelberg and Watzka (2013) we assume that the policy has a positive impact on output and inflation that lasts for a quarter. We also assume that long-term interest rates decline after a QE shock. The monetary policy factor is set to increase as a result of the expansion of money supply and the central bank's balance sheet (as in Gambacorta, Hofmann, and Peersman (2014) and Schenkelberg and Watzka (2013)). It is important to stress that due to the nature of the monetary policy factor that is estimated from a heterogeneous dataset of money supply and private lending, the impulse responses include the credit channel. Sign restrictions for QE are summarized in the left column of Table 3.

Table 3: sign restriction table for Quantitative Easing and Helicopter Money

	QE in US and EA			**HM in US**			**HM in the EA**		
	start	end	sign	start	end	sign	start	end	sign
cic	0	3	+	0	7	+	3	7	+
inf	0	3	+	0	3	+	0	3	+
mpl	0	3	+	0	3	+	0	3	+
tb3									
y10	0	3	-						
rfx									

5.2 Identification of Helicopter Money

Bernanke (2016) defined helicopter money (HM) as an expansionary fiscal policy (an increase in public spending or a tax cut) financed by a permanent increase in the money stock. This policy option is expecially attractive because as a fiscal program it should have expansionary effects on output without affecting househoulds' projected path of taxation. Indeed, when a spending increase or tax cut is paid for by debt issuance, as in the standard case, future debt service costs and thus future tax burdens rise. To the extent that households today anticipate that increase in taxes - or if they simply become more cautious when they hear that the national debt has increased - they will spend less today, offsetting some of the program's expansionary effect. So far central banks have never adopted such a policy due to the potential risk on macroeconomic governance, and to our knowledge there is little debate on the effect that such a policy could have in major economic areas.[9]

We consider helicopter money as government spending financed by increasing money supply. Since government does not directly enter into our model we should postulate the effect of fiscal policy on the business cycle factors in US and Euro Area. This implies postulating whether increasing government spending has expansionary effects on GDP in US and in the 4 countries of the EU and whether these effects arise immediately or with some lags.

To answer these questions we estimated a simplified model at the country-level. In particular for US, Germany, France, Italy and Spain we estimated a small-scale monetary VAR on the following variables: annual growth rate of government expenditure (g_t), real GDP(y_t), CPI(π_t) and 3-month government rate ($tb3_t$). We ordered the variables in the following way $[g_t, y_t, \pi_t, tb3_t]$ and we identified a fiscal policy shock à la Sims (1980). Finally we aggregate impulse responses on GDP growth of the Euro Area using ECB capital key as for QE shocks. The results are presented in Figure A4. The response of GDP growth is positive in both areas but interestingly fiscal policy in the US seems to have an immediate effect on GDP growth while in the Euro Area expansionary effects appear only at the end of the first quarter after the shock. We took into account these different responses in imposing sign restrictions on the business cycle factors in the two areas. Sign restrictions for Helicopter Money are summarized in the second and third column of Table 3.

5.3 Results

Domestic effects of monetary policy shocks in the Euro Area are presented[10] in Figure 2. Conventional monetary policy in the Euro Area is usually effective in stimulating growth across European countries but it fails to stimulate inflation. Unconventional monetary

[9]Buiter (2014) derives theoretical conditions that must be satisfied for helicopter money always to boost aggregate demand.

[10]In particular the time profile of impulse responses for a specific variable/country from period 0 to 3 years ahead have been synthetized in a boxplot.

Figure 2: Domestic effects of ECB Monetary Policies (from 0 to 3 years ahead)

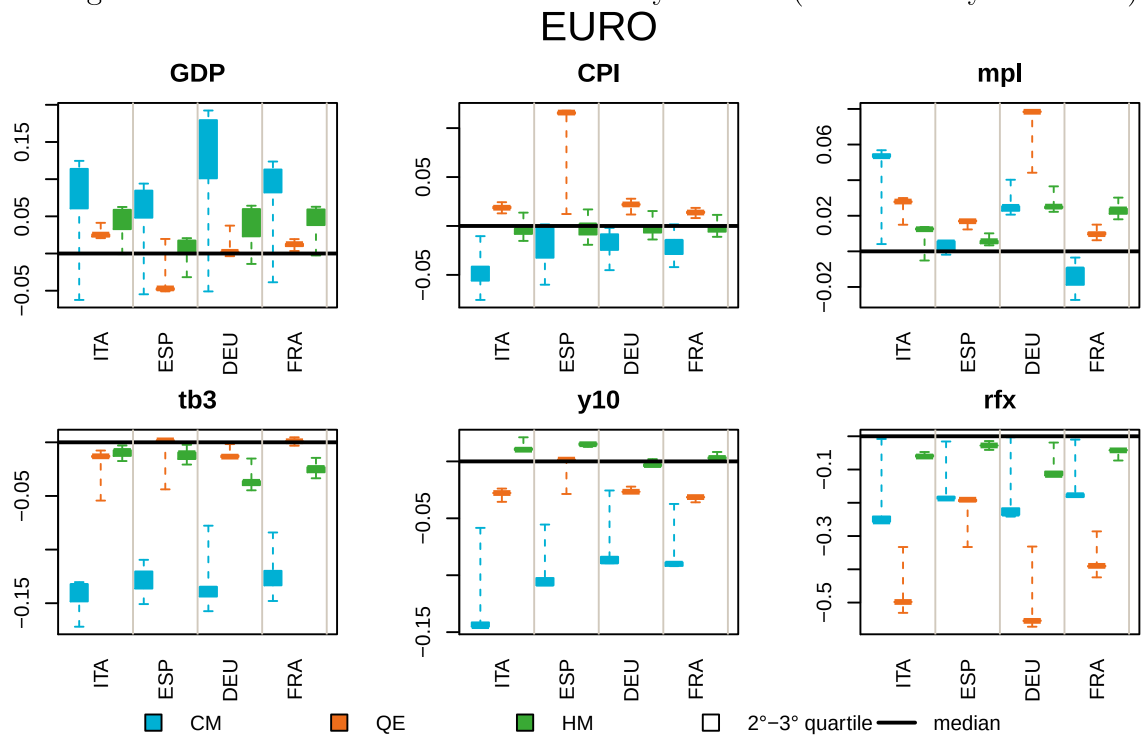
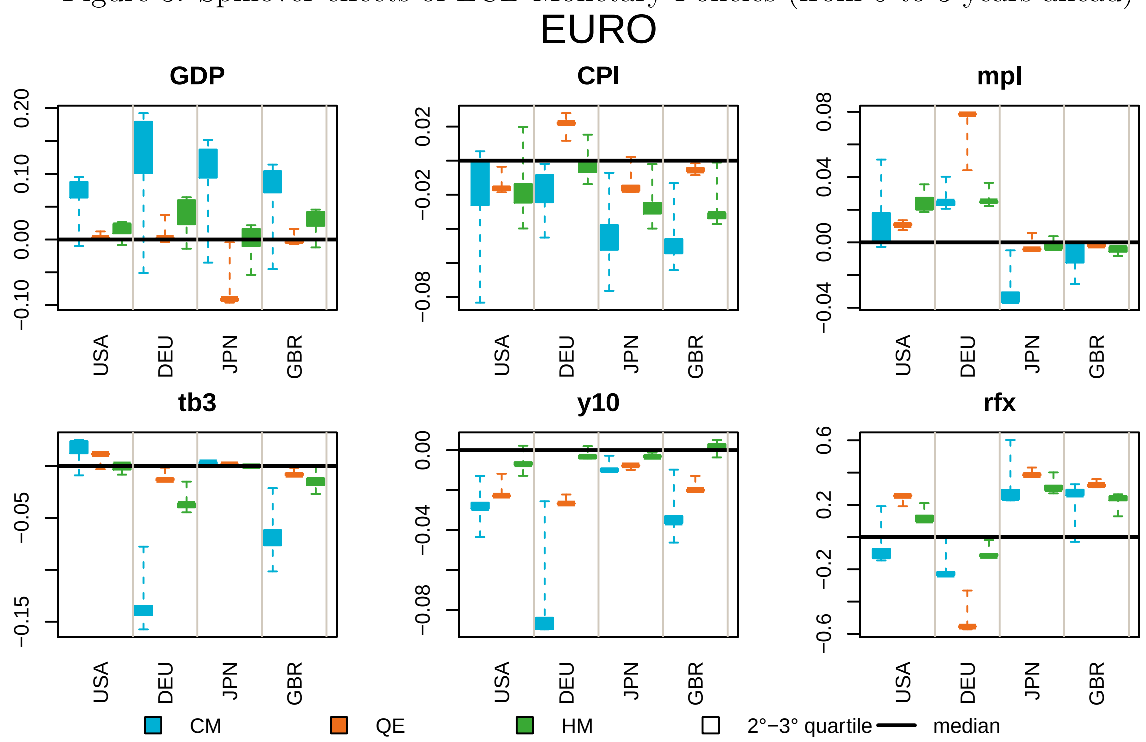


Figure 3: Spillover effects of ECB Monetary Policies (from 0 to 3 years ahead)

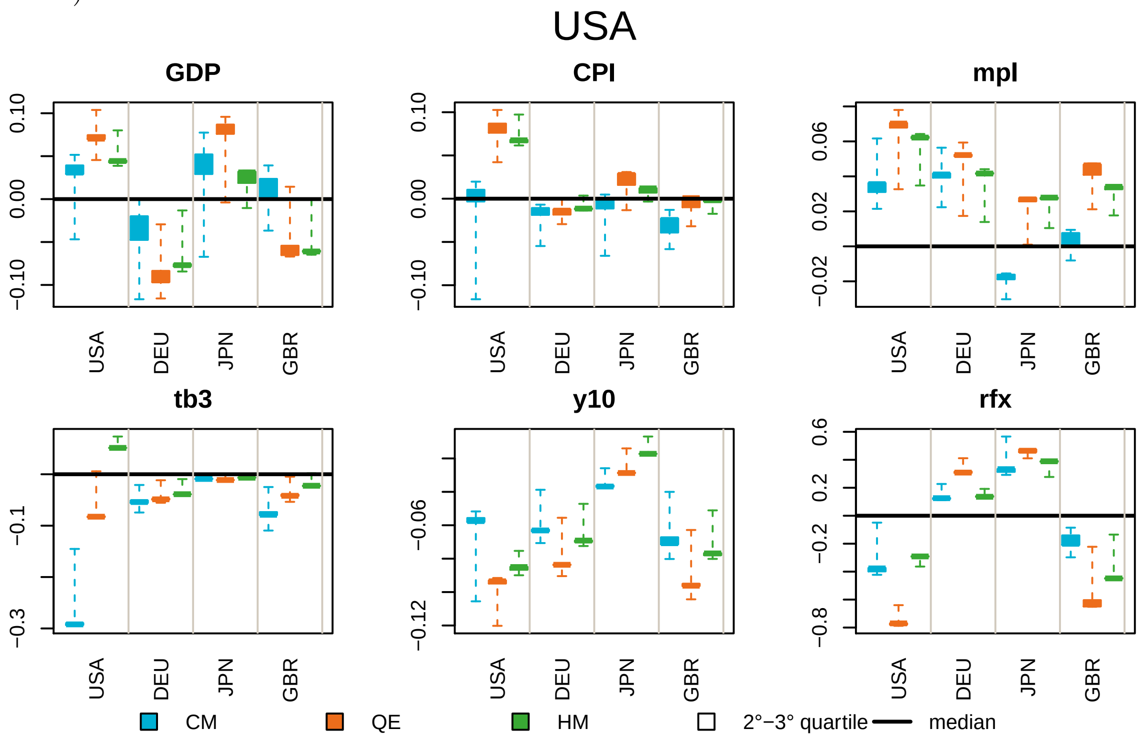


policies (QE and HM) are usually effective in pursuing both targets of spurring inflation and output growth. In contrast to Peersman (2011), we found that QE is a more effective tool compared to CMP. As expected QE reduces long-term interest rates across European countries; furthermore, the policy results in a compression of the differentials between Italian and French long-term interest rate vs the German rates (for Spanish bonds the compression is only temporary). The ECB's QE leads to a stronger depreciation of real exchange rates compared to the other policies, leading to stronger growth in more export oriented countries (Italy and Germany), at least in the short-run. Helicopter money in the Euro Area looks more effective (in terms of size and persistency) in stimulating growth compared to all the other policies, while the effect on inflation is not long lasting. This is explained by the positive reaction of long-term interest rates, that leads to an appreciation of real effective exchange rates. Domestic currency appreciation implies that inflation increases by a lower extent, compared to the QE case, because of lower prices of imported goods.

In Figure 4 we present the effect of Fed monetary policies on the US economy and on the other core countries. CMP have positive effects on output and inflation, but these effects are temporary. UMPs (both QE and HM) have instead long lasting effects on output and inflation. Domestic effects of unconventional monetary policies are stronger in the US than in the Euro Area. This result is consistent with the findings of Chen et al. (2015) and Baumeister and Benati (2010). Compared to the Euro Area case, HM seems less effective than QE on growth, while on inflation the effect is similar. Finally long-term interest rates decline also in the HM case but by less than what happens with QE, resulting in a depreciation of the real effective exchange rate.

Regarding spillover effects, Fed monetary policies have stronger effects on sovereign long-term interest rates around the globe than ECB's measures. Focusing on the Treasury and the Bund, long-term rates decline by approximatively 9 basis points following Fed's QE, but only 2 basis points after ECB's QE. ECB's asset purchases have limited effects on US GDP, while US output strongly reacts after Fed's QE. This result is consistent with Chen et al. (2015) that found that US is resilient to a shock originating in the Euro Area. Regarding spillover effects on macroeconomic variables from the US to Europe we found, surprisingly, negative spillovers on growth. This results from the appreciation of real exchange rates in the Euro Area. It would expecially hurt European countries whose

Figure 4: Domestic and Spillover effects of Fed Monetary Policies (from 0 to 3 years ahead)



economies are more export-oriented compared than the US.

To summarize, UMPs are generally more effective in stimulating both growth and inflation domestically. For this reason they are preferable to CMPs in pursuing the targets of central banks. Nevertheless this result may be biased by the relative weight of post crisis data in the estimation sample. Long-term interest rates differentials between Euro area countries and Germany decline after the ECB's QE at least in the short-run. The US economy seems resilient to monetary policies originating in the Euro Area, while this is not true for those from the US to the Euro Area. Helicopter money is generally less effective in stimulating inflation in both Aresa. Instead HM seems preferable to QE in stimulating growth in the Euro Area. The opposite is true in the US.

6 Performance Analysis

In this section we present pseudo out-of-sample performances of the iDREAM. The model is evaluated out of sample from April 2008 to October 2013 for a total of 66 out of sample iterations. This implies that out-of-sample performances have been evaluated excluding the precrisis period and therefore, making the exercise particularly challenging. For every out-of-sample iteration we select the number of lags according to the BIC and we run trace and maximum eigenvalue tests to choose the appropriate number of cointegrating relationship in the local-country model as in Section 4.2. According to these tests we estimate the model and the weight matrix on the sample available. Latent factors have not been re-estimated at each step:[11] we used the full sample estimate that ends in October 2016. For each iteration we check the stability of the model in two ways: a) we verify that the largest eigenvalue of the coefficient matrix of lagged endogenous variables is not larger than unity; b) we inspect persistency profiles.[12]

In Figure A5 we show the results of the stability tests performed over time from April 2008 to October 2013 for different weight matrix (red bars represent unstable models). According to this plot, the weight matrix calculated from the responses of the business cycle delivers more stable estimates (only 4 out of 66 iterations have been found to be unstable). These episodes can be clustered in two different periods that correspond to the peaks of the financial crisis and of Eurozone debt crisis.

- **Financial crisis** (January and February 2009): peak negative effect of the financial crisis on economic activity;
- **Eurozone Sovereign Debt Crisis** (December 2011 and January 2012): Berlusconi resigned as Prime Minister of the Italian government; ECB started Long Term Refinancing Operations; S&P downgrades sovereign ratings of peripheral countries.

These two episodes represent the most relevant financial turmoils occurred in the last decades worldwide, and it is likely that they corresponded to structural breaks resulting in model instability. For this reason we omit these iterations from the computation of the performance ratio below.

[11] However we tested that factor estimates are stable over time.

[12] In particular we verified that all persistency profiles lie below 1 from 3 years horizon onwards. This means that any discrepancy from the long-run relationship originated from an exogenous shocks should not be larger than the size of the discrepancy at time 0, after 3 years.

In Tables B10 and B11 in the appendix we report ratios of RMSE of the iDREAM versus different benchmarks (Random walk and AR(1)) for all endogenous variables at different horizons. Forecasts from the iDREAM seem to do particularly well for the business cycle, monetary policy and long-term interest rates when compared to the AR(1). For inflation and short-term interest rates the evidence is more mixed: we do better than AR(1) in the long-run in Japan, UK and Germany, while the error is very large for the US short-term rate. This is not surprising: the out-of-sample period corresponds almost entirely with the ZLB on the Fed Funds rate. Out of sample forecasting performances are always worse than the benchmark for the annual growth rate of real effective exchange rate and oil. When we compare the model to the random walk, we do better than the benchmark for the business cycle and inflation in the short-run (first 3-month) and for long-term interest rates of the Euro Area at a 3 year horizon. Very interestingly the model seems to perform relatively well for long-term interest rates, while other studies have found more difficulties in forecasting this variable (Pesaran, Schuermann, and Smith (2009)).

In Tables B12 and B13 we report a measure of forecasting performance in terms of direction. For each variable we compute the ability of the model to capture changes in the direction of the variable at different forecast horizons. We compute an Accuracy ratio defined as the number of successful direction forecasts over the total number of forecasts.The left side of Table B12 shows the performance of the iDREAM, while the right side presents the performances of the AR(1). The model performs quite well in terms of direction expecially in the long-run for the business cycle and inflation, for which the ratio is larger than 0.5 in most cases. The model performs quite well also for real effective exchange rate and for the price of oil, while this is not true when looking at RMSE. Compared to the performances of the AR(1) in terms of direction, iDREAM performs better than the benchmark on average for all variables, except for long-term interest rates.

Finally we evaluated the forecasting performances of iDREAM by comparing it with alternative modelling strategies. As a first benchmark we estimated a model by changing the two main novel contributions introduced in the estimation of the iDREAM.

1. **We replace latent factors** with observable macroeconomic variables:
    - Real GDP annual growth for business cycle;
    - CPI inflation for Inflation;
    - M1 annual growth for Monetary Policy.
2. **We use weight matrix estimated from trade flows** in Dees, Mauro, et al. (2007) as an average over 2000-2012 period.

As a result of both changes, the first benchmark model resembles the GVAR model estimated in Dees, Mauro, et al. (2007). We compute pseudo out-of-sample forecasts[13] as we did for the iDREAM above. The first evidence is that this model is more unstable: only 11 out-of-sample iterations are found to be stable.[14] We compare the iDREAM with the GVAR model[15] in a short common sample of 10 iterations. The ratios of the RMSE of the iDREAM and GVAR are presented in the left side of Table B14 for long and short-term interest rates, real effective exchange rate and the price of oil.[16] According to these ratios our model performs much better than the GVAR for interest rates, while this is not generally the case for exchange rates. The second benchmark that we selected is an iDREAM model where the macroeconomic variables are observable. We want to verify whether estimating latent factors instead of observed variables conveys useful information for forecasting interest rates. The weight matrix is estimated as in the iDREAM setup with different endogenous variables. The results are presented in the central columns of Table B14 (iDREAM obs.). Performances have been evaluated in a common sample of 40 stable iterations. Also in this case the iDREAM model has a superior performance for long-term interest rates. For the short term interest rates, performances are more disappointing than those of the GVAR benchmark, while exchange rates forecasts are more accurate. Finally on the right side of table B14 we show the results of a test of the IDREAM versus an alternative version where the weight matrix corresponds to the trade matrix of the GVAR (IDREAM trade weight). Ideally, we would like to measure

[13]Trade weight matrix is fixed across different out-of-sample iterations.

[14]Only 35 out of sample iterations have eigenvalues lower and equal to one, while persistency profiles are stable in only 11 iterations.

[15]iDREAM and the other benchmark models have been reestimated excluding Russia from the sample, since trade flows were not available for this country.

[16]We focus only on these variables because they are included in both models.

the marginal contribution of estimating the weight matrix by using the proposed network approach. In this case, we found 19 stable iterations to evaluate performances. Our model strongly outperforms the benchmark for interest rates and exchange rates.

7 Conclusions

In this paper we propose a novel approach to model global macrofinancial interconnections. iDREAM (international Data Rich Environment Autoregressive Model) combines three main contributions in the empirical literature to overcome the curse of dimensionality: a) data shrinkage; b) international network estimation based on parameters shrinkage; 3) Global VARs. We estimate the model on a dataset including observable financial variables and unobservable latent macroeconomic variables for 11 countries. iDREAM is proposed as an useful tool for economic policy evaluation and for forecasting macro-financial variables. In Section 5 we use the model to estimate domestic and spillover effects of monetary policies (conventional and unconventional) originated in the US and in the Euro Area. In particular we identified two types of unconventional monetary policies: asset purchase programs (Quantitative Easing) and money financed fiscal policies (Helicopter Money). We found that unconventional policies are more effective in stimulating growth and inflation domestically. QE in the Euro Area is effective in reducing long-term interest rates differentials with the Bund, at least in the short-run. Helicopter money seems preferable in stimulating growth while inflation increases less than as result of QE because of a smaller depreciation of exchange rates. The model forecasting performance is tested versus standard benchmarks. We found that the model is stable over time and performs well compared to AR(1) process in terms of Root Mean Squared Error and Accuracy ratio. Finally, iDREAM forecasts are more accurate than forecasts obtained from a “GVAR version” of the iDREAM, where interconnections are estimated using trade flows and macroeconomic variables are observables. We also show that both our approaches of modelling international interconnections and estimating latent macroeconomic variables are necessary to obtain better forecasting performances.

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Appendix

Figure A1: Persistence profiles of the effect of system wide shocks to the cointegrating relations

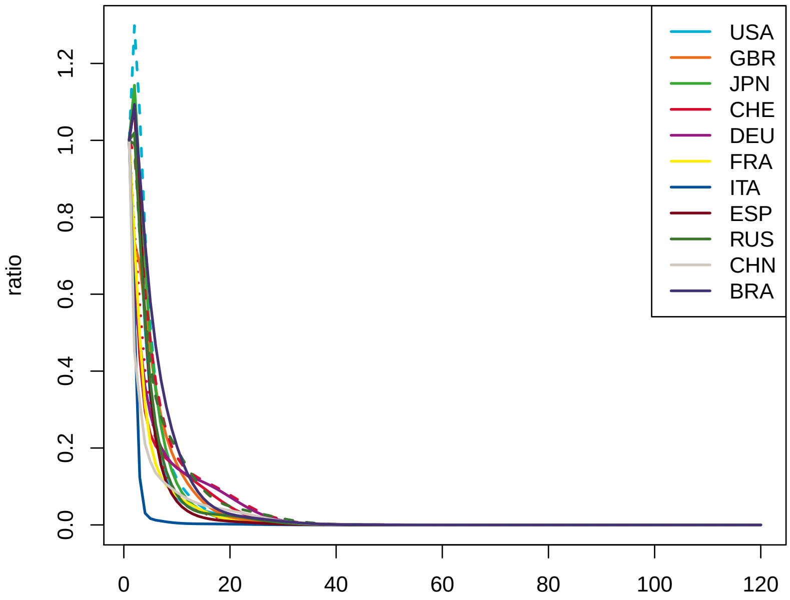

Figure A2: Eigenvalues (excluding unitary ones)

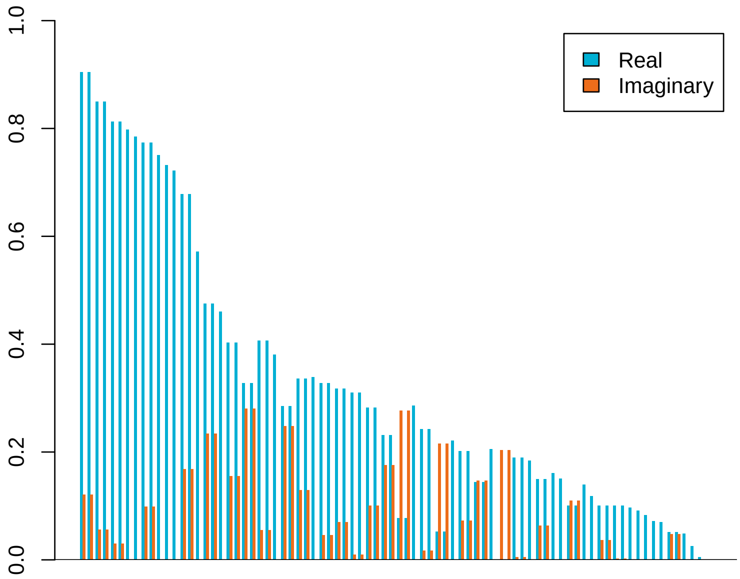

Figure A3: US endogenous variables and most correlated macroeconomic time series to each latent factor

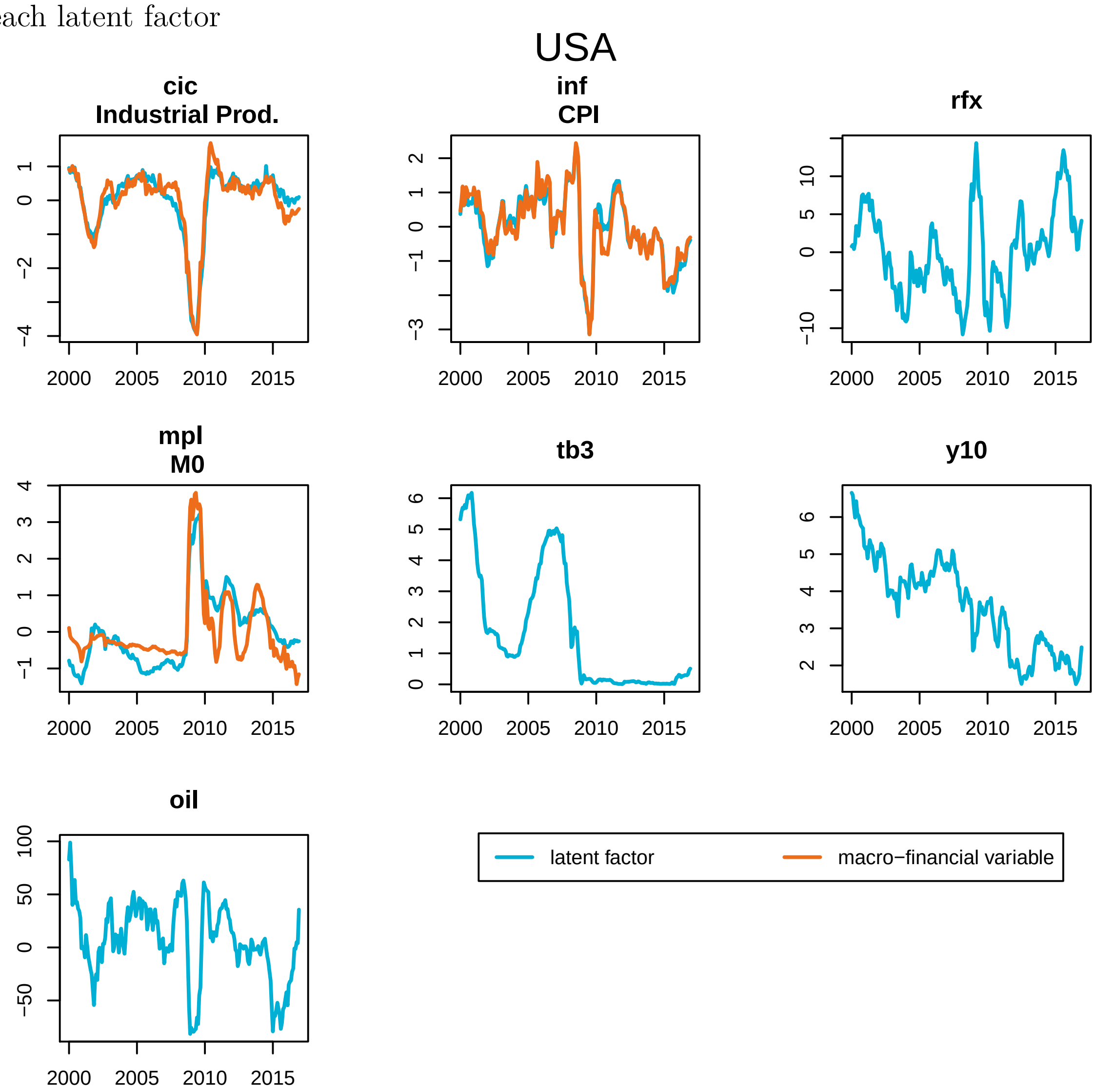

Figure A4: Effect on Real GDP growth of expansionary fiscal policy in a standard monetary VAR

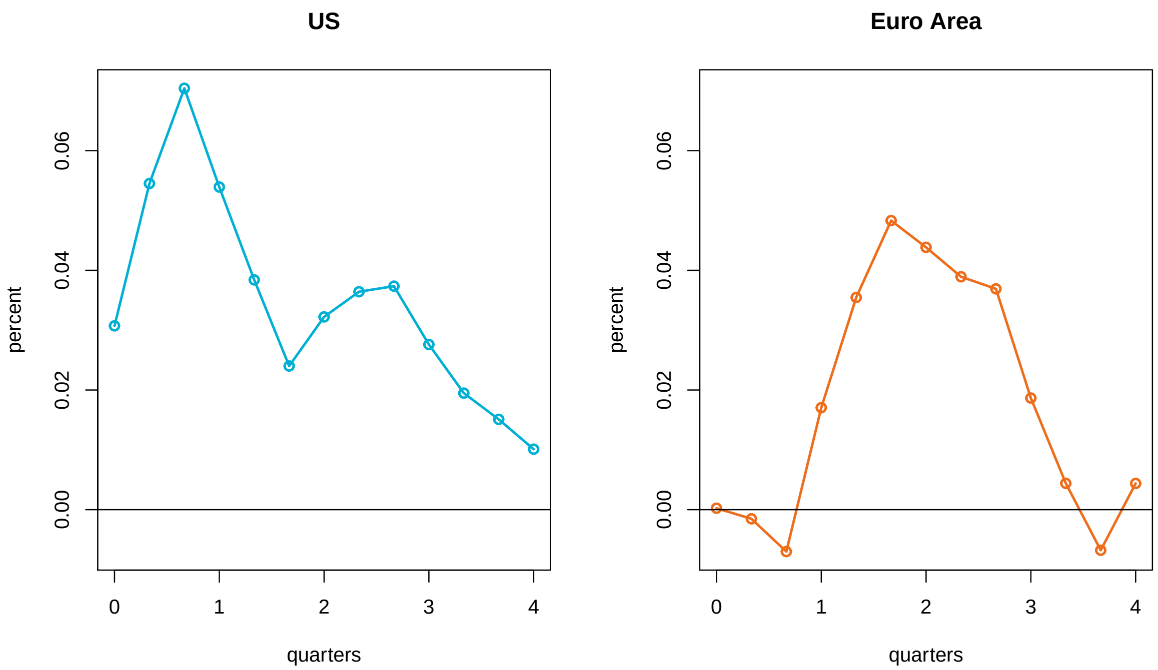

Figure A5: Stable models across time using different weight matrix

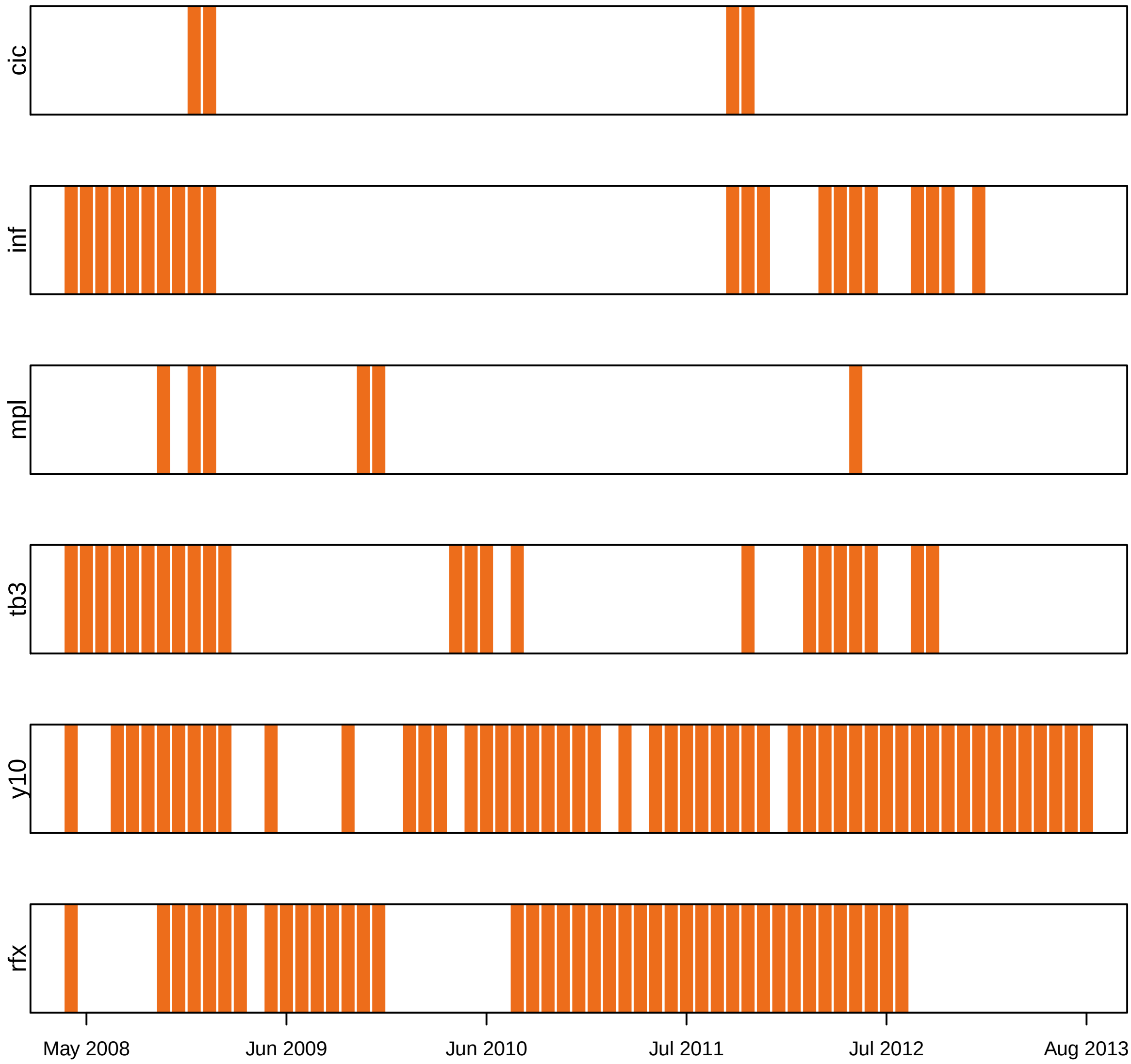

Table B1: Variables entering in the estimation of the business cycle latent factor

	USA	Germany	Italy	France	Spain	Japan	Switzerland	UK	Brazil	China	Russia
industrial production	total	total	total	total	total	total	total	total	total	total	total
	cons. goods	cons. goods	cons. goods	manufacturing	cons. goods	cons. goods	manufacturing	cons. goods	cons. goods	energy	manufacturing
	cons. goods durables	cons. goods durables	cons. goods durables	cars	manufacturing	manufacturing		manufacturing	cars	oil	cars
	cons. goods non durables	cons. goods non durables	cons. goods non durables		cars	cars		cars	manufacturing	steel	fuel
	manufacturing	manufacturing	manufacturing								
	mining	mining	mining								
	energy	energy	energy								
	motors	motors	cars								
	computers	technology									
pmi manufacturing	1	1	1	1	1	1	1	1	1	1	1
orders	capital goods	manufacturing	manufacturing	manufacturing	manufacturing	manufacturing	manufacturing	manufacturing	manufacturing	total	manufacturing
	durables	cons. goods durables	cons. goods durables	durables	cons. goods durables	cons. goods durables	cons. goods durables	cons. goods durables	cars	export	constructions
	cons. goods materials	cons. goods non durables	cons. goods non durables	construction	constructions	cars	constructions	constructions			
	capital goods (other)	investment goods	investment goods	cars	cars		cars	cars			
		constructions	constructions								
		cars	cars								
confidence indicator		manufacturing	manufacturing	manufacturing	manufacturing	manufacturing	manufacturing	manufacturing	manufacturing		manufacturing
		trend	trend	finished goods	finished goods		constructions	orders	retail sales		orders
		orders	orders				finished goods	export			
		export	export					finished goods			
		finished goods	finished goods								
		employment	employment								
		services	services								
		employment (fwd 3m)	employment (fwd 3m)								
capacity utilization rate	manufaturing	Total	manufacturing	Total	Total	Total	Total	Total	Total		Total
	durable	manufacturing	durables								
	computers	durables	technology								
		technology									
employment	total	total	construction								
	industry	construction	manufacturing								
	construction	manufacturing	services								
	manufacturing	trade	government								
	trade	finance									
	finance	services									
	professionals	government									
	education	other services									
	others										
housing started	1										
car selling	1										
car registrations	1	1								1	
GDP	Total	Total	Total	Total	Total	Total	Total	Total	Total	Total	Total
	Current Account	Current Account	Current Account	Current Account	Current Account	Current Account	Current Account	Current Account	Current Account	Primary	Current Account
	NPISH Consumption	NPISH Consumption	NPISH Consumption	NPISH Consumption	NPISH Consumption	NPISH Consumption	NPISH Consumption	NPISH Consumption	NPISH Consumption	Secondary	NPISH Consumption
	Gov. Consumption	Gov. Consumption	Gov. Consumption	Gov. Consumption	Gov. Consumption	Gov. Consumption	Gov. Consumption	Gov. Consumption	Gov. Consumption	Secondary, costruction	Gov. Consumption
		Capital Formation	Capital Formation	Capital Formation	Capital Formation	Capital Formation	Capital Formation	Capital Formation	Capital Formation	Secondary, industry	Capital Formation
	Private Inventory	Private Inventory	Private Inventory	Private Inventory	Private Inventory	Private Inventory	Private Inventory	Private Inventory	Private Inventory	Tertiary	Private Inventory
										Tertiary, Intermediary fin.	
										Tertiary, Real Estate	
										Tertiary, Trasportation	
										Tertiary, Wholesale	
Net government savings	1										
pce	durables										
	non durables										
	services										
	goods										
retail sales										consumer goods	
										consumer goods (city)	

Table B2: Variables entering in the estimation of Inflation latent factor

	USA	Germany	Italy	France	Spain	Japan	Switzerland	UK	Brazil	China	Russia
PPI	consumption goods	consumption goods	consumption goods	consumption goods	consumption goods	consumption goods	consumption goods	consumption goods	consumption goods	finished goods	total
	intermediate goods	intermediate goods	intermediate goods	intermediate goods	intermediate goods	intermediate goods	intermediate goods	intermediate goods	intermediate goods	intermediate goods	
	crude	crude	crude								
CPI	total	total	total	total	total	total	total	total	total	total	total
	food	food	food	food	food	food	food	food	food	food	food
	housing	private&no profit	private&no profit	health	transports	transports	transports	transports	transports	less food&energy	transports
	transports	transports	transports	goods&services	health	health	health	health	health	services less energy	health
	health	health	health		goods&services	goods&services	goods&services	goods&services	culture	housing	goods&services
	commodities	goods&services	goods&services							transports	
										medical care	
GDP deflator		1	1	1	1	1	1	1	1		1
house prices	1	1	1	1	1	1	1	1	1	1	
wages		total	total		total	total	total	total	total	total	total
		construction	construction								
		manufacturing	manufacturing								
export prices		1	1								

Table B3: Variables entering in the estimation of Monetary Policy latent factor

	USA	Germany	Italy	France	Spain	Japan	Switzerland	UK	Brazil	China	Russia
Monetary Aggregates	M0	M1	M1	M1	M1	M1	M1	M0	M1	M0	M1
	M1	M2	M2	M2	M2	M2	M2	M1	M2	M1	M2
	M2	M3	M3	M3	M3	M3	M3	M2	M3	M2	M3
	M3				M1 (Euro Area)			M3		M3	
Loans	commercial	Non Fin. Corp.	Non Fin. Corp.	Non Fin. Corp.	Non Fin. Corp.	Non Fin. Corp.	Non Fin. Corp.	Non Fin. Corp.	Non Fin. Corp.	Non Fin. Corp.	Non Fin. Corp.
	secured real estate	Households	Households	Households	Households	Households	Households	Households	Households	Households	Households
	Non Fin. Corp.	consumer credit	consumer credit	consumer credit	consumer credit	consumer credit		consumer credit			
	Households	house purchases	house purchases	house purchases	house purchases	house purchases		house purchases			
Total Assets Central Bank	1	1	1	1	1	1	1	1	1	1	1
Banks gov securities holding	1										
Securities holding Central Bank	1										
Reserves Bank Credit	1										

Table B4: Data Trasformation

business cycle	**Trasf**	**inflation**	**Trasf**	**monetary policy**	**Trasf**
Industrial production	2	PPI	2	Monetary Aggregates	2
Pmi manufacturing	0	CPI	2	Loans	2
Orders	2	GDP deflator	2	Total Assets Central Bank	2
Confidence indicator-surveys	0/1	House prices	2	Banks gov securities holding	2
Capacity utilization rate	1	Wages	2	Securities holding Central Bank	2
Employment	2	Export prices	2	Reserves Bank Credit	2
Housing started	2				
Car selling	2				
Car registrations	2				
GDP	2				
Net government savings	1				
Pce	1				
Retail sales	2				
GDP Change in inventories	1				
Current account	1				

Table B5: Descriptive statistics

	USA	**GBR**	**JPN**	**CHE**	**DEU**	**FRA**	**ITA**	**ESP**	**RUS**	**CHN**	**BRA**
tb3	1.64	2.75	0.13	0.80	1.77	1.77	1.97	1.92	8.41	3.57	14.40
	(1.92)	(2.20)	(0.20)	(1.24)	(1.73)	(1.68)	(1.51)	(1.53)	(4.56)	(1.10)	(4.42)
y10	3.60	3.72	1.14	1.90	3.09	3.37	4.16	4.12	11.28	3.55	14.89
	(1.26)	(1.29)	(0.50)	(1.19)	(1.52)	(1.37)	(1.18)	(1.22)	(7.47)	(0.53)	(3.81)
rfx	0.08	-1.06	-2.38	0.84	-0.60	-0.42	-0.04	0.44	2.64	1.79	0.89
	(5.64)	(6.26)	(9.67)	(4.61)	(3.36)	(2.95)	(3.13)	(2.79)	(10.52)	(5.56)	(14.71)
oil	5.44										
	(35.61)										

Table B6: Acceptance of Unit root hypothesis on the levels of the variables

	USA	**GBR**	**JPN**	**CHE**	**DEU**	**FRA**	**ITA**	**ESP**	**RUS**	**CHN**	**BRA**
cic	-1.92	-2.34	-3.41*	-3.03	-2.26	-2.59	-2.34	-1.96	-2.61	-1.98	-2.99
inf	-3.95**	-2.06	-2.96	-2.55	-2.66	-2.59	-2.77	-3.69**	-3.35*	-2.30	-3.21*
mpl	-2.40	-1.25	-1.81	-2.35	-2.86	-2.48	-1.59	-1.13	-2.52	-2.15	-3.30*
tb3	-1.91	-2.48	-1.38	-1.96	-2.31	-2.15	-2.93	-2.65	-3.29*	-2.65	-1.96
y10	-3.80**	-2.94	-2.01	-2.42	-2.78	-2.51	-1.68	-1.36	-6.58***	-2.72	-2.61
rfx	-3.57**	-1.91	-2.67	-3.52**	-3.95**	-3.92**	-4.15***	-4.29***	-5.72***	-3.33*	-3.54**
oil	-3.86**										

*** 1% Significance level, ** 5% Significance level, * 10% Significance level

Table B7: Lag Order and Cointegration Rank for each country

	p	**q**	**case**	**r**
USA	2	1	II	2
GBR	2	1	II	1
JPN	2	1	II	1
CHE	2	1	II	3
DEU	2	1	II	1
FRA	2	1	II	1
ITA	2	1	II	1
ESP	2	1	II	1
RUS	2	1	II	2
CHN	2	1	II	1
BRA	2	1	II	1

Table B8: F-statistic for testing weak exogeneity of country-specific foreign variables

	oil	**cic_star**	**inf_star**	**mpl_star**	**tb3_star**	**y10_star**	**rfx_star**
USA		3.97**	1.20	3.18*	0.00	0.00	1.84
GBR	0.01	3.33*	3.49*	2.75*	1.15	0.20	0.22
JPN	0.31	4.95**	4.06**	0.59	1.11	1.26	0.31
CHE	1.33	15.66***	6.09**	0.00	0.00	1.30	0.25
DEU	0.55	2.24	2.91*	2.48	0.13	0.53	2.05
FRA	0.01	0.00	1.77	0.25	0.02	0.01	0.70
ITA	1.93	4.05**	1.91	0.94	1.47	0.60	0.25
ESP	0.00	1.12	4.70**	0.45	1.99	0.00	0.19
RUS	2.72	5.14**	0.28	0.39	0.05	0.50	0.73
CHN	0.00	0.04	2.20	0.00	0.58	0.21	1.91
BRA	0.02	0.13	0.00	0.27	0.25	0.07	3.27*

*** 1% Significance level, ** 5% Significance level, * 10% Significance level

Table B9: Country-specific FAVECM(p_i, q_i) R^2

	USA	**GBR**	**JPN**	**CHE**	**DEU**	**FRA**	**ITA**	**ESP**	**RUS**	**CHN**	**BRA**
cic	0.42	0.39	0.32	0.62	0.65	0.62	0.49	0.47	0.45	0.19	0.40
inf	0.60	0.47	0.30	0.43	0.75	0.42	0.54	0.74	0.24	0.25	0.47
mpl	0.36	0.28	0.23	0.23	0.19	0.13	0.12	0.22	0.32	0.33	0.28
tb3	0.31	0.58	0.13	0.27	0.33	0.36	0.32	0.18	0.29	0.03	0.11
y10	0.10	0.41	0.13	0.36	0.36	0.44	0.36	0.30	0.46	0.16	0.12
rfx	0.19	0.18	0.11	0.12	0.24	0.19	0.48	0.31	0.34	0.33	0.22
oil	0.46										

Table B10: Ratio Root Mean Squared Error vs Benchmarks (a)

	y10							
	RW				AR(1)			
	+3m	+12m	+24m	+36m	+3m	+12m	+24m	+36m
USA	1.28	1.03	1.10	1.22	1.22	0.86	0.85	0.86
GBR	1.16	1.08	1.08	1.06	1.09	0.89	0.82	0.79
JPN	1.13	1.24	1.02	1.02	1.06	0.84	0.71	0.75
CHE	0.98	1.01	0.95	0.92	0.98	0.97	0.91	0.86
DEU	1.11	1.18	1.03	0.97	1.09	1.09	0.94	0.87
FRA	1.16	1.07	0.94	0.93	1.14	0.97	0.82	0.79
ITA	1.20	1.07	1.01	1.01	1.19	1.14	1.12	1.15
ESP	1.16	1.05	0.96	0.94	1.15	1.10	1.09	1.12
RUS	1.62	1.87	1.97	2.51	1.79	2.68	2.74	3.55
CHN	1.12	1.84	1.90	2.50	1.13	1.97	2.19	2.58
BRA	1.47	1.38	1.21	1.19	1.47	1.33	1.14	1.15

	tb3							
	RW				AR(1)			
	+3m	+12m	+24m	+36m	+3m	+12m	+24m	+36m
USA	1.53	2.66	4.32	4.61	1.57	2.86	4.46	4.14
GBR	1.16	1.29	1.30	1.32	1.13	1.10	0.71	0.44
JPN	1.18	1.14	1.19	1.15	1.14	0.99	0.93	0.86
CHE	1.10	1.24	1.32	1.27	1.10	1.22	1.29	1.23
DEU	1.09	1.14	1.25	1.16	1.08	1.08	1.08	0.92
FRA	1.09	1.18	1.29	1.24	1.08	1.12	1.15	1.04
ITA	1.23	1.32	1.50	1.80	1.22	1.24	1.30	1.34
ESP	1.08	1.09	1.27	1.41	1.07	1.01	1.01	0.97
RUS	1.09	1.35	1.28	1.35	1.08	2.17	1.88	1.86
CHN	0.98	1.06	1.03	1.16	0.98	1.22	1.33	1.35
BRA	1.89	1.69	1.51	1.44	1.80	1.57	1.44	1.36

	Business Cycle							
	RW				AR(1)			
	+3m	+12m	+24m	+36m	+3m	+12m	+24m	+36m
USA	0.83	0.93	1.00	1.07	0.76	0.62	0.37	0.22
GBR	0.78	0.94	1.00	1.15	0.72	0.82	0.74	0.43
JPN	0.98	1.13	1.11	1.15	0.91	0.69	0.15	0.05
CHE	0.56	0.84	1.04	1.23	0.55	0.77	0.83	0.74
DEU	0.83	0.89	0.89	1.10	0.77	0.71	0.49	0.26
FRA	0.85	0.85	0.78	0.89	0.80	0.68	0.45	0.25
ITA	0.85	0.92	0.91	1.20	0.81	0.81	0.70	0.52
ESP	0.93	0.96	0.91	1.10	0.85	0.62	0.33	0.16
RUS	0.95	1.27	1.48	1.58	0.89	1.06	0.87	0.64
CHN	1.06	1.21	1.28	1.50	1.07	1.31	1.24	1.27
BRA	1.02	1.19	1.33	1.28	1.05	1.35	1.59	1.42

	Inflation							
	RW				AR(1)			
	+3m	+12m	+24m	+36m	+3m	+12m	+24m	+36m
USA	0.88	1.04	1.20	1.29	0.90	1.23	1.44	1.48
GBR	1.00	1.42	1.79	1.67	0.91	1.04	0.96	0.60
JPN	0.95	1.07	1.39	1.86	0.92	1.02	1.31	1.31
CHE	0.86	1.24	1.39	1.23	0.86	1.36	1.31	1.02
DEU	0.85	1.16	1.41	1.47	0.84	1.17	1.32	1.29
FRA	0.75	1.17	1.35	1.30	0.71	1.00	0.73	0.44
ITA	0.86	1.15	1.29	1.38	0.80	1.01	0.85	0.63
ESP	0.86	1.13	1.48	1.33	0.81	0.85	0.50	0.23
RUS	1.45	1.06	1.26	1.19	1.29	0.93	1.07	1.01
CHN	0.94	1.05	1.17	1.49	0.96	1.11	1.44	2.25
BRA	1.37	2.17	2.67	2.01	1.40	2.36	2.95	1.98

Table B11: Ratio Root Mean Squared Error vs Benchmarks (b)

	Monetary Policy							
	RW				AR(1)			
	+3m	+12m	+24m	+36m	+3m	+12m	+24m	+36m
USA	0.98	1.11	1.34	1.16	0.91	0.73	0.31	0.16
GBR	1.12	1.25	1.25	1.16	0.95	0.96	0.65	0.41
JPN	1.07	1.03	1.04	0.96	0.99	0.94	0.83	0.81
CHE	0.90	1.08	1.14	1.25	0.89	1.00	0.87	0.87
DEU	1.09	1.37	1.59	1.93	1.13	1.54	2.01	2.67
FRA	0.96	0.84	0.85	0.91	0.85	0.83	0.88	0.74
ITA	1.32	1.24	1.41	1.32	1.14	0.99	1.06	1.03
ESP	0.97	1.03	1.17	1.09	0.92	0.89	0.92	0.72
RUS	0.84	1.10	1.35	1.64	0.72	0.62	0.30	0.18
CHN	0.89	0.91	1.02	1.16	0.80	1.08	1.37	1.55
BRA	1.17	2.09	2.73	2.79	1.18	2.26	3.09	3.05

	Real Effective Exchange Rate							
	RW				AR(1)			
	+3m	+12m	+24m	+36m	+3m	+12m	+24m	+36m
USA	1.05	1.08	1.00	1.28	1.10	1.28	1.24	1.38
GBR	1.13	1.15	1.11	1.08	1.16	1.30	1.22	1.20
JPN	1.03	1.04	1.13	1.10	1.02	1.22	1.58	1.61
CHE	1.05	1.02	1.02	1.09	1.07	1.22	1.38	1.56
DEU	1.28	1.39	1.17	1.27	1.33	1.73	1.40	1.80
FRA	1.33	1.49	1.42	1.45	1.39	1.82	1.56	1.76
ITA	1.27	1.32	1.16	1.15	1.32	1.62	1.30	1.56
ESP	1.25	1.21	1.21	1.31	1.30	1.42	1.28	1.28
RUS	1.21	1.41	1.25	1.15	1.27	1.58	1.26	1.11
CHN	1.07	1.17	1.21	1.69	1.10	1.36	1.60	2.20
BRA	1.02	1.07	0.91	1.15	1.07	1.40	1.14	1.18

	Oil							
	RW				AR(1)			
	+3m	+12m	+24m	+36m	+3m	+12m	+24m	+36m
USA	1.16	1.15	1.30	1.34	1.25	1.62	1.80	1.72

Table B12: Accuracy ratios (a)

	y10							
	IDREAM				AR(1)			
	+3m	+12m	+24m	+36m	+3m	+12m	+24m	+36m
USA	0.52	0.47	0.52	0.53	0.47	0.44	0.49	0.49
GBR	0.40	0.57	0.53	0.57	0.37	0.44	0.53	0.44
JPN	0.47	0.47	0.32	0.26	0.42	0.39	0.29	0.26
CHE	0.47	0.53	0.50	0.39	0.37	0.49	0.52	0.37
DEU	0.44	0.47	0.49	0.36	0.39	0.53	0.40	0.32
FRA	0.34	0.44	0.36	0.31	0.36	0.52	0.34	0.32
ITA	0.42	0.39	0.44	0.42	0.44	0.34	0.42	0.44
ESP	0.52	0.50	0.45	0.47	0.53	0.49	0.47	0.42
RUS	0.52	0.53	0.52	0.47	0.45	0.53	0.45	0.49
CHN	0.40	0.44	0.60	0.52	0.32	0.53	0.58	0.65
BRA	0.45	0.53	0.53	0.61	0.44	0.57	0.58	0.52

	tb3							
	IDREAM				AR(1)			
	+3m	+12m	+24m	+36m	+3m	+12m	+24m	+36m
USA	0.42	0.42	0.42	0.60	0.45	0.53	0.50	0.40
GBR	0.58	0.58	0.50	0.36	0.44	0.40	0.55	0.47
JPN	0.47	0.39	0.40	0.45	0.50	0.37	0.36	0.37
CHE	0.58	0.52	0.53	0.55	0.47	0.37	0.52	0.50
DEU	0.52	0.50	0.45	0.50	0.39	0.40	0.60	0.49
FRA	0.60	0.50	0.37	0.55	0.45	0.39	0.60	0.37
ITA	0.62	0.55	0.55	0.42	0.44	0.47	0.50	0.47
ESP	0.47	0.52	0.49	0.52	0.47	0.47	0.49	0.45
RUS	0.36	0.45	0.49	0.61	0.45	0.53	0.57	0.65
CHN	0.62	0.50	0.57	0.58	0.57	0.52	0.50	0.52
BRA	0.57	0.49	0.36	0.40	0.53	0.45	0.42	0.40

	Business Cycle							
	IDREAM				AR(1)			
	+3m	+12m	+24m	+36m	+3m	+12m	+24m	+36m
USA	0.44	0.50	0.47	0.53	0.42	0.52	0.52	0.66
GBR	0.47	0.49	0.60	0.68	0.34	0.52	0.63	0.57
JPN	0.29	0.55	0.45	0.71	0.24	0.62	0.50	0.63
CHE	0.55	0.49	0.55	0.57	0.32	0.49	0.55	0.60
DEU	0.44	0.47	0.65	0.68	0.36	0.50	0.55	0.61
FRA	0.53	0.42	0.55	0.61	0.37	0.44	0.52	0.65
ITA	0.40	0.42	0.52	0.61	0.28	0.39	0.53	0.70
ESP	0.42	0.45	0.50	0.60	0.34	0.42	0.55	0.60
RUS	0.47	0.47	0.55	0.57	0.45	0.50	0.52	0.57
CHN	0.53	0.50	0.44	0.49	0.45	0.52	0.42	0.47
BRA	0.42	0.45	0.58	0.49	0.53	0.53	0.60	0.42

	Inflation							
	IDREAM				AR(1)			
	+3m	+12m	+24m	+36m	+3m	+12m	+24m	+36m
USA	0.37	0.49	0.42	0.57	0.39	0.50	0.42	0.52
GBR	0.50	0.29	0.37	0.58	0.36	0.36	0.45	0.47
JPN	0.47	0.49	0.60	0.55	0.40	0.52	0.55	0.58
CHE	0.45	0.40	0.40	0.52	0.39	0.44	0.44	0.45
DEU	0.53	0.45	0.49	0.60	0.37	0.37	0.52	0.58
FRA	0.55	0.44	0.57	0.52	0.36	0.40	0.52	0.52
ITA	0.55	0.52	0.52	0.49	0.29	0.36	0.52	0.53
ESP	0.53	0.39	0.47	0.47	0.28	0.34	0.55	0.50
RUS	0.52	0.52	0.58	0.42	0.39	0.50	0.57	0.50
CHN	0.37	0.45	0.52	0.65	0.37	0.44	0.57	0.61
BRA	0.37	0.47	0.39	0.55	0.47	0.50	0.47	0.44

Table B13: Accuracy ratios (b)

	Monetary Policy							
	IDREAM				AR(1)			
	+3m	+12m	+24m	+36m	+3m	+12m	+24m	+36m
USA	0.40	0.52	0.57	0.37	0.39	0.52	0.53	0.34
GBR	0.45	0.39	0.49	0.57	0.36	0.45	0.50	0.52
JPN	0.57	0.45	0.45	0.49	0.36	0.55	0.34	0.45
CHE	0.39	0.47	0.45	0.45	0.37	0.44	0.52	0.53
DEU	0.49	0.37	0.50	0.65	0.37	0.42	0.45	0.66
FRA	0.53	0.52	0.55	0.58	0.39	0.44	0.58	0.47
ITA	0.62	0.45	0.49	0.53	0.58	0.45	0.52	0.53
ESP	0.31	0.49	0.37	0.32	0.31	0.47	0.40	0.29
RUS	0.47	0.39	0.53	0.58	0.42	0.44	0.66	0.57
CHN	0.47	0.44	0.45	0.53	0.44	0.47	0.45	0.50
BRA	0.53	0.36	0.57	0.57	0.36	0.53	0.52	0.49

	Real Effective Exchange Rate							
	IDREAM				AR(1)			
	+3m	+12m	+24m	+36m	+3m	+12m	+24m	+36m
USA	0.42	0.45	0.42	0.61	0.36	0.49	0.47	0.53
GBR	0.36	0.47	0.55	0.58	0.40	0.50	0.49	0.50
JPN	0.40	0.47	0.47	0.47	0.45	0.52	0.55	0.45
CHE	0.52	0.45	0.53	0.57	0.45	0.47	0.50	0.57
DEU	0.45	0.34	0.60	0.52	0.39	0.42	0.52	0.53
FRA	0.50	0.42	0.60	0.63	0.40	0.47	0.50	0.49
ITA	0.45	0.37	0.58	0.45	0.49	0.42	0.55	0.47
ESP	0.42	0.45	0.57	0.55	0.40	0.49	0.47	0.52
RUS	0.50	0.42	0.52	0.45	0.57	0.50	0.52	0.45
CHN	0.40	0.50	0.53	0.55	0.44	0.52	0.49	0.49
BRA	0.50	0.53	0.39	0.55	0.45	0.60	0.53	0.49

	Oil							
	IDREAM				AR(1)			
	+3m	+12m	+24m	+36m	+3m	+12m	+24m	+36m
USA	0.39	0.53	0.45	0.58	0.45	0.53	0.45	0.58

Table B14: Ratio Root Mean Squared Error vs alternative models

	y10														
	GVAR					IDREAM obs.					IDREAM Trade Weight				
	+1m	+3m	+12m	+24m	+36m	+1m	+3m	+12m	+24m	+36m	+1m	+3m	+12m	+24m	+36m
USA	0.89	1.36	0.88	0.47	0.39	1.04	0.96	1.00	0.90	0.95	0.87	0.75	0.52	0.28	0.26
GBR	0.91	1.05	0.72	0.49	0.46	1.16	0.97	0.95	0.92	0.99	0.86	0.76	0.69	0.52	0.37
JPN	1.04	0.93	0.83	0.61	0.73	1.08	0.94	1.02	0.93	0.99	0.80	0.54	0.34	0.28	0.29
CHE	0.87	0.74	0.81	0.39	0.60	0.90	0.82	0.98	0.99	1.00	0.68	0.54	0.38	0.38	0.32
DEU	0.95	0.91	0.65	0.48	0.51	0.98	0.89	1.02	1.00	1.01	0.89	0.74	0.51	0.45	0.34
FRA	0.79	0.85	0.81	0.75	0.63	1.04	0.98	1.14	0.93	0.96	0.91	0.72	0.47	0.41	0.32
ITA	0.90	1.03	0.96	1.74	1.05	1.05	1.01	1.05	0.97	0.96	0.96	0.67	0.56	0.57	0.48
ESP	1.20	1.24	0.97	1.26	1.06	0.90	0.78	0.85	0.85	0.89	0.82	0.64	0.54	0.61	0.49
CHN	1.16	0.79	1.04	1.42	1.08	0.89	0.95	1.38	1.41	1.36	0.91	1.02	1.05	0.75	0.60
BRA	0.81	0.92	0.94	0.87	0.39	0.89	0.86	0.99	0.86	0.90	0.90	0.67	0.71	0.56	0.55

	tb3														
	GVAR					IDREAM obs.					IDREAM Trade Weight				
	+1m	+3m	+12m	+24m	+36m	+1m	+3m	+12m	+24m	+36m	+1m	+3m	+12m	+24m	+36m
USA	1.41	2.07	1.54	1.69	1.02	1.51	1.51	1.16	0.88	0.65	1.00	0.96	1.09	0.58	0.36
GBR	0.47	0.49	0.42	0.34	0.46	0.88	0.90	0.84	0.86	0.85	0.91	0.96	0.90	0.60	0.44
JPN	1.03	1.69	1.51	1.87	1.73	0.88	0.84	0.76	0.82	0.96	1.07	0.66	0.88	0.78	0.78
CHE	0.84	0.84	0.71	1.16	1.51	0.86	1.22	1.38	1.47	1.43	1.07	1.23	1.08	1.16	0.97
DEU	1.13	0.64	0.40	0.25	0.28	1.03	0.93	1.05	1.15	1.18	1.14	1.21	1.26	1.21	1.19
FRA	0.88	0.62	0.43	0.32	0.30	1.02	1.04	1.19	1.28	1.17	1.17	1.29	1.29	1.06	0.91
ITA	0.66	0.63	0.42	0.97	0.36	1.08	1.15	0.99	1.29	1.19	1.12	1.18	1.26	1.26	1.14
ESP	0.80	0.82	0.35	0.50	0.28	1.04	1.09	1.24	1.44	1.28	1.03	1.12	1.19	1.45	1.39
CHN	1.01	1.03	0.78	1.69	1.02	1.02	1.06	0.97	1.06	1.10	1.08	0.99	0.98	0.70	0.62
BRA	0.99	1.05	1.53	1.99	1.58	1.15	0.91	1.00	0.94	0.75	0.96	0.79	1.03	0.61	0.65

	rfx														
	GVAR					IDREAM obs.					IDREAM Trade Weight				
	+1m	+3m	+12m	+24m	+36m	+1m	+3m	+12m	+24m	+36m	+1m	+3m	+12m	+24m	+36m
USA	1.04	1.11	0.91	2.09	1.61	0.95	0.83	0.85	0.94	0.82	0.75	0.68	0.66	0.48	0.31
GBR	0.70	0.60	1.10	0.83	0.58	0.96	0.87	0.97	1.05	0.84	0.93	0.79	1.18	1.37	0.97
JPN	1.27	0.67	1.13	2.78	2.71	0.87	0.86	0.93	0.91	0.93	0.91	0.86	1.36	0.97	1.18
CHE	0.94	0.95	1.06	1.73	1.19	0.96	0.84	0.76	0.90	1.05	0.50	0.41	0.28	0.32	0.29
DEU	1.29	1.14	1.31	1.31	1.18	0.91	0.73	0.90	0.73	0.68	0.70	0.69	0.50	0.39	0.13
FRA	0.96	0.77	1.35	1.43	0.69	1.01	0.82	0.90	0.84	0.68	0.48	0.49	0.43	0.29	0.11
ITA	1.17	0.85	1.14	2.84	1.30	0.97	0.74	0.80	0.68	0.64	0.50	0.46	0.37	0.29	0.11
ESP	1.02	0.82	1.01	1.12	0.67	0.91	0.86	0.76	0.90	0.49	0.62	0.57	0.53	0.45	0.18
CHN	0.99	1.12	1.27	1.75	2.28	0.91	0.88	1.24	1.16	1.32	0.98	0.83	0.79	0.32	0.64
BRA	1.16	0.75	0.49	0.74	0.90	0.93	0.92	0.74	0.96	0.99	0.91	0.76	1.04	0.62	0.61

oil														
GVAR					IDREAM obs.					IDREAM Trade Weight				
+1m	+3m	+12m	+24m	+36m	+1m	+3m	+12m	+24m	+36m	+1m	+3m	+12m	+24m	+36m
1.06	0.99	0.73	1.06	1.25	0.98	1.06	1.08	1.19	0.96	1.07	1.01	0.92	0.88	0.50