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Forecasting macro-financial variables in an International Data-Rich Environment Vector Autoregressive Model (iDREAM)*

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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 show that our approach outperforms alternative forecasting models, including a standard Global VAR, in particular for predictions on international business cycles and long term interest rates.

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

Keywords: Spillover, Weak and Strong Cross Section Dependence, High-Dimensional VAR, Network Analysis, Factor Models

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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 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 on 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 Vector 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 two 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 and 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 a monetary policy latent factor, which should describe the central banks' 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 with 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).

We apply our econometric framework to a panel of 11 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 with a network connectedness framework.

The paper is organised as follows. Section 2 presents the iDREAM approach: in particular, the extraction of latent factors, local-country models and the estimation if the weight matrix. Section 3 introduces the dataset used for estimation and describes our procedure to extract latent macroeconomic factors. Section 4 presents the results: the specification of country-specific models, weak exogeneity tests and detailed evidence on the stability of the model. Section 5 evaluates the forecasting performance of the model. Section 6 offers some concluding remarks.

2 The methodology

Vector-Autoregressions (VAR) are a useful tool for forecasting purposes and economic policy evaluation (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 countries tends to infinity, such that

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

where $K < \infty$ is a constant term (independent of i and N). 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:

$$x_{i,t} = \left(cic_{i,t}^{'}, inf_{i,t}^{'}, mpl_{i,t}^{'}, tb3_{i,t}^{'}, y10_{i,t}^{'}, rfx_{i,t}^{'}\right)'$$

for $i \neq$ United States, and

$$x_{US,t} = (cic_{US,t}^{'}, inf_{US,t}^{'}, mpl_{US,t}^{'}, tb3_{US,t}^{'}, y10_{US,t}^{'}, rfx_{US,t}^{'}, oil_t^{'})'$$

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, *tb*3 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 in the world economy and international financial markets.

By stacking local endogenous variables in the vector

$$x_t = \left(x_{1,t}^{'}, x_{2,t}^{'}, ..., x_{N,t}^{'}\right)'$$

we can define the vector of country i's 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

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

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's 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 channels 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 VAR framework (see Banbura, Giannone, and Reichlin (2010)), by 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 0 elsewhere.

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.

3 Data

Our approach relies on estimating country-specific latent factors on partitions of the full dataset on international business cycles, inflation rates and monetary policies. In particular, given a data matrix $X_{i,j}$ specific to country i, category j of dimension $T \times N_{i,j}$ we estimate a single factor $F_{i,j}$, 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 hand, 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, listed in Table 1. The countries included account for 55% of World GDP in 2016. A detailed description of the variables entering the estimation of each factor is presented in Tables B1-B3 in the Appendix. The business cycle factor is estimated on variables such as industrial production, PMI, orders, confidence indicators, capacity utilization rate, employment, GDP components and other series. For most of these variables we also included sectoral indicators. For the inflation factor, we used different components of 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 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. The monetary policy factor has been included in the model as one of the driving forces of global macrofinancial comovements. Nevertheless, this factor does not capture only the 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 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

[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).

we included more disaggregated data, resulting in a larger sample size, in order to get more precise 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. To guarantee a common interpretation of each estimated factor across countries, we chose, when possible, similar variables for each country.

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 a 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, since it should convey similar information to the annual growth rate of industrial production. For the same reason we did not transform PMI manufacturing indexes. A summary of different transformations is presented in Table B4. We coded transformations in the following way.[2] Given Z_t the original time series and $\tilde{Z}_t$ the transformed variable:

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

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

We interpret each factor by running univariate regressions between the factor and each underlying 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 using Consumer Price Indices and are

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

[3] Some differences with respect to Stock and Watson (2002) are worth emphasizing. Due to the strong persistence of the time series and the relative small size of the dataset for some country/category, the goodness of fit of the EM algorithm for quarterly variables was in some case very poor. To deal with this issue, we proceeded by temporally disaggregating quarterly series to monthly frequency using the Denton-Cholette interpolation method (Denton (1971)).

included in each country model as annual growth rates. For government bond yields, we considered 3-month short-term yields and 10-year Constant Maturity Par Yields as long term yields.[4] Oil is defined as the annual growth rate of the Brent price. The data source is Thomson Reuters Datastream. The model has been estimated on monthly observations from January 2000 to October 2016. In Table B5 in the Appendix we present summary statistics for the endogenous variables of our model (latent factors are omitted since they are standardized).

In Figure A3 we present the endogenous variables of the US model. We associate each latent factor to the most correlated underlying 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 growth rate of the Consumer Price Index. Finally, Monetary policy is closely associated to the growth rate of M0.

The interpretation of business cycle or inflation latent factors is, by construction, homogeneous across coutries. The most correlated variable with the inflation factor is always represented by the annual growth rate of the Consumer Price Index (or one of his components), while, for the business cycle, industrial production is the most correlated underlying variable in 7 out of 11 countries.

The interpretation of the monetary policy latent factor is more heterogenous 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 the year-on-year growth rate in private lending in Italy, Spain, UK and Brazil, while monetary aggregates are usually the most correlated variables in the other countries. Large correlation between the latent factor and private lending could be symptomatic of an impaired transmission mechanism of the monetary policy in these countries.

In Tables B6 in the Appendix we report the ADF test statistic on the level of endogenous

[4]To achieve a balanced panel with the other countries, we extended backward all interest rate time series not available before January 2000. In particular, we derived the Chinese 10-year government interest rates, not available before June 2002, conditional to Chinese 3-month interbank interest rate 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.

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 out of 11 countries. On the other hand, there is strong evidence that the annual growth rate of real effective exchange rates and the oil price are I(0). For inflation, the evidence is more mixed.[5] These results support our modelling strategy estimating local Small Open Economy models in a Factor-Augmented Vector Error Correction Model fashion.

4 Estimation

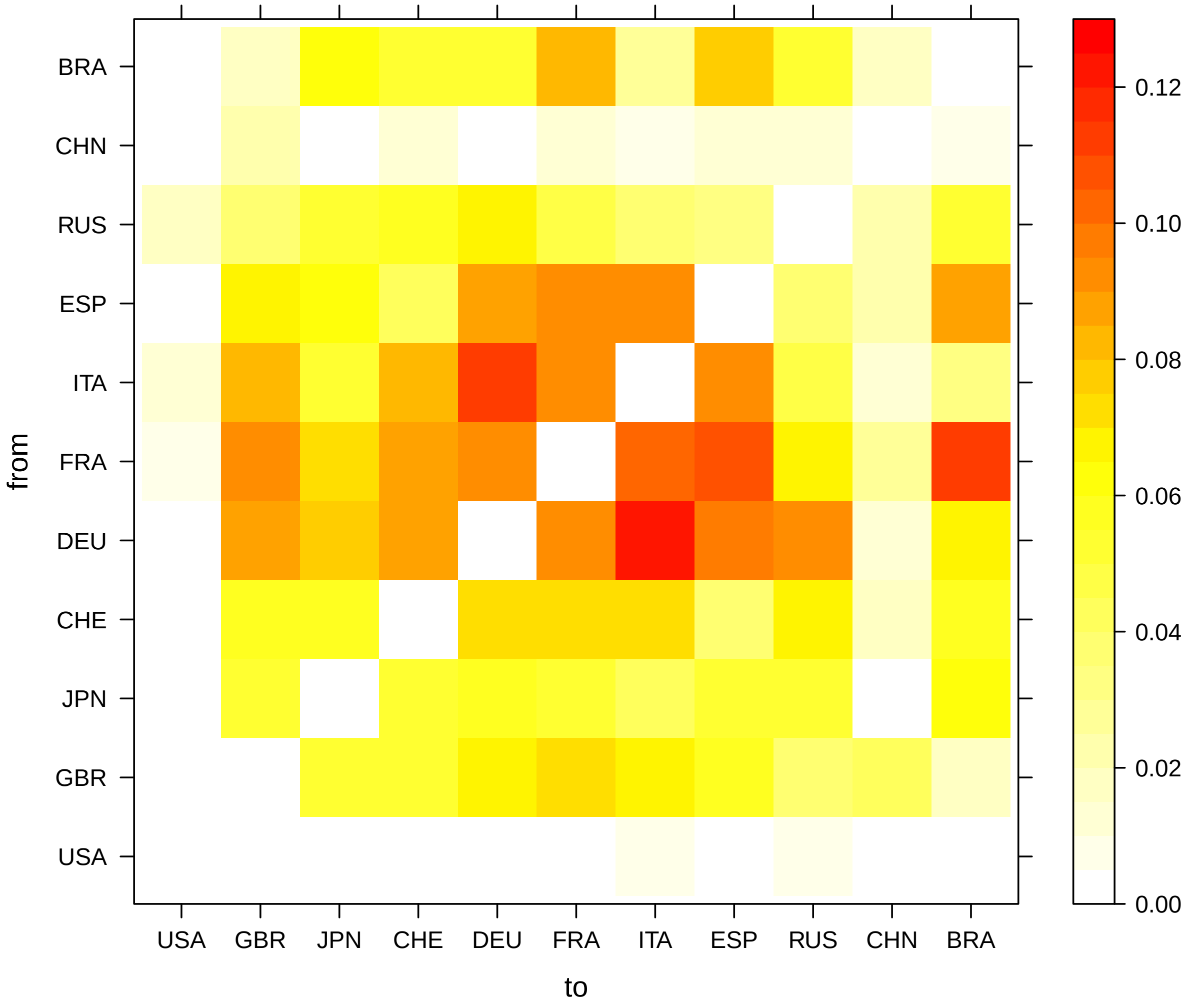
4.1 The Weight Matrix

Previous IVAR or GVAR applications used trade or financial weights to construct foreign variables, choosing a fixed or time-varying weight matrix. Instead, 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 find that the business cycle weight matrix is the most performing (see the Section 5 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 Emerging countries. Nevertheless, the nearly null interconnection from and to the US is quite

[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).

surprising, because the weights of US trade are 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.

Figure 1: Adjacency matrix estimated on business cycle



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 eigenvalue 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 specification of the model, cointegration rank is chosen from the minimum rank supplied by the 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 inflation 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 results on the business cycle and the inflation factor, while real effective exchange rates has a lower goodness of fit. The government bond yields for developed and emerging countries have a heterogeneous pattern among , 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 the 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 Performance Analysis

In this section we present the forecasting ability evaluation of the iDREAM. The model is evaluated out-of-sample from April 2008 to October 2013 recursively for a total of 66 iterations. The starting date for out-of-sample analysis has been set to guarantee a sufficiently long dataset from the first iteration (at least half the observations of the complete dataset). We evaluate the model on a 3 years horizon; the final date of the out of sample analysis is chosen consequently. Therefore, our forecasting evaluation exercise excludes the pre-crisis period, making the exercise particularly challenging. For each out-of-sample iteration and each local-country model, the number of lags is selected according to the information criterion (BIC), the number of cointegrating relationships is chosen according to the maximum eigenvalue test, as in Section 4.2, and the weight matrix is estimated on the sub-sample observations. According to these tests, we estimate the model and the weight matrix on the sample available. For each iteration, we check

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

the stability of the model in two ways: a) we verify that the eigenvalues of the coefficient matrix of the lagged endogenous variables lie inside the unit circle; b) we verify 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 shock should not be larger than the size of the discrepancy at time 0, after 3 years.

In Figure A4 we show the results of the stability tests performed from April 2008 to October 2013 for different weight matrices (orange bars represent unstable models). The weight matrix obtained from international business cycle factors delivers more stable estimates (only 4 out of 66 iterations are unstable). The episodes of model instability tend to occur at the peak of the financial crisis and the Eurozone debt crisis, and in particular at the two following events:

- **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 are the most relevant financial turmoils in our sample and they probably represent structural breaks resulting in model instability. For this reason we excluded these unstable iterations from our performance analysis.

The performance analysis is conducted in terms of quantitative forecast precision and directional accuracy.

For quantitative forecast errors, in Tables B10 and B11 in the Appendix we report the ratios of RMSE of the iDREAM versus different benchmarks (Random walk and AR(1)) for all endogenous variables at different horizons. The iDREAM clearly outperforms the AR(1) in forecasting international business cycles, monetary policies and long-term interest rates, whereas the evidence is mixed for inflation and short-term interest rates: our model outperforms AR(1) in the long-run for Japan, UK and Germany, while it tends to exhibit larger forecast errors for the US short-term rate. This is not surprising: the out-of-sample window corresponds almost entirely to the period of Zero Lower Bound on the Fed Funds rate. The model always underperforms the benchmarks for the year-on-year growth rate of real effective exchange rates and oil price.

The iDREAM outperforms the Random Walk in forecasting international business cycles and inflation rates in the short-run (1 quarter ahead) and for long-term interest rates of the Euro Area over a longer horizon (3-year ahead). It is worth mentioning that the model seems to perform relatively well for long-term interest rates, while similar econometric approaches (the Global VAR) proved to be less performing in forecasting this variable (Pesaran, Schuermann, and Smith (2009)).

In Tables B12 and B13 we report a measure of forecasting performance in terms of the ability of the model to forecast the direction of endogenous variables, i.e. for each variable we compute the ability of the model to predict the direction of the variable at different forecast horizons. The Accuracy Ratio is then defined as the number of correct directional forecasts over the total number of forecasts. The left-hand side of Table B12 shows the forecasting performance of the iDREAM, while the right-hand side shows the corresponding figures for the AR(1). The model performs extremely well in terms of directional predictive ability, especially in the longer-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 the real effective exchange rate and for the price of oil (while this is not true when looking at RMSEs). In general, the iDREAM ouperforms the AR(1) on average for all variables, except for long-term interest rates.

We conducted a final performance evaluation comparing the forecasting ability of the iDREAM to alternative modeling strategies. We decided to compare the iDREAM with alternative specifications, in which we remove the two main novel features introduced in the estimation of our model. The goal of this exercise is to evaluate the contribution of these new features to the predictive ability of the model. In particular, we selected three alternative econometric models: the Global VAR, with both observable endogenous variables and a weight matrix derived from trade flows; an alternative version of the iDREAM, in which we replace latent factors with observable endogenous variables, maintaining weights estimated from the international network; and, finally, a version of the iDREAM with latent factors and trade weights. The two alternative iDREAMs can be described as follows:

1. a model with latent factors replaced by observable macroeconomic variables:
   - Real GDP annual growth replaces business cycle factors;[7]
   - CPI inflation replaces inflation factors;
   - M1 growth replaces monetary policy factor.
2. a model with a weight matrix estimated from average trade flows over the 2000-2012 period, as in Dees, Mauro, et al. (2007).

In Table B14 we present the results of the comparison between the different specifications. The ratios between the RMSEs of the iDREAM and the GVAR are presented in the first part of the table, whereas the evaluation of the two alternative specifications of the iDREAM is presented in the second (iDREAM obs.) and third (iDREAM trade weight) columns of the Table, respectively. In all pseudo out-of-sample iterations, the trade weights are maintained fixed.[8] We obtain the following evidence.

First, the GVAR model is more prone to instability: only 11 iterations present eigenvalues lying inside the unit circle and stable persistency profiles.[9] Second, in the short common sample of 10 iterations, the iDREAM outperforms the standard GVAR in forecasting interest rates, while the same is not generally true for exchange rates and the oil price.[10] Third, we find that, in the common sample of 40 stable iterations, the version of the iDREAM with observable variables underperforms the complete version of the iDREAM, in particular for long-term interest rates and exchange rates forecasts, while the same is not always true for short-term forecasts. Finally, in a common sample of only 19 stable

[7]We used a monthly disaggregation of Real GDP growth following the Denton-Cholette interpolation method (Denton (1971))

[8]The iDREAM and the other benchmark models have been re-estimated excluding Russia, since trade flows were not available for this country.

[9]The number of stable iterations increases to 35 if only the eigenvalues criterion is considered.

[10]We focus on the evaluation of the variables which are included in all the compared specifications.

iterations, our model strongly outperforms the version of the model with trade weights and latent factors for interest rates and exchange rates forecasts.

Overall, both novel contributions of our paper, namely introducing latent factors among the endogenous variables and a weight matrix estimated from the international network of business cycles, prove to be effective in improving the forecasting ability of the iDREAM.

We have compared our model in terms of forecasting performance with two standard time series model widely used in the literature, nevertheless other approaches have been proved to be effective in forecasting interest rates. A more careful analysis and comparison with other models could be done in future research.

6 Conclusions

In this paper we propose a novel approach to model global macrofinancial interconnections. The iDREAM (international Data Rich Environment Vector Autoregressive Model) combines the three main approaches to overcome the curse of dimensionality of Vector Autoregressions adopted in the empirical literature: a) data shrinkage; b) parameters shrinkage; 3) Global VARs. We estimate the model on a dataset including observable financial variables and unobservable latent macroeconomic variables for 11 countries. We find that the iDREAM is a useful tool for forecasting macro-financial variables. We evaluate the forecasting ability of the model versus different alternative benchmarks. The main evidence of the iDREAM evaluation is the following. First, our model outperforms simple benchmarks, like the Random Walk and the AR(1), in forecasting macro-financial variables, and in particular international business cycles, inflations and long-term interest rates. Second, our model is particularly effective in predicting the future direction of endogenous variables. Our model appears less effective in predicting exchange rates, given their high volatility, and short-term interest rates, given that international monetary policies are at the Zero Lower Bound for almost the entire out-of-sample evaluation period. Third, both novel contributions of our paper, namely including latent factors in the set of endogenous variables and a weight matrix estimated from the international network of business cycles, prove to be effective in improving the forecasting ability of our model when compared to alternative econometric specifications, namely a standard GVAR, a model with observable variables and network weights and a model with latent factors and trade weights.

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Appendix

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

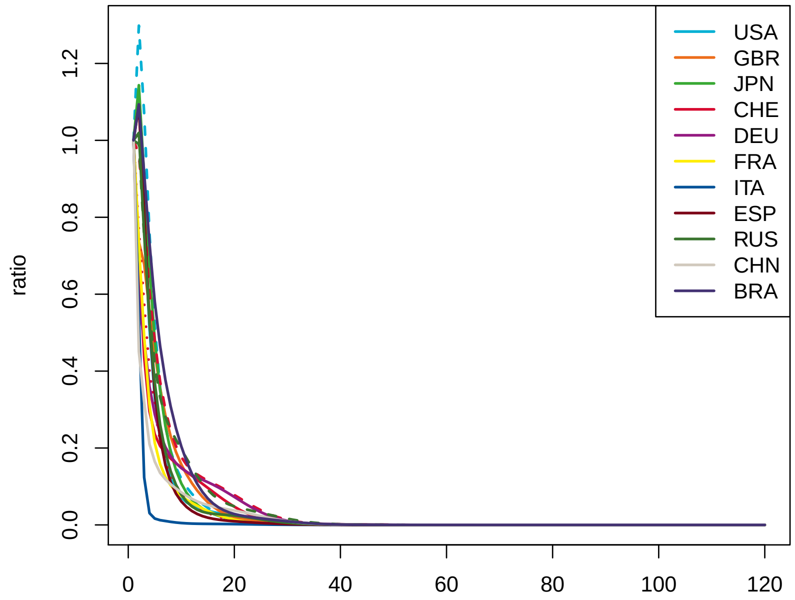

Figure A2: Eigenvalues (excluding unitary ones)

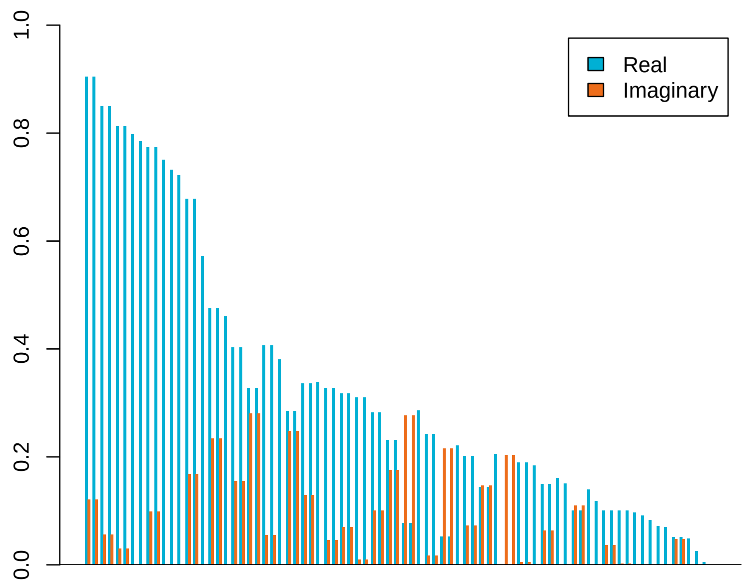

Figure A3: US endogenous variables and most correlated macroeconomic time series to each latent factor

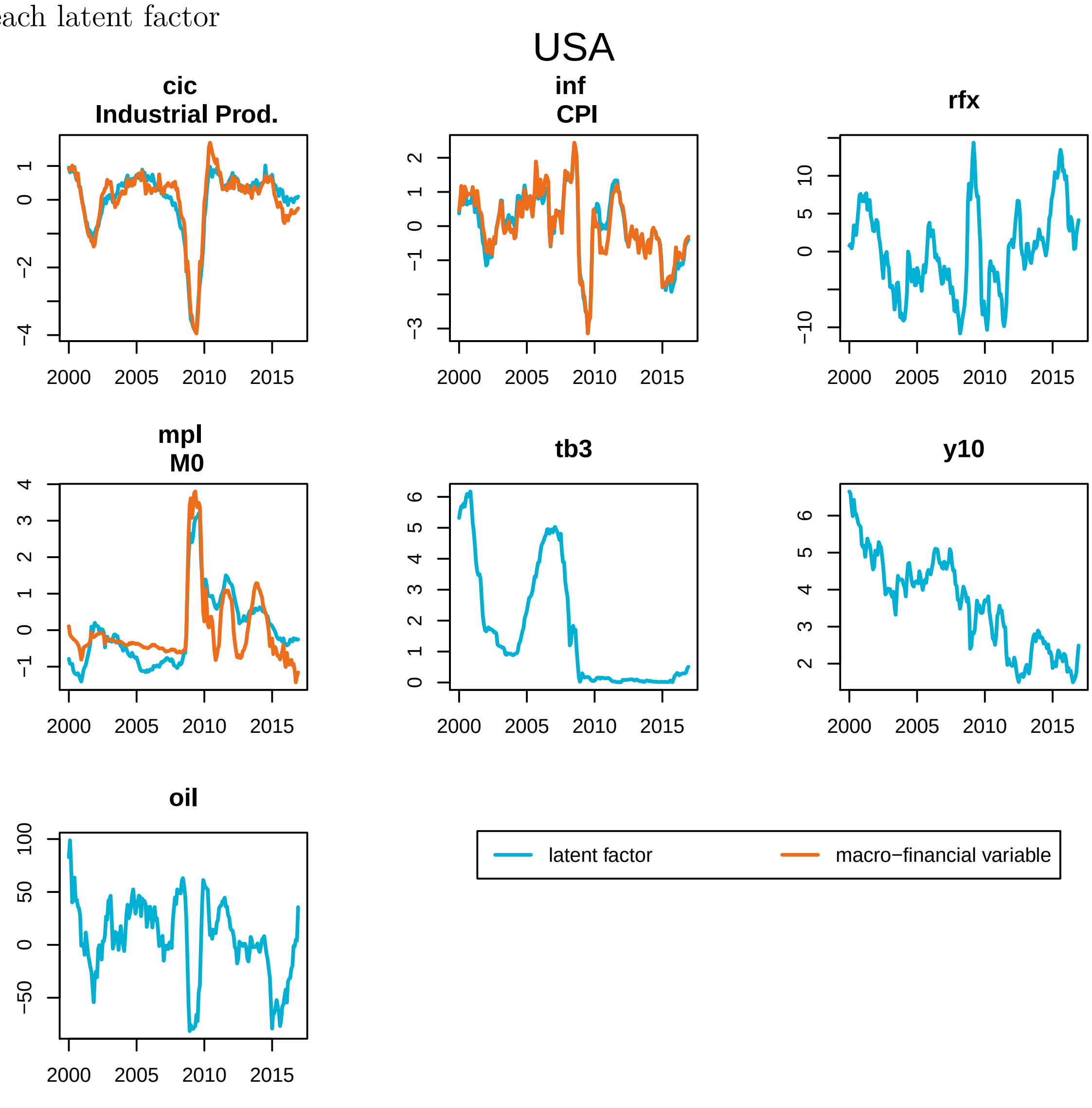

Figure A4: Stable models across time using different weight matrix

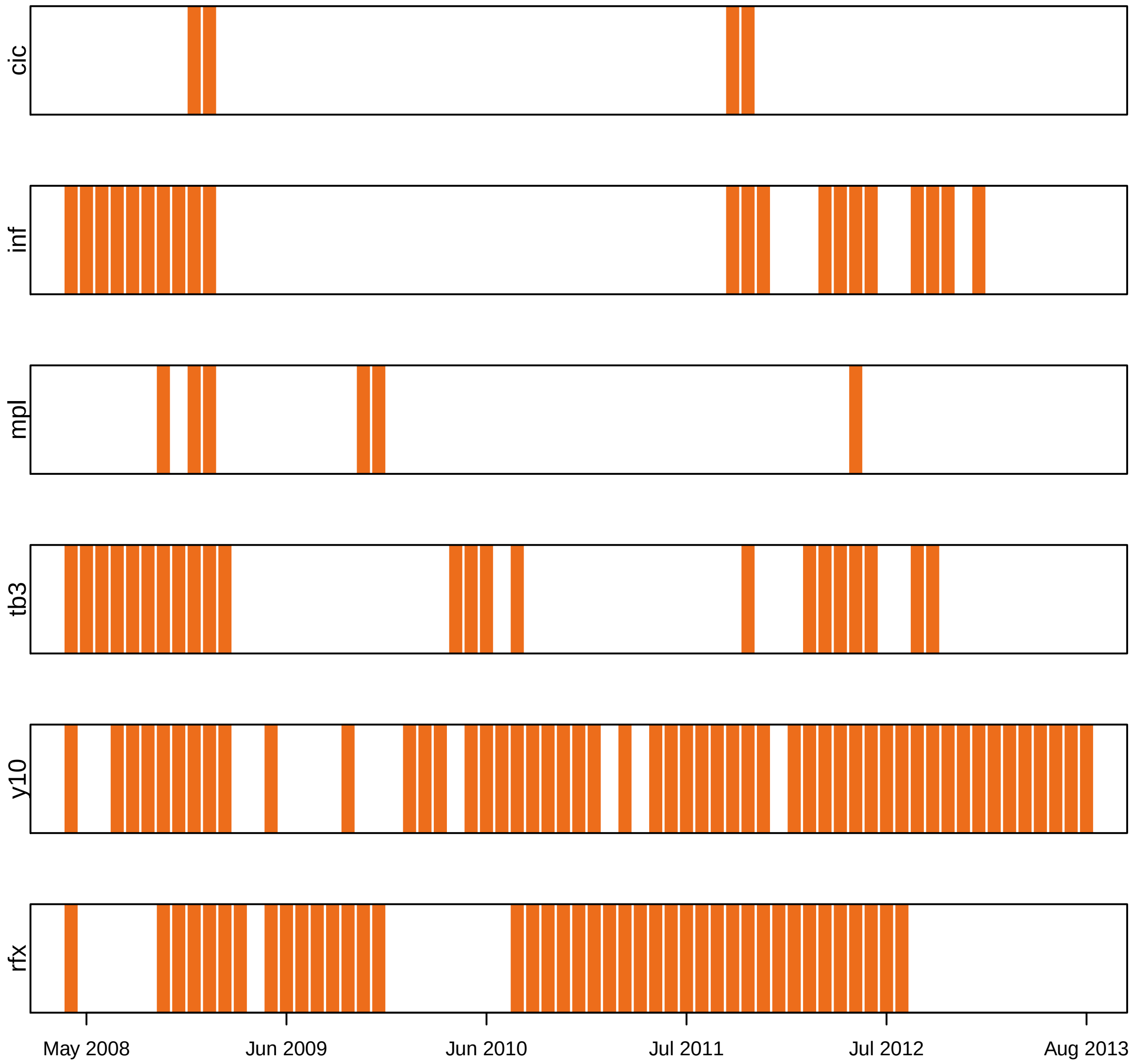

Table B1: Variables entering in the estimation of the business cycle latent factor

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