RUHR

ECONOMIC PAPERS

Gabriel Arce-Alfaro

Boris Blagov

Heterogeneity, Co-movements and Financial Fragmentation within the Euro Area

RGS econon rwi UNIVERSITÄT DUISBURG ESSEN Offen im Denken

#927

Imprint

Ruhr Economic Papers

Published by

RWI – Leibniz-Institut für Wirtschaftsforschung
Hohenzollernstr. 1-3, 45128 Essen, Germany

Ruhr-Universität Bochum (RUB), Department of Economics
Universitätsstr. 150, 44801 Bochum, Germany

Technische Universität Dortmund, Department of Economic and Social Sciences
Vogelpothsweg 87, 44227 Dortmund, Germany

Universität Duisburg-Essen, Department of Economics
Universitätsstr. 12, 45117 Essen, Germany

Editors

Editorial Office

Ruhr Economic Papers #927

Responsible Editor: Torsten Schmidt

ISSN 1864-4872 (online) – ISBN 978-3-96973-085-0

Ruhr Economic Papers #927

Gabriel Arce-Alfaro and Boris Blagov

Heterogeneity, Co-movements and Financial Fragmentation within the Euro Area

Bibliografische Informationen der Deutschen Nationalbibliothek

The Deutsche Nationalbibliothek lists this publication in the Deutsche Nationalbibliografie; detailed bibliographic data are available on the Internet at **http://dnb.dnb.de**

RWI is funded by the Federal Government and the federal state of North Rhine-Westphalia.

http://dx.doi.org/10.4419/96973085
ISSN 1864-4872 (online)
ISBN 978-3-96973-085-0

Gabriel Arce-Alfaro and Boris Blagov [1]

Heterogeneity, Co-movements and Financial Fragmentation within the Euro Area

Abstract

In this article we analyse the degree of commonality across euro area countries in the bank lending rates and credit volumes. Using a time-varying two-level dynamic factor model, we disentangle the relative importance of country-specific and common components in explaining the variance of the macro and financial variables. Our results show that a high share is explained by the common component. However, we find a persistent decline in the importance of the common factor in the bank lending rates, indicating the presence of financial fragmentation. There is heterogeneity across member states, specifically those hit hard by the crisis. We observe high commonality in the financial variables, which increases in periods of high financial volatility.

JEL-Code: C11, C38, E43, E52

Keywords: Co-movements; financial fragmentation; dynamic factor model

January 2022

1 Gabriel Arce-Alfaro, RGS Econ and UDE; Boris Blagov, RWI. *– We would like to thank Christoph Hanck, Ludger Linnemann, Raúl Ibarra Ramírez, Torsten Schmidt, and participants of the 2021 EEFS Annual Conference and PhD Summer Internship at Bank of Mexico for their valuable comments. Boris Blagov is grateful to the Deutsche Bundesbank for financial support. This work is dedicated to Prof. Ansgar Belke who was originally part of the project.* *– All correspondence to: Gabriel Arce Alfaro, RGS Econ, Hohenzollernstr. 1-3, 45128 Essen, Germany, e-mail: gabriel.arcealfaro@rgs-econ.de*

1. Introduction

The period during and after the Global Financial Crisis was characterized by a profound and synchronized decline in economic activity. The rapid spread of the financial crisis globally highlighted the importance of the analysis of financial cycles and degree of interconnectedness among financial sectors. Financial cycles are broadly referred to common dynamics of financial variables within or across countries. For example, stock prices, house prices and credit demand typically increase during expansions. The existence of a medium-term global financial cycle has been greatly supported by recent literature (Rey, 2015; Miranda-Agrippino and Rey, 2020), which reinforces the importance of studying the degree of common dynamics (henceforth commonality) within the financial sector across countries. Originally, co-movement was referred to as patterns of positive correlation (Baur, 2003). However, recent contributions have taken this concept to the analysis of common underlying drivers that explain a high fraction of the changes in the macro-financial variables (Del Negro and Otrok, 2008; Mumtaz and Surico, 2012; Mumtaz and Musso, 2021).

The concept of financial cycles is highly important for the euro area. Higher synchronization, especially in financial variables could imply efficacy of monetary and macroprudential policies as a centralised action would be sufficient to dampen economic shocks. Cross-country heterogeneity, however, be that due to difference in financial regulations, fiscal policies or country specific shocks reduces the commonality across macro-financial variables Corsetti et al. (2020). Thus, financial fragmentation increases - businesses and economic agents face different financing conditions and divergent prices for otherwise similar assets, rendering a one-size-fits all solution ineffective.[1]

The sovereign debt crisis was a prime example. Financial fragmentation manifested, among other ways, in divergent dynamics of the bank lending rates across member states. While the European Central Bank lowered and then kept the policy rate at record low

[1] A good discussion on various aspects of the term financial fragmentation may be found in Claessens (2019).

levels, lending rates for businesses and consumers in some countries stagnated and even increased. As a consequence of fiscal and financial stress the interest rate pass-through broke down in Italy, Spain, Ireland, Portugal, and Greece reducing investment demand and stifling the recovery (Ciccarelli et al., 2013; Blagov et al., 2015). These countries have since then recovered (before the world plunged in the recession triggered by the pandemic). However, how has the degree of financial fragmentation in bank lending rates evolved? Is it a cyclical phenomenon? Has the commonality, which declined throughout the sovereign debt crisis, as evident by the breakdown in pass-through, increased again? To answer these questions, we analyse the evolution of the co-movement in the bank lending rates and credit volumes in the euro area using a large monthly dataset for the seven largest euro area members. To this end, we employ a sectoral multi-level dynamic factor model (DFM) with time-varying parameters. The sectoral aspect is that we group macro and financial variables by categories which permits attaching an economic interpretation to the factors. The multi-level feature of the DFM allows for a differentiation between fluctuations driven by a common component for all countries and such that have a local origin, i.e. driven by country-specific dynamics. The time-varying parameters allow for a dynamic variance decomposition analysis - we can capture the evolution of the explanatory power of common and country specific fluctuations over time. The combination of these features allows us to quantify the extent to which the dynamics of the bank lending rates and credit volumes is explained by common drivers and how this has evolved throughout the past 20 years.

We find that overall the common component explains on average a high share of the variance in the bank lending rates and credit volumes, ranging between 34% and 53% for the former, and 26% and 50% for the latter. However, we find a clear downward trend in the relative importance of the common factor with respect to the bank lending rates. The commonality has declined throughout the sovereign debt crisis and never returned to pre-crisis levels. This result holds when we look into the different categories of lending rates. For the credits sector, the common factor explains a high share of the variation in the data, increasing in periods of high financial volatility. In contrast with the bank lending rates, we do not observe a trend in the relative importance of the common component within this category. Finally, we observe a clear distinction with regard to the common factor importance in the countries who experienced fiscal or financial stress throughout the crisis, i.e. Italy, Spain, Portugal, and Ireland compared to Germany, France and the Netherlands. These findings suggest that financial fragmentation in the euro area has persistently increased, at least with respect to firms' financing conditions. Large heterogeneity and a "north-south" divide appear to continue to exist.

The remainder of this article is organized as follows: the next section lays out the empirical methods and their estimations, as well as the data used in this article. Sections 3 and 4 discuss the results and the concluding remarks, respectively.

2. Methodology

In order to capture the degree of commonality and investigate the main drivers of the variations in the macro-financial variables, we estimate a two-level dynamic factor model as in Kose et al. (2003) and incorporate the contributions by Del Negro and Otrok (2008) by including time-varying factor loadings and stochastic volatilities. By employing this methodology we capitalize on an extensive data set while reducing the number of explanatory variables to a small set of factors. Another characteristic is that the multi-level structure allows us to disentangle between the explanatory characteristics associated with each individual country and the ones that are common to all of them. The following equations characterize the model:

$$Y_{it} = B_{it}^{C} F_{t}^{C} + B_{it}^{E} F_{t}^{E} + u_{it} \tag{1}$$

Where Y_{it} is a $N \times 1$ matrix of endogenous macro-financial variables with $i = 1, \ldots, N$ and $t = 1, \ldots, T$. The observational equation (1) relates the panel of endogenous variables Y_{it} to a set of K^{C} unobserved country-specific factors F^{C}, a set of K^{E} unobserved common factors F^E and the u_{it} idiosyncratic components.

We collect the factors in a matrix F_t of size $T \times (N^C \times K^C) + K^E$, where N^C is the number of countries. Given the orthogonality of the factors, we can describe the VAR(p) process for each of the F_t in the following transition equation:

$$F_{kt} = c_k + \sum_{j=1}^{P} b_{kj} F_{kt-j} + \sigma_{kt}^{1/2} e_{kt}, \quad e_{kt} \sim N(0,1) \tag{2}$$

The idiosyncratic components of the observational equation (1) follow an AR(q) process

$$u_{it} = \sum_{j=1}^{q} d_{ij} u_{it-j} + h_{it}^{1/2} v_{it}, \quad v_{it} \sim N(0,1) \tag{3}$$

The stochastic volatilities of the factors and idiosyncratic components σ_{kt} and h_{it} correspondingly, are modelled as AR(1) processes:

$$\ln \sigma_{kt} = \ln \sigma_{kt-1} + g_k^{1/2} \epsilon_{kt}, \quad \epsilon_{kt} \sim N(0,1) \tag{4}$$

$$\ln h_{it} = \ln h_{it-1} + G_i^{1/2} \eta_{it} \quad \eta_{it} \sim N(0,1) \tag{5}$$

We model the time-variation in the factor loadings following Del Negro and Otrok (2008). The law of motion characterizing the time-varition in the factor loadings is described by a random walk

$$B_{it} = B_{it-1} + Q_i^{1/2} \gamma_t, \quad \gamma_t \sim N(0,1) \tag{6}$$

Where the matrix B_{it} collects the corresponding factor loadings associated with the common components, B_{it}^E, and with the country-specific ones, B_{it}^C.

2.1. Estimation

We estimate the model described in equations 1 to 6 using Bayesian methods. The procedure follows Mumtaz and Musso (2021). Rewriting the observational equation (1) as $\hat{Y}_{it} = B_i \hat{F}_t + v_{it}$ eases the implementation of the Kalman Filter. The matrix, $\hat{F}_t$, now collects both the country-specific and common factors, which are initialised via principal component analysis. We utilize a training sample to set informative priors. The variance prior for Q_i in the transition equation (6) has an inverse Wishart distribution with a scale parameter $Q_{0,i} = var(B_i) \times T_0 \times \kappa$. The hyperparameter κ determines the amount of time-variation and is set as in Cogley and Sargent (2005) at $\kappa = 3.5 \times 10^{-4}$ to ensure gradual parameter changes and thus capture long-term structural shifts. The initial conditions for the stochastic volatilities, σ_{k0} and h_{i0}, are set following Del Negro and Otrok (2008) to address the issue of unidentified scale of the factors. The authors highlight that the corresponding sign of the factors and their loadings are not identified independently. This is not an issue here since our analysis relies on the variance decomposition, which, as a product of the two, is invariant to the sign identification.

The estimation is carried out via the Gibbs sampler, the steps can be summarized as follows:

1. Conditional on the draw of the factors and stochastic volatilities, the time-varying factor loadings are drawn from the conditional posterior distribution using the Carter and Kohn (1994) algorithm.

2. Similarly using the Carter and Kohn (1994) algorithm, conditional on the factor loadings, the stochastic volatilities $\sigma_{kt}^{1/2}$ and $h_{it}^{1/2}$, and the autoregressive coefficients b_{kj}, we obtain the draws from the conditional posterior distribution of the factors F_{kt}.

3. Finally, conditional on the factors, the stochastic volatilities of the model: $\ln \sigma_{kt}$ and $\ln h_{it}$ are drawn using the particle Gibbs sampler following Lindsten et al. (2014).

We use 35,000 iterations discarding the first 25,000 as burn-in to ensure convergence of the algorithm.

2.2. Data description

The data set is composed of 30 macroeconomic and financial variables for each of the 7 countries analysed: Germany, France, Ireland, Italy, the Netherlands, Portugal, and Spain. The country and variable selection was dictated by data availability. Including additional countries would have resulted in a smaller dataset per country. We aim to disentangle possible differences between countries that experienced significant financial and fiscal stress and non-stressed countries. Therefore we consider the following two groups: Germany, France, and the Netherlands as the non-stressed group and Ireland, Italy, Portugal, and Spain as the group of countries that experienced significant periods of financial and fiscal distress as in Altavilla et al. (2020). The data is monthly and spans from January 2003 until December 2020.[2]

We use the Monetary and Financial Institutions (MFI) data set from the ECB that collects harmonized financial variables. This allows us to examine different categories of credits volumes and lending rates while ensuring that they are directly comparable. The data is grouped into 5 categories: interest rates, credit volumes, real sector, prices and forward-looking variables.

[2] A comprehensive list of the variables per country with data sources and corresponding transformations is available in Table A1 in the Appendix.

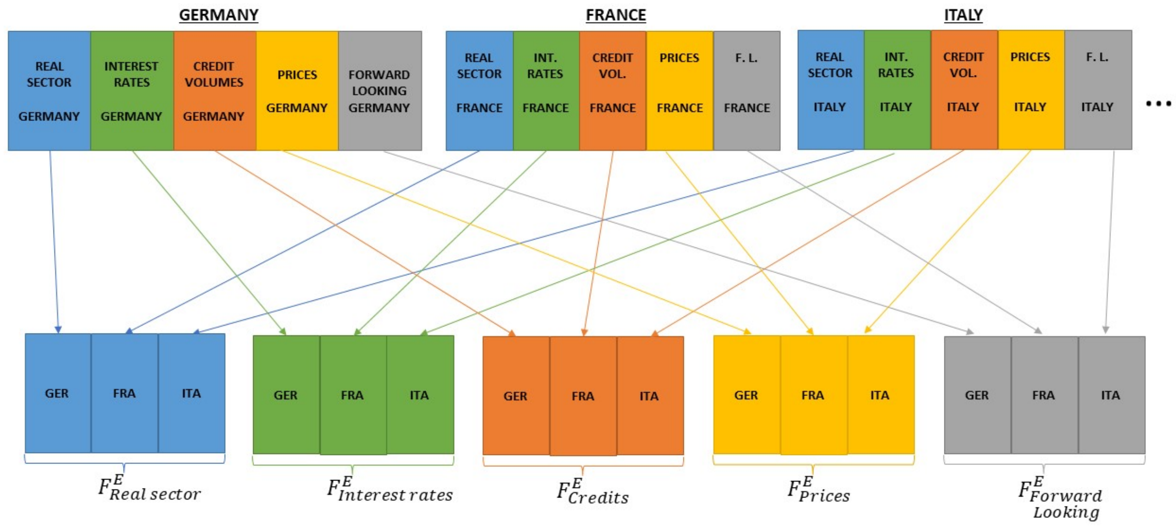


Figure 1: An example for Germany, France, and Italy of the categorisation and common factor extraction for the *first level* of the Dynamic Factor Model. The full dataset includes also Spain, the Netherlands, Portugal and Ireland.

Figure 1 illustrates the corresponding five categories for Germany, France, and Italy that are used to extract the common components of the model, i.e. the first level of the DFM (in the model we use all seven countries). At the second level of the DFM we obtain the country-specific dynamics of the categories. We do so by estimating a linear regression on the common components per country and category, thus orthogonalizing the country-specific datasets to the common factors.[3]

Figure 2 shows the estimated common factors together with the observed time series of each of the categories. The interest rate factor exhibits a downward trend following the Great Recession, this results are in line with Del Negro et al. (2019) who find a downward trend in interest rates among industrialized countries. The estimated factors for the real sector and forward-looking categories seem to capture mostly the business cycle dynamics, as evident by their particular movements around the crisis periods, both the global financial crisis and the recent pandemic. Notably, the real sector factor appear to

[3]A visual interpretation with both levels is available in the Appendix, Figure A.2

follow primarily the developments of the unemployment rates, which increased sharply in 2008 and even more so in 2020. The common credit volume factor does not exhibit notable volatility around the crises. Finally, the prices common factor fluctuates throughout the entire sample, showing an important decrease during the Great Recession.

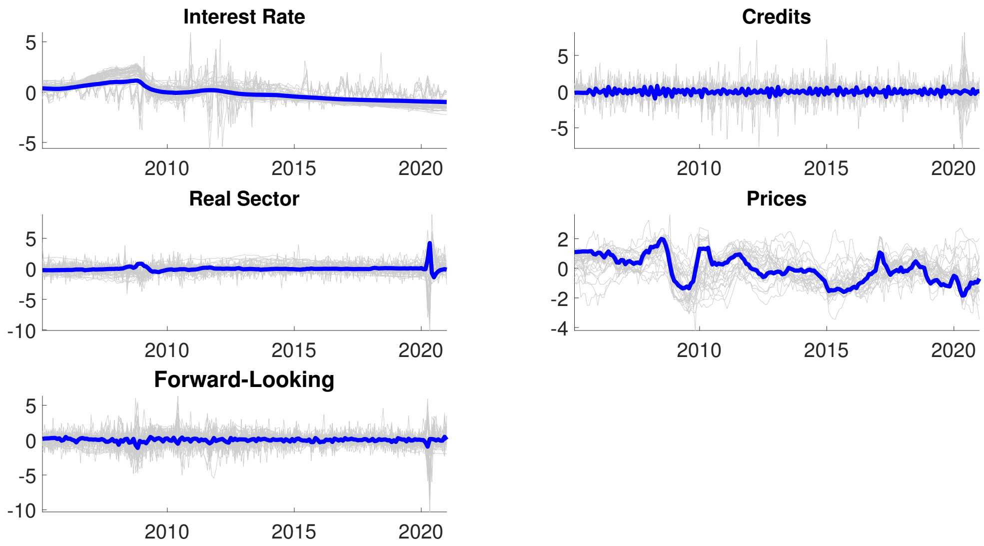


Figure 2: Estimated common factors. Blue line shows the median estimate of the common factors. Gray lines are the observed time series of the corresponding categories.

2.3. Model specification

To determine the optimal number of lags in equation (1) we employ information criteria tests, specifically the Bayesian Information Criteria, which suggests a lag order of 6.

The number of factors in factor models is always a subject for careful consideration. We have allocated the variables in our dataset to five categories with the purpose of being able to attach economic interpretation to the factors. The hierarchical structure of the two-level DFM induces proliferation in the factor count. For example, assuming one common and one country-specific factor per category results in 5 common factors (1 per category) and 35 country-specific factors (7 countries in total, each with 5 categories), while a "two-two" factor setup would result in 80 factors. Our dataset consists of 30 variables per country, which dictates our choice for a more parsimonious specification. Therefore we set the number of common and country specific factors to one per category.

Another route is to use formal testing. For example, the test of Bai and Ng (2002), performed on the whole dataset without conditioning on any number of categories, suggests the use of 6 factors. Hence, our choice of 5 factors (while categorizing the data) does not appear disconnected.

3. Results

To tackle the question of how important the common latent factors within the euro area are in explaining the volatility in the bank lending rates and credit volumes, we calculate the variance decomposition for each series as

$$var(Y_{it}) = (B_{it}^C)^2 var(F_t^C) + (B_{it}^E)^2 var(F_t^E) + var(u_{it}) \tag{7}$$

Equation (7) captures the fraction of the variance of the observed variables which is explained by the common components $S_t^E = \frac{(B_{it}^E)^2 var(F_t^E)}{var(Y_{it})}$ and the country-specific component $S_t^C = \frac{(B_{it}^C)^2 var(F_t^C)}{var(Y_{it})}$.

We obtain a variance decomposition for each series, i.e. the index i in equation (7) runs from 1 to 210. Thus, the model allows for a broad spectrum of the analysis since the variance decomposition can be aggregated across various dimensions. We will begin the analysis by first taking averages across all countries per category before diving into more granular data: decomposition per individual time series, such as short or long-term interest rates and decompositions across the country dimension.

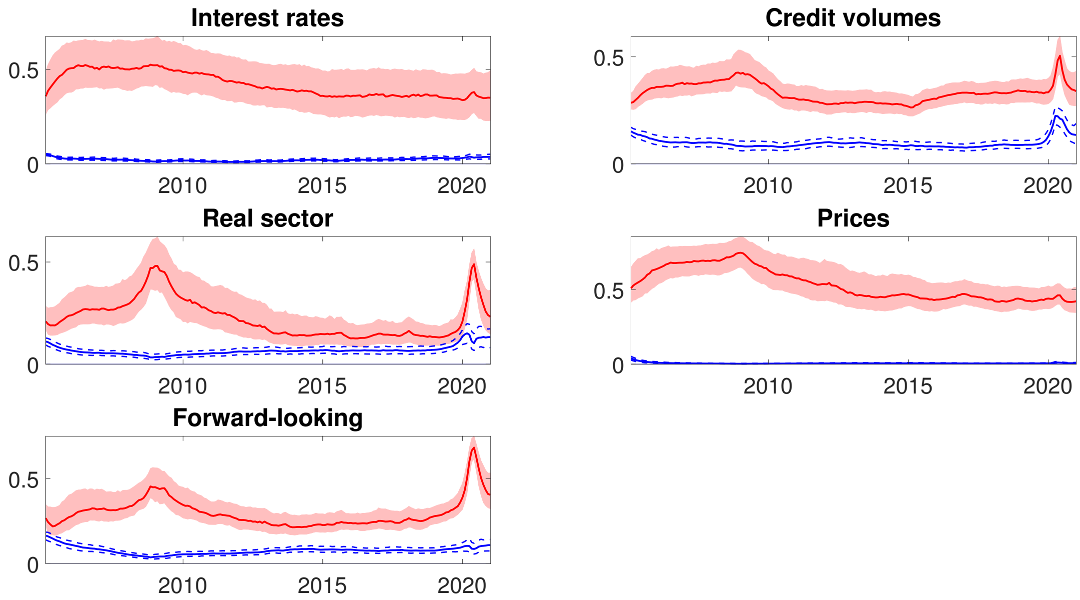


Figure 3: Average variance decomposition per category. Solid red line shows the contribution of the common component. Solid blue line represents the contribution from the country-specific component. Median estimates are plotted with their corresponding 68% probability intervals.

Figure 3 depicts the relative contribution of each of the factors in explaining the average variance of the data in each of the categories for all countries. We present the median estimate for each of the contributions to the variance decomposition, together with the 68% credible sets[4].

For all categories we observe that the common factors are the main component explaining a high share of the variation in the data relative to the country-specific one. The top panel of Figure 3 shows how the importance of the common factor has evolved on average over all lending rates in our dataset. There is a clear downward trend which starts around the global financial crisis and continues throughout the sovereign debt crisis up until around 2015. Notably, the average contribution of the common component has not returned to the pre-crises levels. The common factor now explains approximately 35% of the variation of the interest rates compared to the 52% in the pre-crisis period. This finding illustrates that financial fragmentation has on average increased during the sovereign debt crisis, at

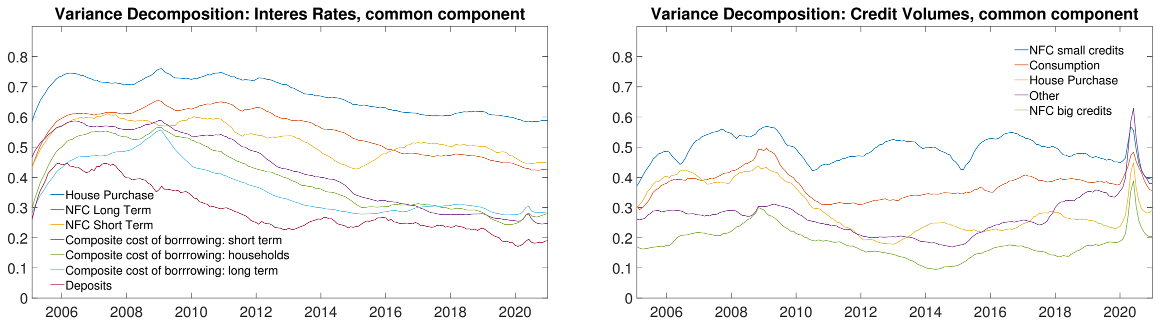
[4]We display the average contribution of the country-specific and common components for each member states in Figure A.1 of the Appendix.

least when it comes to the financing conditions that businesses face. More importantly, however, it has remained elevated ever since. This suggests, that this was not a cyclical phenomenon. While financial fragmentation did increase, it did not decline endogenously as the economies recovered out of the crisis.

In contrast, credits category depicts an important share of the variation explained by the common factor throughout the whole sample analysed, increasing during the periods of high financial volatility, in addition to the later, the country-specific factor explains on average almost 20% of the variation of the credit volumes with an important increase in the recent downturn driven by the pandemic. The real sector exhibits high commonality during recessionary periods, raising its importance up to 50% of the variance explained by the common factor and with the country-specific factor ranging from 5% to 15%. Similarly, the forward-looking factor follows very closely the dynamics displayed in the real sector category, with the distinction that it presented an even higher level of commonality during the global pandemic, with a common component explaining up to 69% of the variance in this category.

The country-specific components exhibit a smaller contribution to the variance decomposition compared to the common component. For the credits category, the country-specific component reaches the highest level during the current Covid-19 pandemic. Throughout the first half of the 2020 the country-specific component explained up to 25% of the variance. For the real sector and forward-looking categories, the country-specific component explains between 10% to 15%. For nominal variables, i.e. the interest rate and prices categories the country factors do not seem to explain a considerable amount of the variation in the data.

We capitalize on the richness of the harmonized data set from the MFI by analysing the dynamics within the different types of bank lending rates and credit volumes. Figure 4 displays the average contribution of the common factors on the two different categories calculated across countries. Figure 4a shows a clear downward trend in all categories of the interest rates. This trend begins around the global financial crisis and continues throughout the sovereign debt crisis with varying slopes for the different rates. The average contribution of the common component has not returned to the pre-crisis level for any of the time series considered, suggesting that this was not a cyclical phenomenon. In terms of magnitude, we observe that lending rate to house purchases exhibit the highest level of commonality throughout the entire sample analysed. This results contrast the findings by Breitung and Eickmeier (2016) who find low levels of co-movements in the housing market. Additionally, we observe that lending rates to non-financial corporations - both short and long term - co-move more in comparison with other categories of composite cost of borrowing. This result is also reflected in Figure 4b were within the different categories of credit volumes, small credits (below one million euros) to non-financial corporations present the highest level of commonality. This is not the case for large credits to non-financial corporations which can be explained by the specifics of how large firms obtain funds. To minimise risk, banks may group with other banks to give out a large credit to one corporation. In general, market forces play little role with credits of such magnitudes. Overall the credit volumes present a high fraction of the variance explained by the common factors throughout the time period analysed, with increases in the importance during periods of high financial volatility.



(a) Interest rates category

(b) Credit volumes category

Figure 4: Contribution of the common component in the interest rates and credit volumes categories per components. NFC stands for "non-financial corporations". Small credits are below one million euros. Short and long term refer to maturities below and above one year, respectively.

Next we disaggregate the relative contribution of the common factors among countries and categories. We find a clear distinction between the stressed countries (Ireland, Italy, Portugal and Spain) and countries which did not face a financial stress period (Germany, France and the Netherlands).

This difference is shown in Figure 5 where we plot the relative importance of the common factors for the stressed countries in pale blue color and the non-stressed countries in black. We observe a high degree of country heterogeneity in the interest rate, the real sector and the forward-looking categories. The first subfigure decomposes the interest rate category per country. We draw the attention to the countries that experienced financial stress, which all exhibit much lower commonality than the rest. In the case of Portugal and Spain, the dynamics of the lending rates can be explained only about 20% to 30% by the variance of the common component. Italy and Ireland also appear detached from the common european dynamics, however to a smaller extent. Notably, for all countries classified as "non-stressed", namely Germany, France and the Netherlands, the common component explains a much larger fraction of the variance of the interest rates, which goes as high as 75%. However, even for Germany, France, and the Netherlands a downward trend in the interest rate category is evident.

Similar developments are also evident in the prices category on Figure 5. Naturally, the peak of the explanatory power of the common component dynamics was during the global financial crisis, when many macroeconomic variables, including prices, jointly plunged. However, in the years afterwards the importance of the common component has gone down in all countries, similarly to the interest rates category. In the case of prices, however, we do not find a distinction between stressed or non-stressed member states.

These findings are particularly relevant during times of expansive monetary policy and low and stable interest rate environment. A prolonged period of unchanging interest rates would ideally translate into stable lending rates for businesses and consumers alike as well as stable price dynamics. Nonetheless, we find that the opposite is the case - the idiosyncratic component has gained much more relevance compared to the late 2000s across all possible dimensions: countries, categories and individual interest rate series.

On the other hand, we find neither distinction of stressed versus non-stressed member states nor particular trends in the other categories. Perhaps a somewhat unexpected finding is the low commonality across the variables associated with the real sector. One could expected that a more integrated euro area should lead to synchronised business cycles. However, high synchronisation seems to arise only during large recessions as all variables exhibit large (mostly downward) movements.

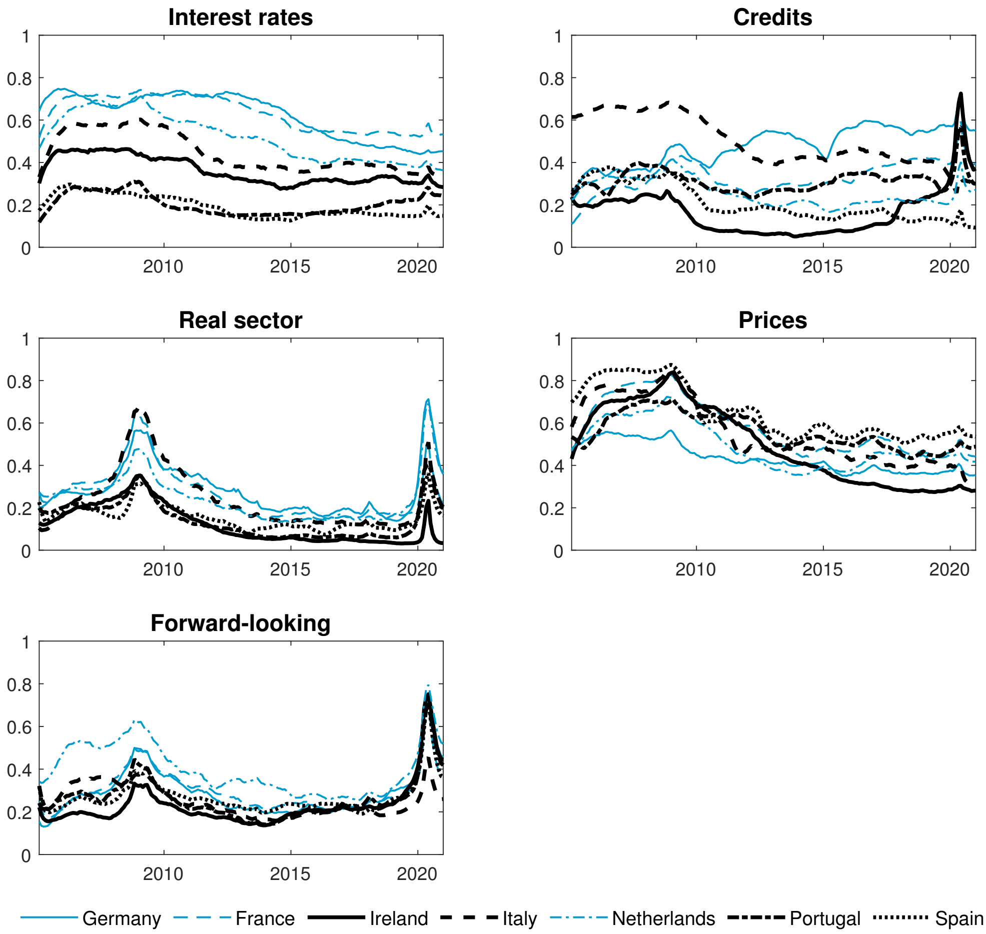


Figure 5: Country-wise relative contribution of the common component in each category. The **black** lines group the the non-stressed countries while the light blue lines indicate which countries experienced severe financial stress during the sovereign debt crisis.

4. Conclusions

We use a two-level dynamic factor model to investigate the relative importance of the common factors in explaining the variations in the bank lending rates and credit volumes for the euro area between the period of January 2003 to December 2020. We observe that the common factors explain a high share of the variations in the data for all five categories analysed. Within the interest category we recognize a downward trend in the relative importance of these common factors in explaining the variation in the data. This decrease in the commonality started after the Great Recession and has not returned to the pre-crisis level, implying an increase in the financial fragmentation among the euro area countries. The trend is evident across all dimensions of the data: across countries, across categories and at an individual level.

When comparing the financially stressed countries with their non-stressed counterparts, we observe a clear heterogeneity in the fraction explained by the common factors in the interest rate, real sector and forward-looking category. The heterogeneity is mostly visible when it comes to the lending rates, where the commonality is extremely low in Spain, Italy, Ireland, and Portugal. The fraction of the variance of the rates explained by the common component is only between 20% to 40%, versus 40% to 60% for Germany, France, and the Netherlands. Such a large divide suggests continued impairment of the monetary policy transmission presenting potential avenues for future research.

We do not find such heterogeneities when it comes to the amount of credits as measured by the credit volumes or in the price category. There does not appear to be a particular divide between the two groups of countries. Finally, the real sector, as well as the forward-looking variables that reflect mostly the economic situation, exhibit an expected increase in the level of commonality during recessionary periods. Otherwise the degree of co-movement appears surprisingly low. During expansions the common business cycle factor explains only about 20% of the variation of the variables.

References

Altavilla, C., Canova, F., and Ciccarelli, M. (2020). Mending the broken link: Heterogeneous bank lending rates and monetary policy pass-through. *Journal of Monetary Economics*, 110:81–98.

Bai, J. and Ng, S. (2002). Determining the number of factors in approximate factor models. *Econometrica*, 70(1):191–221.

Baur, D. G. (2003). What is co-movement? *EUR Working Paper No. 20759.*

Blagov, B., Funke, M., and Moessner, R. (2015). Modelling the time-variation in euro area lending spreads. BIS working paper No 526, Bank for International Settlements.

Breitung, J. and Eickmeier, S. (2016). Analyzing international business and financial cycles using multi-level factor models: A comparison of alternative approaches. In *Dynamic factor models*. Emerald Group Publishing Limited.

Carter, C. K. and Kohn, R. (1994). On gibbs sampling for state space models. *Biometrika*, 81(3):541–553.

Cascaldi-Garcia, D., Ferreira, T. R., Giannone, D., and Modugno, M. (2021). Back to the Present: Learning about the Euro Area through a Now-casting Model. *International Finance Discussion Paper*, 2021(1312):1–46.

Ciccarelli, M., Maddaloni, A., and Peydró, J.-L. (2013). Heterogeneous transmission mechanism: monetary policy and financial fragility in the eurozone. *Economic Policy*, 28(75):459–512.

Claessens, S. (2019). Fragmentation in global financial markets: good or bad for financial stability? BIS Working Papers 815, Bank for International Settlements.

Cogley, T. and Sargent, T. J. (2005). Drifts and volatilities: monetary policies and outcomes in the post wwii us. *Review of Economic dynamics*, 8(2):262–302.

Corsetti, G., Duarte, J., and Mann, S. (2020). Modelling the time-variation in euro area lending spreads. CERP discussion paper 14968, Centre for Economic Policy Research.

Dées, S. and Zorell, N. (2012). Business cycle synchronisation: disentangling trade and financial linkages. *Open Economies Review*, 23(4):623–643.

Del Negro, M., Giannone, D., Giannoni, M. P., and Tambalotti, A. (2019). Global trends in interest rates. *Journal of International Economics*, 118:248–262.

Del Negro, M. and Otrok, C. (2008). Dynamic factor models with time-varying parameters: measuring changes in international business cycles. *FRB of New York Staff Report*, (326).

Kose, M. A., Otrok, C., and Whiteman, C. H. (2003). International business cycles: World, region, and country-specific factors. *American Economic Review*, 93(4):1216–1239.

Lindsten, F., Jordan, M. I., and Schon, T. B. (2014). Particle gibbs with ancestor sampling. *Journal of Machine Learning Research*, 15:2145–2184.

Miranda-Agrippino, S. and Rey, H. (2020). U.S. Monetary Policy and the Global Financial Cycle. *The Review of Economic Studies*, 87(6):2754–2776.

Mumtaz, H. and Musso, A. (2021). The evolving impact of global, region-specific, and country-specific uncertainty. *Journal of Business & Economic Statistics*, 39(2):466–481.

Mumtaz, H. and Surico, P. (2012). Evolving international inflation dynamics: world and country-specific factors. *Journal of the European Economic Association*, 10(4):716–734.

Onatski, A. (2009). Testing hypotheses about the number of factors in large factor models. *Econometrica*, 77(5):1447–1479.

Rey, H. (2015). Dilemma not trilemma: the global financial cycle and monetary policy independence. *National Bureau of Economic Research*.

A. Appendix

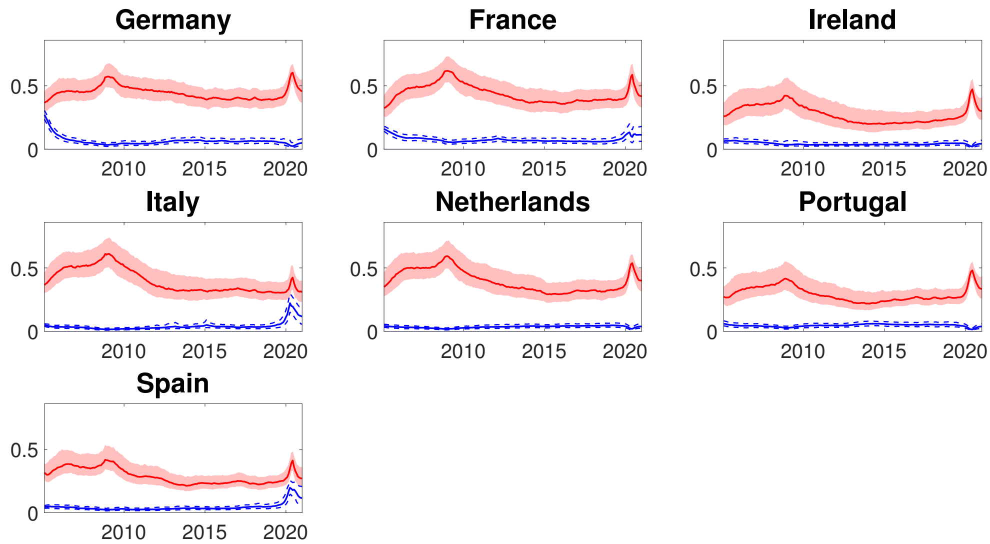


Figure A.1: Average variance decomposition by country. Solid red line shows the contribution of the common component. Solid blue line represents the contribution from the country-specific component.

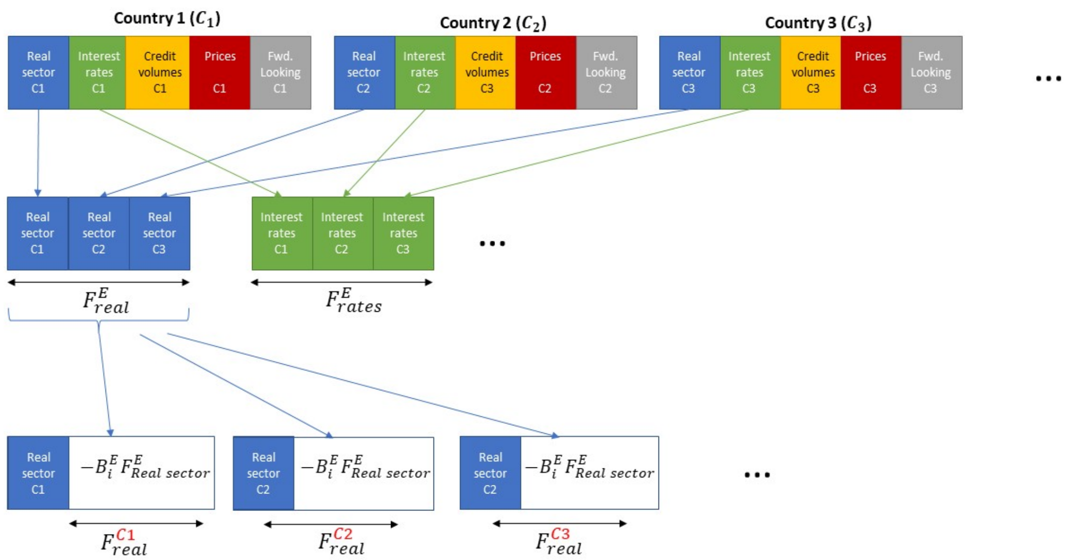


Figure A.2: Summarizes the structure of the model where the country-specific are obtained after extracting the effects of the common factor at a country-level.

Variable	Source	Transformation	Category
Unemployment	Eurostat	1	Real sector
Imports	Eurostat	5	Real sector
Exports	Eurostat	5	Real sector
Internation Trade	Eurostat	1	Real sector
Real Exchange Rate	IMF	1	Prices
Harmonised Index of Consumer Prices	Eurostat	1	Prices
Produce Price Index	Eurostat	1	Prices
Commodity Import Price Index	IMF	1	Prices
Core Inflation	Eurostat	1	Prices
Stock Prices Index	MacroBond	5	Forward-Looking
Government Bonds: 10 Years	MacroBond	2	Interest rates
Yield Curve	MacroBond	1	Forward-Looking
Composite Cost of Borrowing: Households	ECB, MFI statistics	1	Interest rates
Composite Cost of Borrowing: Long Term	ECB, MFI statistics	1	Interest rates
Composite Cost of Borrowing: Short Term	ECB, MFI statistics	1	Interest rates
Interest Rate for House Purchase	ECB, MFI statistics	1	Interest rates
Interest Rate to Non-Financial Corporations: short term	ECB, MFI statistics	1	Interest rates
Interest Rate to Non-Financial Corporations: long term	ECB, MFI statistics	1	Interest rates
Interest rate to deposits	ECB, MFI statistics	1	Interest rates
Sentiment Indicators: Construction Confidence Indicator	Eurostat	2	Forward-Looking
Sentiment Indicators: Consumer Confidence Indicator	Eurostat	2	Forward-Looking
Sentiment Indicators: Industrial Confidence Indicator	Eurostat	2	Forward-Looking
Index of Financial Stress	ECB	2	Forward-Looking
Sovereign Systemic Stress Composite Indicator	ECB	2	Forward-Looking
Industrial Production	Eurostat	5	Real sector
Credit volumes to non-financial corporations: small (below one million)	ECB, MFI statistics	2	Credits
Credit volumes to non-financial corporations: big (above one million)	ECB, MFI statistics	2	Credits
Credit volumes for consumption	ECB, MFI statistics	2	Credits
Credit volumes for house purchase	ECB, MFI statistics	2	Credits
Credit volumes other credits	ECB, MFI statistics	2	Credits

Table A1: This table summarizes the time series used in the model. Transformation code (TC): 1-level; 2-first difference; 3-second difference; 4-log-level; 5-first difference of logarithm