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THE CREDIT COMPOSITION OF GLOBAL LIQUIDITY

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The Credit Composition of Global Liquidity*

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Abstract

We conceptualize global liquidity as global monetary policy and credit components by means of a large-scale dynamic factor model in the spirit of Eickmeier, Gambacorta, and Hofmann (2014). Going beyond previous work, we decompose aggregate credit components into credit supply and demand flows directed at the public (governments) and private sector (businesses and households). We show that this decomposition enhances the understanding of global liquidity considerably. Whereas global public sector credit supply is best understood as a safe-haven lending factor from an investors perspective, lenders supply the private sector with credit to maximize profits along the business cycle. Moreover, the public sector demands credit in times of bust-episodes, whereas private entities demand credit in times of booms. In particular, we find that our global credit estimates explain substantial variance shares of a large panel of international financial aggregates.

Keywords: global liquidity, credit composition, financial cycle, dynamic factor model
JEL Classification: C32, C38, E32, E44, E51

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1 Introduction

Credit is an essential lubricant of capitalist economies. It enables people to improve their living conditions and advance technology. With the help of credit, entrepreneurs finance groundbreaking ideas, governments uphold infrastructure and public security, students pay for education, and workers afford to own houses. Naturally, credit market shocks translate into business cycle fluctuations and affect economic growth as well as financial stability. Whereas insufficient credit supply can hinder innovation and prosperity, excess credit allocations can destabilize economies. Thus, monitoring credit growth and credit flows within countries and across borders has become a quintessential element of both economic stability policies and academic research. We contribute to the endeavour of understanding credit dynamics by means of an integrated empirical framework that allows the investigation of sectoral credit compositions and credit origins at the global level, and thereby enhances the understanding of linkages between different types of global credit shocks and real economic as well as financial aggregates.

Recent advances in understanding credit have delivered three important insights. First of all, *credit origin*, i.e. whether a credit shock arises from the demand or the supply side, matters for economic and financial stability. Mian and Sufi (2018) characterize a credit supply shock as a shock that resembles lender's increased willingness to issue credit, whereas a credit demand shock is a shock that originates in exogenous changes of borrower's preferences for holding credit. Both expansionary credit demand and supply shocks increase credit volumes, which in turn are predictors of economic stability and financial crises. But credit supply and demand shocks have different effects on the real economy.[1] A well-established strand of literature stresses the relative importance of credit supply shocks for business cycle fluctuations and financial system stability. For example, Krishnamurthy and Muir (2017) suggest that credit supply was key to the recent credit expansions in the US. In line with this, credit spreads, which are commonly taken to resemble changes in lending conditions (e.g. increased leverage), have become prominent predictors of the business cyle and financial crises (Gilchrist et al. 2009, Gilchrist and Zakrajsek 2012, Krishnamurthy and Muir 2017). Moreover, Justiniano et al. (2017) argue that the decoupling of US mortgage interest rates from treasury yields in 2003 attracted large amounts of credit into the US mortgage sector, and thereby lend support to the conjecture that a change in credit supply conditions was leading up to the sub-prime mortgage crisis.

In the second place, *credit composition*, i.e., in which sector credit is channeled (public or private), makes a difference for economic stability. Let the 'private sector' comprise credit flows directed towards businesses and households, whereas 'public' credit is credit borrowed by the general government. Credit composition matters, as credit is not equally productive and stabilizing across sectors. For example, by means of a calibrated dynamic stochastic

[1] Credit, house prices and business cycles are known to be correlated in the medium term, rather than in the short term (Rünstler and Vlekke 2018).

equilibrium model Justiniano et al. (2019) attribute a leading role in the US credit expansion prior to the Great Recession to mortgage credit supply. Moreover, excessive household credit accumulation might have adverse effects on consumption (Dynan 2012), economic growth Samarina and Bezemer (2016) and the risk of banking crises (Büyükkarabacak and Valev 2010). Regarding the growth effects of government credit the literature yet lacks a consensus. Panizza and Presbitero (2013) summarize that theoretical models yield ambiguous results, and that the empirical evidence is inconclusive. Although a significant amount of the studies that they review report negative effects of government credit shocks on economic growth in the long run, they argue that not all of the reviewed findings are in fact convincing. Instead, Panizza and Presbitero (2013) stress the country specific heterogeneity of the findings. Reinhart and Rogoff (2010) report that unlike excessive government credit volumes, medium-sized government debt does not seem to have significantly negative effects on growth.

Third, it matters whether credit grows domestically or internationally. It is well established that simultaneous contractions of the financial and the business cycle lead to more severe recessions than a mere contraction of the business cycle (see Claessens et al. (2012), Drehmann et al. (2012)). In the last years, much evidence has underlined that not only business cycles (Kose et al. 2003), but also financial cycles co-move internationally (see e.g. Rey (2013) for the case of asset price cycles). Recently, Potjagailo and Wolters (2020) have shown the prevalence of financial co-movements in the very long-run. Cross-country financing conditions are in the focus of the global liquidity debate. Global liquidity is widely understood as the ease of global funding and has been conceptualized as a co-movement in credit and house prices across the globe (Eickmeier, Gambacorta, and Hofmann 2014). There is a vast literature investigating the role of global liquidity in transmitting shocks among national credit markets. To name two examples, on the one hand Bernanke (2005) prominently argues for the existence of a „Global Savings Glut“ (SG), i.e., massive capital inflows into riskless US (government) assets. On the other hand Shin (2011) puts forth the „Global Banking Glut“-hypothesis (BG), claiming that international bank lending flows directed towards US credit markets have contributed to lax private credit conditions. Justiniano et al. (2014) substantiate both the SG and the BG hypotheses with empirical evidence. Moreover, Cesa-Bianchi and Sokol (2017) and Miranda-Agrippino and Rey (2020) point out that US monetary policy affects peripheral small open economies through an international credit channel. Since the global financial crisis, significant efforts have been made to understand global liquidity. A study closely related to ours is Eickmeier, Gambacorta, and Hofmann (2014) (henceforth EGH). They argue that global liquidity is best understood as a triad of three global factors, which can be interpreted as credit supply, credit demand and monetary policy. These components explain substantial amounts of variance in a large sample of financial aggregates.

In the light of some of the largest government credit expansions since WW2 due to the COVID-19 crisis, it is crucial to be aware of the diverse roles of global credit, as well as the effects that sectoral credit demand and supply exert on credit growth and financial fragility.

However, the link between global liquidity, credit origin and credit composition has rarely been investigated before. So far, we lack evidence on the composition of global credit demand and supply components. This paper is the first subjecting the interplay of three credit-side determinants of global liquidity (i.e. sectoral supply and demand flows) to an integrated analysis. Building upon EGH, we model structurally identified global credit components for the public and private sectors. We show that our estimates exhibit sizeable and economically relevant correlations with a range of financial market indicators, and relate the global credit components to a large set of country specific variables by means of variance decompositions.

We build an empirical model which allows us to distinguish between global liquidity components (loan and security flows) by receiving sectors from lending sectors. We construct a factor model for a multitude of credit, interest and real activity flows to estimate the credit composition of global liquidity. Subsequently, we endorse our credit components and show by means of variance decompositions that differentiating global liquidity by sectoral destination enhances the understanding of credit flows between economies considerably. The econometric specification, our empirical results and robustness checks are presented and discussed in Sections 2, 3 and 4, respectively. Section 5 concludes.

2 Data and methodology

In this section, we first describe the data. Subsequently, we provide a broad outline of the factor model. For a detailed and step-wise documentation of factor extraction we refer the reader to Appendix A.

2.1 Data

To obtain genuine supply and demand components for credit channeled towards non-financial businesses, households and governments, we construct a data-set along the lines of EGH. In particular, we partial out other co-movements in financial and real-economy covariates and determinants, such as investment or house prices that might bias our global liquidity estimates. Obtained from BIS, IMF, Global Financial Data, and Datastream the quarterly data cover the period 1995Q1 until 2020Q1 and a cross-section of 43 countries. Both the sample period and the cross section of countries are constrained by data availability. At the beginning of the sample, we filled missing data with observations from the dataset of EGH. Moreover, we constructed aggregate credit variable only for periods, for which all volumes of non-financial business, household and government credit were available. Otherwise, we interpolated the aggregate. We employ log-linearisation and we do not remove outliers. Finally, we applied year-on-year transformations on non-interest rate variables. We emphasize that this transformation reliably partials out seasonal effects (see Table A12 for details).

Quarterly data have been taken whenever available. At the beginning of the sample period and mostly for emerging economies data is sparse. For eventual interpolation, we adopt

the following strategy: In case quarterly data was unavailable, we interpolated annual or semi-annual data. At most one half of a time series has been subjected to interpolation, if sufficient annual data was available (otherwise, the respective series was omitted from the analysis). Missing data was interpolated by means of linear interpolation. We checked the plausibility of the interpolated financial series which are used in the sign restriction procedure, and omitted implausibly interpolated series. To account for unconventional monetary policy, we use the shadow rates of Krippner (2020) for the respective zero-lower bound periods in the US, the UK, the Euro-area and Japan to construct interest rate spreads. Details are provided in Table A12. Tables A9, A10 and A12 summarize the variables, countries, data sources and data transformations. Table A11 documents the number of series used in estimation. Estimating the credit composition factor model generates a multitude of auxiliary information, for example, estimates of global co-movements in output or share prices. We will not subject these findings to detailed interpretation, but show them in Appendix C.

2.2 Factor model

Dynamic factor models have become the econometric workhorse approach to estimate latent common components. In macro-econometric research the recent popularity of these models has been initiated with the estimation of the global business cycle in Kose et al. (2003). As our research goal is to differentiate credit and other financial variables from measures of real activity, we construct a factor model that disentangles variable-specific co-movements from cross-variable co-movements and idiosyncrasies. All time series $y_i = (y_{i1}, y_{i2}, \ldots, y_{iT})'$, indexed by $i = 1, ..., N$, and sampled for 43 economies column collected in the data matrix $\mathcal{Y} = [y_1, y_2, \ldots, y_N]'$. Ultimately, we aim at identifying J autoregressive factors of lag order p denoted f_j, $j = 1, \ldots, J$. The matrix comprising all factors is $F = [F_1', F_2', \ldots, F_J']'$, with F_j being a row-vector of factor j, F_t being a column-vector of all factors at time t, and $F_{j,t}$ being a scalar of factor j at time t.

Our goal is to obtain the series of structural innovations to credit demand and supply conditions. The structural innovations originate from any change in economic fundamentals that relate to financing conditions, for example, a change in agents' risk disposition, financial innovation, or changes in financial competition and regulation. Moreover, we estimate the monetary policy component implied by EGH's triad perspective on global liquidity to immunize the credit factors against potential contamination with monetary policy surprises. As the data is subject to serial correlation, it is reasonable to assume that the global liquidity factors will not only be composed of a weighted sum of structural innovations across time, but also of latent serially correlated processes. To account for autocorrelation, we modify the estimation procedure of EGH to obtain dynamic estimates of global credit supply and demand

components. For this purpose, we presume that each factor j allows for a representation

$$\overbrace{\underset{(1\times T)}{\left[F_{j,1}\dots F_{j,t}\dots F_{j,T}\right]}}^{F_j} = \overbrace{\underset{(1\times T)}{\left[\zeta_{j,1}\dots \zeta_{j,t}\dots \zeta_{j,T}\right]}}^{\zeta_j} + \overbrace{\underset{(1\times T)}{\left[\kappa_{j,1}\dots \kappa_{j,t}\dots \kappa_{j,T}\right]}}^{\kappa_j} \tag{1}$$

where ζ_j is a weighted sum of the structural shocks of interest and κ_j is a latent process subject to serial correlation that might incorporate other structural shocks and stochastic components. We remain agnostic regarding the weighting scheme of ζ_j, and only assume stationarity for every factor in levels. By assumption, a set of contemporaneous sign and zero restrictions identifies ζ_j, while excluding κ_j (see Appendices A and B). We explicitly model the autoregressive dynamics in a state-space environment. By implication, the factors cannot be understood as a series of structural shocks alone, and in this sense, they lack a strict structural interpretation. Nevertheless, the factors are highly correlated with the structural innovations by construction. Furthermore, it is important to notice that the factors have an ordinal scale, with higher values indicating favourable credit conditions.

The series-specific idiosyncrasies are denoted with $u_i = (u_{i1}, u_{i2}, \dots, u_{iT})'$ and collected in the matrix in $\mathcal{U}$. As they are not of further interest for the purposes of our study, they can be treated as error-terms. The system is estimated by means of Kalman smoothing. Lag order selection by means of the BIC criterion obtains that $p = 2$ is sufficient to describe factor dynamics. For the following formal state-space exposition, the dimensions of the matrices have to be scaled by the lag order p in the state equation. We state the system period-wise. Let Y_t denote an N-dimensional column vector comprising the sample information available for period t. The observation equation is given by

$$\overbrace{\underset{N\times 1}{\begin{bmatrix} y_{1t} \\ \vdots \\ y_{N,t} \end{bmatrix}}}^{Y_t} = \underset{(N\times J)}{\Theta} \times \overbrace{\underset{(J\times 1)}{\begin{bmatrix} F_{1,t} \\ \vdots \\ F_{J,t} \end{bmatrix}}}^{F_t} + \overbrace{\underset{(N\times 1)}{\begin{bmatrix} u_{1,t} \\ \vdots \\ u_{N,t} \end{bmatrix}}}^{U_t}. \tag{2}$$

The (scaled) state equation is

$$\overbrace{\underset{Jp\times 1}{\begin{bmatrix} F_{1,t} \\ F_{1,t-1} \\ \vdots \\ F_{J,t} \\ F_{J,t-1} \end{bmatrix}}}^{F_t} = \overbrace{\underset{(Jp\times 1)}{\begin{bmatrix} \mu_1 \\ 0 \\ \vdots \\ \mu_J \\ 0 \end{bmatrix}}}^{\mu} + \overbrace{\underset{(Jp\times Jp)}{\begin{bmatrix} \Gamma_1 & 0 & 0 \\ 0 & \ddots & 0 \\ 0 & 0 & \Gamma_J \end{bmatrix}}}^{\Gamma} \times \overbrace{\underset{(Jp\times 1)}{\begin{bmatrix} F_{1,t-1} \\ F_{1,t-2} \\ \vdots \\ F_{J,t-1} \\ F_{J,t-2} \end{bmatrix}}}^{F_{t-1}} + \overbrace{\underset{(Jp\times 1)}{\begin{bmatrix} \zeta_{1,t} \\ 0 \\ \vdots \\ \zeta_{J,t} \\ 0 \end{bmatrix}}}^{\zeta_t}, \tag{3}$$

where Γ is a block diagonal matrix with typical blocks Γ_j, which is the companion matrix of

autoregressive coefficients $\gamma_{j,p}$ belonging to factor j at lag p, i.e.

$$\overbrace{\underbrace{\begin{bmatrix} \Gamma_1 & 0 & 0 \\ 0 & \ddots & 0 \\ 0 & 0 & \Gamma_J \end{bmatrix}}_{(Jp \times Jp)}}^{\Gamma} = \underbrace{\begin{bmatrix} \gamma_{11} & \gamma_{12} & 0 & 0 & \dots & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 & \dots & 0 & 0 & 0 \\ 0 & 0 & \gamma_{21} & \gamma_{22} & \dots & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & \dots & 0 & 0 & 0 \\ \vdots & \vdots & 0 & \vdots & & \vdots & \vdots & \vdots \\ 0 & 0 & \vdots & 0 & \dots & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & \dots & 0 & \gamma_{J1} & \gamma_{J2} \\ 0 & 0 & 0 & 0 & \dots & 0 & 1 & 0 \end{bmatrix}}_{(Jp \times Jp)}. \tag{4}$$

In (2) Y_t is the t-th column of the data matrix $\mathcal{Y}$, F_t is the t-th column of the matrix of all factors F, μ is a vector of intercepts, Θ is the factor loading matrix, U_t is the t-th column of the matrix of idiosyncratic components $\mathcal{U}$, with U_t following the normal distribution $U_t \sim \mathcal{N}(0, \Phi)$. In (3) Γ is the state loading matrix, ς_t is normally distributed white noise $\varsigma_t \sim \mathcal{N}(0, \Sigma)$. The covariance matrices Φ and Σ are positive-definite and diagonal of dimensions $N \times N$ and $J \times J$, respectively. Diagonality is not overly restrictive but required to fulfill central assumptions of the dynamic factor model. In particular, it is justified for Σ, as we require orthogonality for factor identification (see Appendix A step 9). All co-movements are captured by the factors by construction, otherwise the model would be ill-specified; see Barhoumi et al. (2013) and Stock and Watson (2010)), and it is justified for Φ to avoid numerical instability. Doz et al. (2012) show that under the assumption of diagonality of Φ, the idiosyncratic processes are still consistently estimated. We impose zero-restrictions on Θ that are presented in Section 3.

Following EGH, static factors can be structurally identified by means of sign-restrictions. EGH rely on a rotation approach, i.e., principle components are subjected to rotation until their loadings on economic variables (e.g. interest rates or credit volumes) match the sign restrictions. Along these lines, we obtain 100 draws, and, subsequently, select the factor that is closest to the median value in the time domain. We only do so for the credit and monetary policy factors of interest and leave the controls (e.g. output factors) structurally unidentified. To implement sign-restrictions in the spirit of EGH feasibly in a state-space context, we estimate the dynamic model given in (2) and (3) by means of quasi maximum likelihood (QML) (Wang 2010, Stock and Watson 2010, Bai and Ng 2013, Breitung and Eickmeier 2016). We employ the principle component version of the QML procedure described in Doz et al. (2012), with some modifications that have been outlined in Bai and Ng (2013), Breitung and Eickmeier (2016), Kim and Nelson (1999), Stock and Watson (2010) and Wang (2010).

3 Empirical analysis

In this section, we discuss estimation results.[2] For benchmarking purposes we first provide updated, dynamic factors of the credit components estimated by EGH. Two issues naturally arise from our findings. First of all, the rationale of global lenders remains opaque, as it is unclear from the aggregate model to whom they lend and why they do. Moreover, there are no obvious micro-founded candidate explanations of the properties of aggregate credit supply and demand. Therefore, we underline that a distinction of credit into flows directed to private and public sectors enhances the understanding of global financing conditions considerably.

To improve readability, we focus on the credit factors and move further interesting results into appendices. We present identification restrictions in Appendix B. Static estimates are shown in Appendix F. Moreover, we depict the non-credit factors as well as a comparison of our dynamic estimates with the factors obtained from EGH in Appendices C and E, respectively. We do not present an exact replication of EGH. First of all, EGH rely on static principal components that, by construction, are likely to overstate the importance of the US, mainly because they include a large set of US variables in addition to their cross-country panel. With respect to sample information and unlike this study, EGH include data for banking credit and other financial aggregates like implied volatility. Moreover, EGH do not model or partial out a global factor, whereas we partial out (see Appendix A, step 9) the global factor from the entire sample. We document the monetary policy factors associated with the aggregate credit and the credit composition model in Appendix D. Both models yield rather similar monetary policy factor estimates.

In this section we undertake a structural interpretation of the extracted credit aggregates. In this context it is important to recall that the factors can only be interpreted in an ordinal manner. The higher the value of the supply factor, the better are the financing conditions in the sense of a better availability of international credit. The higher the value of the demand factor, the more credit is demanded. The credit supply factor indicates the change in credit *supplied* in total or to the respective sectors (private and public), whereas a credit demand factors indicate the change in credit *demanded* at the aggregate level or by the distinct sectors. For assigning economic interpretations to the factor information we partly rely on linear correlations between the factors and a variety of (international) financial indicators (see Appendix J for a full list). Although we do not draw conclusions on potential causal effects from such exercises, we consider them to unravel economic states that are (un)favorable for spurring global liquidity in total or in some of its important components. Estimates of dynamic credit composition components are shown in Figure 1. Correlation estimates are depicted graphically in Figure 3.

[2] All computations have been performed in R.

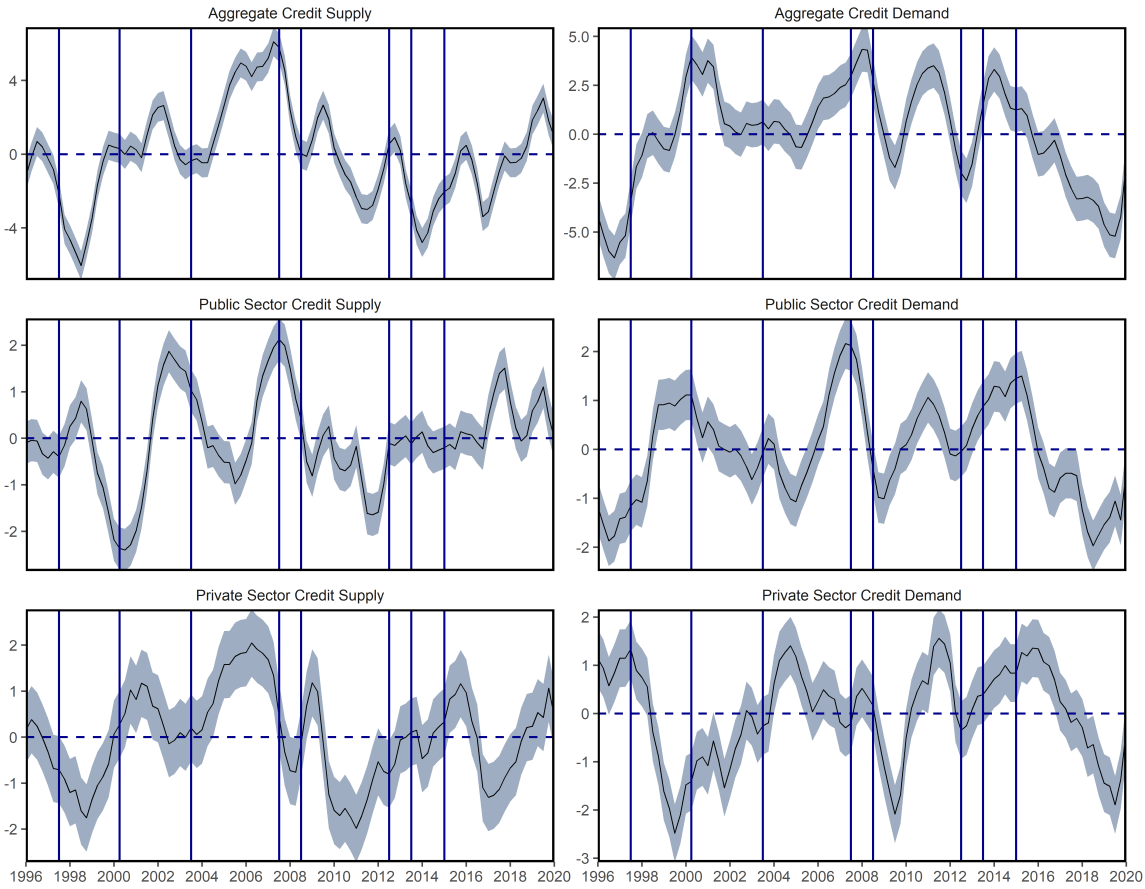

Figure 1: Global credit cycles: Supply (demand) components are shown in the left (right) hand side panel. From top to bottom: Aggregate credit, public sector credit, private sector credit. Dynamic factor estimates are based on 100 static draws that accord with the sign-restrictions (Tables A1 and A3). For the full identification procedure see Section 2 and Appendix A. Shaded areas indicate 95% coverage bands as described in step 10 of Appendix A. The sample covers important events in international finance (indicated with horizontal lines), i.e. (i) the Asian crisis (1997Q3), (ii) the burst of dotcom bubble (2000Q2), (iii) the beginning of the US mortgage credit expansion in 2003Q3 (Justiniano et al. 2017), (iv) the financial turmoil of 2007Q3, (v) the bankruptcy of Lehman Brothers (2008Q3), (vi) Mario Draghi's 'whatever it takes' statement during the European banking and sovereign debt crisis (2012Q2), (vii) the Fed's 'taper tantrum' (2013Q2), and (viii) the beginning of the ECB's public sector purchase program (2015Q1).

3.1 Aggregate credit model

We begin with the analysis of an aggregate credit specification in the spirit of EGH. Since dynamic estimates are not perfectly uncorrelated, we orthogonalize in the following order (see step 9, Appendix A): Credit, monetary policy, share prices, inflation and output, such that credit is least and output is most informative for economy-wide fluctuations. Following

EGH, aggregate credit factors are normalized to have the same standard deviation and to be positively correlated with average domestic credit growth across all countries. As it is apparent from Figure 2, aggregate credit supply is well-identified after dynamic estimation and accounting for global macroeconomic and share price co-movements: On average, the factor loads positively on aggregate credit and cross-border credit, and negatively or (close to) zero on all three interest rates and interest rate spreads. Identification of aggregate credit demand appears less clear cut. Its loadings on aggregate and cross-border credit are positive or not significantly different from zero, and its loadings on government bond yields and the mortgage rates are positive or zero. In total, both interest rates account for more than one half of the sample information on interest rates. Therefore, the average negative loading on corporate interest rates does not indicate a violation of the identification restrictions.

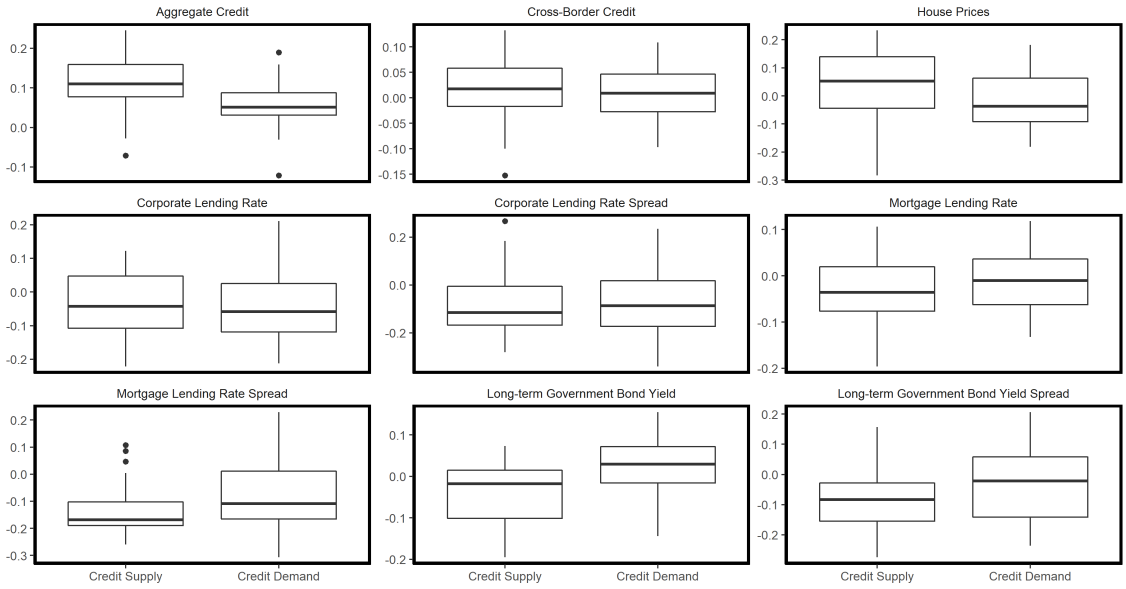

Figure 2: Loadings aggregate model.

3.1.1 Aggregate credit supply

Conceptually, higher values of the aggregate credit supply indicate increased willingness (e.g., due to increased risk-taking or animal spirits) or opportunities to lend (e.g., due to deregulation or financial innovation). As displayed in the upper left hand side panel of Figure 1, aggregate credit supply was tight during the late 1990s and during the Asian crisis 1997 – 1999. Similar to EGH, we find that credit supply conditions improve at the beginning of the new millennium, with a subsequent and temporary tightening that coincides with the dotcom crisis (see Figure 1). After 2003 the global credit supply factor rises, possibly resembling the international flow of funds described by the SG and BG hypotheses (Bernanke 2005, Shin 2011). We note that the increase of credit supply also coincides with the US and European mortgage credit expansions which have been described abundantly in the literature (Mian

and Sufi 2010, Mian et al. 2013, 2017, Mian and Sufi 2018, Justiniano et al. 2017, 2019). Indicating a strong decline in the international availability of credit, the credit supply factor drops in the wake of the 2007/08 financial crisis. Going beyond the sample period considered by EGH (1995Q1 – 2011Q2), we observe that global credit supply conditions massively tightened during the European banking and sovereign debt crisis in 2012/2013. Subsequently, credit supply conditions improve with a tendency to stabilize after 2015/16.

To assess which global economic conditions coincide with favourable lending conditions, we perform linear correlation analyses. As displayed in Figure 3, correlations unravel that aggregate credit supply is not significantly correlated with bank leverage measures across the world. Moreover, aggregate credit supply is negatively correlated with global financial sector risk, which is approximated by the asset price risk and risk aversion components in the spirit of Miranda-Agrippino and Rey (2020). Economically, this means that lenders increase credit supply in times of low (perceived) financial market risk.

3.1.2 Aggregate credit demand

As displayed in the upper right hand side panel of Figure 1, aggregate credit demand was low prior to the Asian crisis, and prevailed on a moderate level from 2001 until 2003. After the 2007/08 financial crisis, the volatility of credit demand increased substantially and remained high until 2015. Subsequently the factor decreased steadily until the end of the sample. Recall that higher values of the demand factor indicate an increased willingness (e.g., to finance future investments) or necessities to borrow (e.g., to fulfil obligations). Two increases of global credit demand are especially noteworthy: (i) after the financial crisis (2007-09) and (ii) during the European banking and sovereign debt crisis (2009-12). These events are likely to resemble the increased demands of businesses to bear vital expenses, and of governments to finance social policies designed to absorb adverse economic shocks, respectively.

Economic theory does not provide an unequivocal picture of the interplay of global credit demand and the international financial system. Numerous mechanisms might be at work. On the one hand, international credit demand might be high in times of high risk and leverage because of short-term profit-maximization. On the other hand, in uncertain times borrowers may reduce credit demand to consolidate their balance sheets in the fear or expectation of future busts. Due to this lack of *unequivocal* theoretical guidance with regard to potential correlation patterns, we do not argue in favour of specific mechanisms and let the data speak about the relationship of credit demand and the global financial system. Correlation patterns (see Figure 3) reveal a negative relationship between aggregate credit demand and global risk. Correlations with leverage are ambiguous. As for the case of aggregate credit supply, however, it is not possible to attribute these features to the rationales of specific agents.

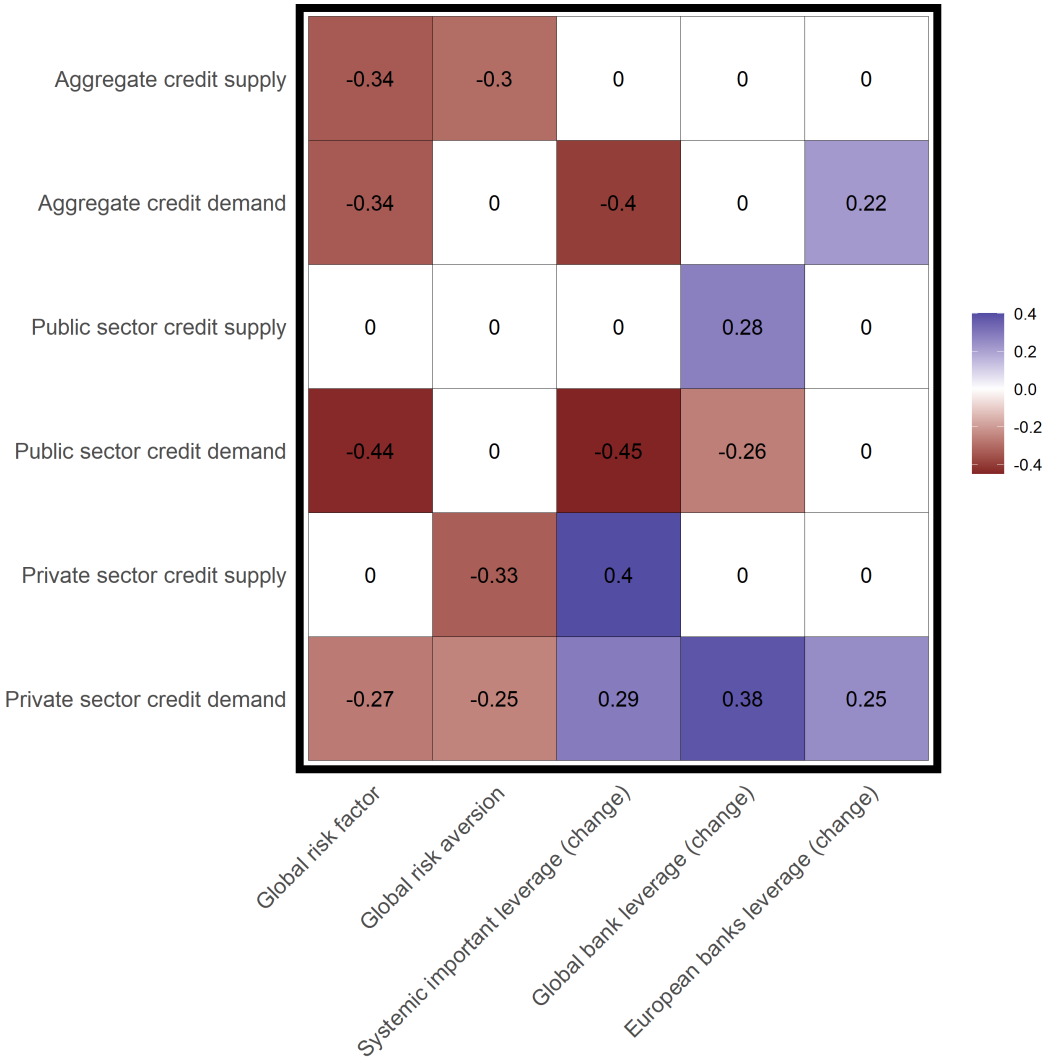

Figure 3: Heatmap for the credit models. Not all indicators are available for the entire sample period. Hence, the rule-of-thumb threshold $\pm 1.65/\sqrt{T}$ that we use to test significance is not identical for all correlation coefficients. When a Pearson correlation coefficient is not statistically different from zero, we set it to zero. We obtain the long-series of the global risk factor from Silvia Miranda-Aggripino's website and construct the risk aversion index as described in Miranda-Agrippino and Rey (2020). We invert the risk index to simplify interpretation, i.e. higher values imply higher risk premia. The leverage indicators are taken from Miranda-Agrippino and Rey (2020).

3.2 Credit composition model

To unravel the underlying structural dependencies between heterogeneous borrowers and lenders, we proceed by decomposing the credit components of global liquidity into public and private sectors for which plausible economic narratives are available. As we need five factors to model the supply and demand components for credit directed towards the public and the private sectors (and a monetary policy factor), we extract the principle components associated

with the five largest eigenvalues from data comprising business, household, government and cross-border credit volumes, the business lending rate and its spread over the policy rate, the long-term government bond yield and its spread over the policy rate, the mortgage rate and its spread over the policy rate, M0, M3, house prices and the overnight rate. All five corresponding eigenvalues are larger than 1. We structurally identify the factors as described in Section 2.2. As dynamic estimates are correlated, we orthogonalize in the following order: Private credit, public credit, monetary policy, share prices, inflation, output. Following EGH, the public (private) sector credit factors are normalized to have the same standard deviations as average domestic government (private) credit growth.

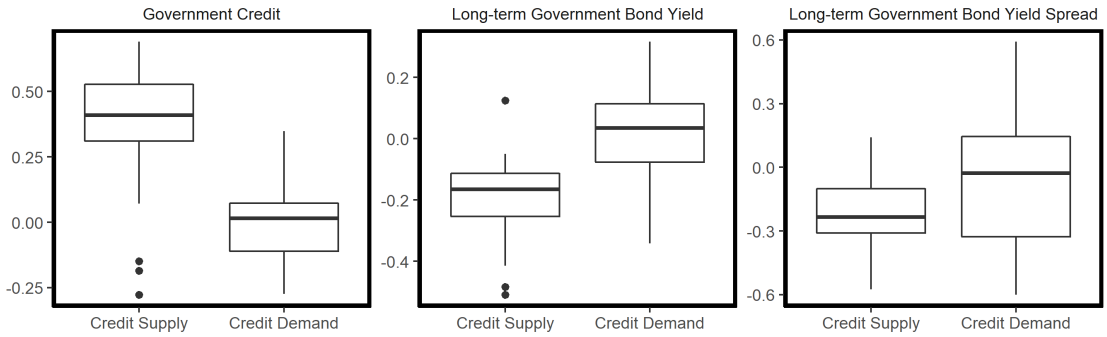

Figure 4: Loadings of public sector credit factors.

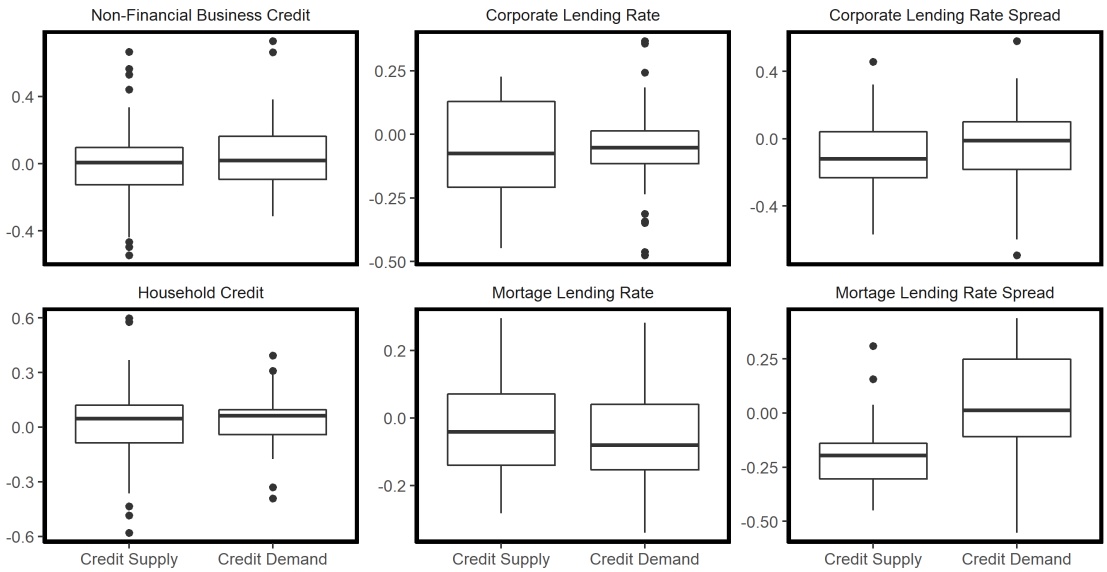

Figure 5: Loadings private sector credit factors.

As is apparent from Figure 4 (public sector) and Figure 5 (private sector), the model is identified after dynamic estimation and orthogonalization. The loadings of public sector credit supply on government credit (government bond yields) are positive (negative) throughout,

and the government bond yield spread restriction is clearly fulfilled as well. Similarly, public sector credit demand is unequivocally identified. Moreover, both private sector components fulfill the sign-restrictions on business and household credit, i.e. the average loadings are insignificant or positive. Private sector credit supply clearly satisfies the restrictions on corporate and mortgage rates and its spreads. Interestingly, private credit demand loads only weakly on nearly all depicted variables. Small loadings might point to minor importance of private sector credit demand after accounting for macroeconomic, monetary and financial aggregates on the global level. This is in line with related insights into the relative importance of credit demand shocks in the literature (e.g., see Mian and Sufi (2018)).

3.2.1 Credit composition supply components

We begin by outlining an intuitive account of the rationales of global lenders to supply liquidity to public or private agents. In a second step, we discuss our empirical results of public and private sector credit supply flows.

An intuitive account of global lenders' portfolio choice Flows of cross-border credit (loans) and securities (bonds and various kinds of asset backed securities) are the essence of global liquidity. Following the framework of Miranda-Agrippino and Rey (2020), global banks and asset anagers are the most important global lenders. Both are subject to a value-at-risk constraint. Kalemli-Ozcan et al. (2012) emphasize that unlike commercial banks, global investment banks leveraged significantly prior to the 2007 financial bust. According to Avdjiev et al. (2017) the responsiveness of (bank) lending to global risk has been declining steadily since 2014. So far it is unclear which rationale lenders have to lend either to private or public entities. In the following, we provide an intuition for the case of a continuum of global banks that only differ with regard to their value-at-risk constraints.

A global bank aiming at profit maximization and facing a value-at-risk constraint will adopt a portfolio which contains just enough low-yield quasi risk-free assets (e.g., high rated government securities) to hedge against risks implied by private sector lending at higher yields. The remainder of the investment volume will be divided by each bank between inter-bank credit (which we do not consider in this work) and credit supplied to non-financial businesses and households (i.e., the private sector). The exact ratio between household and business credit depends on the respective yields and risks as well as on monetary policy (for the role of monetary policy in a heterogeneous agent framework see Coimbra and Rey (2017, 2018)). We presume this strategy to imply a stable intertemporal credit market equilibrium with stationary leverage and debt-service ratios. This equilibrium is subject to change once economic fundamentals are shocked. For instance, if risk-appetite increases, financial intermediaries shift lending towards the higher-yield sector. Eventually they engage in excess risk-taking, e.g. as a results of the concentration of risky assets. This may also occur, for instance, due to loose monetary policy (as was the case prior to sub-prime mortgage crisis, see Justiniano

et al. (2017) and Appendix D) or due to higher yields on either business or household securities. High yields and decent profit opportunities imply that the private sector lending is mainly active during upswing-episodes of the business cycle. In the vein of Kalemli-Ozcan et al. (2012), institutions with weaker value-at-risk constraints (e.g., investment banks) will be more exposed to balance sheet risks than those with stronger risk aversion (e.g., commercial banks). Cetorelli and Goldberg (2012) emphasize the role of bank-internal capital re-allocations in deleveraging.[3] These shifts of liquidity supply and risk are intricate as they neither show up in aggregate credit supply, nor in the real economy, thus highlighting the importance of sectoral credit market monitoring. We now turn to the discussion of empirical evidence on the credit supply of global lenders to private and public agents.

Public sector credit supply is depicted in the second row on the left hand side of Figure 1. Lending conditions deteriorated substantially during the Asian crisis and after the 2007 financial turmoil. The 2007 decrease in public sector credit supply is plausible in the light of the upcoming European banking and sovereign debt crisis that has invoked a sudden change in lenders' perceptions of government assets. Seemingly, key events in international finance related to monetary policy, such as the 'taper tantrum' in the US or the ECB's public security purchasing program have hardly affected public credit supply. This encourages the view that the factor is not contaminated by monetary policy shocks, even though many of the 'quantitative easing' policies intervene in government security markets.[4]

In normal times, corporate bond and mortgage yields are higher than government bond yields, assuming similar currency and maturity. This is due to a risk premium that reflects a higher probability of default and the general risk-taking capacity of the financial sector (see, e.g., Gilchrist and Zakrajsek 2012). By implication, it is rational for lenders to supply corporations and households before supplying governments with credit at the margin. Therefore, we expect that government credit supply is likely to correspond to 'save-haven' or 'flight to quality' lending, since investors increasingly lend to governments in times of high economic uncertainty and volatility. Moreover, other institutional reasons might be in place to engage in safe-haven, low profit lending. For instance, some lenders need to do so because of legal requirements to invest in highest grade assets, e.g. pension funds or life insurers. The diagnosed inter-dependencies with international financial indicators strongly support these conjectures: As can be seen from Figure 3, public sector credit supply is not significantly correlated with global asset risk, indicating that risk-aversion does not seem to play a role in lenders' rationales. Moreover, it is positively correlated with changes of global bank leverage ($\hat{\rho} = 0.28$). Economically, this underpins that lending to governments follows a substantially

[3] Cetorelli and Goldberg (2011) consider three distinct transmission channels of global shocks via global banks: „a contraction in direct, cross-border lending by foreign banks; a contraction in local lending by foreign banks' affiliates in emerging markets; and a contraction in loan supply by domestic banks resulting from the funding shock to their balance sheet induced by the decline in inter-bank, cross-border lending".

[4] Moreover, recall that we make extensive use of shadow rate estimates to account for unconventional monetary policy.

different rationale than lending to businesses and households.

Private sector credit supply is low at the outset of the new millennium and tends to deteriorate in times of crises, e.g., after the collapse of Lehman Brothers in 2008Q3 (third row on left hand side of Figure 1). Subsequent to most of these scenarios, the factor recovers within about 1 – 2 years. Hence, global lending to non-financial businesses adjusts relatively fast after (severe) negative shocks. Moreover, private sector credit supply gained momentum after 2003, which coincides with the US mortgage credit expansion (Demyanyk and Van Hemert 2011, Justiniano et al. 2017). The factor reaches a minimum when the global macro-economy was already recovering from the financial crisis in 2011. Private sector credit supply recovered more or less smoothly until 2016, collapsing again and recovering until the end of the sample period. Since 2011 the factor evolves quite similar to aggregate credit supply (see Figure 1).

According to theoretical considerations, lending to the private sector follows a profit maximization rationale along the business cycle. We cannot directly address the conjecture that private sector lending follows the business cycle, as global output co-movements were partialled out. However, we can do so indirectly by means of considerations of favourable lending conditions that (i) are likely to occur during favourable states, i.e. during the boom-phase of the business cycle, but (ii) unlikely to be captured by the business cycle factor. For example, risk taking and leveraging are well known to co-move with business cycles (Adrian and Shin 2010). But there are hardly convincing reasons to assume that risk taking behaviour and leveraging are *caused* by the business cycle beyond amplification or financial accelerator effects. Thus, correlations of private sector credit supply with risk taking might provide insights into the connection between the former and states of the business cycle. As shown in Figure 3, the private sector credit supply factor behaves in line with theoretical considerations: If risk aversion increases, less credit is supplied to private entities ($\hat{\rho} = -0.33$). This conjecture is further supported by the positive correlations with systemic important bank's leverage growth ($\hat{\rho} = 0.40$). Put differently, global credit is supplied to private entities during boom-episodes of the business cycle, indicated by increased leverage and low risk premia.

3.2.2 Credit composition demand components

We now turn to discussing components of credit demand. Again, we begin with an intuitive account of potential incentives of borrowers. Subsequently, we discuss our findings on credit demanded by the public and private sectors from global lenders.

Borrowing by public and private agents Unlike the case of credit supply, we not only need to understand the decision problem of representative agents (global lenders), but of two rather distinct sectors (public and private). We first elaborate on risk taking behaviour and proceed with brief comments on the cyclicality of sectoral borrowing. Each group of agents in the public and private sector (businesses, households, governments) is exposed to distinct degrees of economic risk. Unlike the private sector (businesses and households), the internal

financing of the public sector is relatively stable due to tax revenues. Even though tax volumes might fluctuate over the business cycle, the public sector generates tax income from the *entire* distribution of households and businesses. On the contrary, households generate internal finance through *specific* labor markets. Moreover, businesses generate internal finance by means of engaging in *specific* product markets. Thus, households and businesses are more directly exposed to the business cycle fluctuations. Put differently, the public sector can guarantee a relatively stable stream of income to its lenders, making its securities relatively less risky to default. In contrast, debt services of the private sector depend more on the states of the business cycle such that its securities are relatively more risky to default.[5]

With regard to borrowing behaviour over the business cycle, it is worth noticing that businesses maximize present shareholder value subject to an intertemporal borrowing constraint. This constraint reflects a manifold of determinants such as cash flows, physical asset collateral or the risk-free borrowing rate (Ağca and Celasun 2012, Lian and Ma 2020). Therefore, businesses have a strong incentive to invest pro-cyclically. Households, who maximize life-time utility and face an intertemporal borrowing constraint borrow until the marginal return of external finance approaches zero (e.g. due to risk constraints). Their constraint is subject to house prices, household age, credit scores and non-household determinants (Mian and Sufi 2011, Cloyne et al. 2019). Given a household with a constant relative-risk utility function and facing an intertemporal budget constraint, we expect rational households to cut their spending and consolidate their balance sheets in the light of increasing uncertainty with regard to their future wealth and to expand their spending in times of economic prosperity. In sum, the private sector has a strong incentive to borrow pro-cyclically. Governments, on the contrary, are run by politicians who maximize their short- to medium-term share of voters. This might result in counter-cyclical borrowing. Therefore, sovereign borrowing is motivated by many reasons that are not necessarily related to the state of the economy.[6] For example, some governments may expand their balance sheet by means of debt instruments due to a lack of internal financing. This might increase the global public credit demand factor. To summarize, we argue in favour of substantial heterogeneity in the equilibrium determinants of sectoral credit markets that we expect to show up in the two credit demand factors.

Public sector credit demand is low at the outset of the new millennium, followed by minor fluctuations until 2005 (second row on right hand side of Figure 1). After a large positive shock prior to the financial crisis, the factor drops with the default of Lehman Brothers. Starting in 2015 the factor decreases until the end of 2018, followed by a moderate increase at the end of the sample period. Unlike public sector credit supply which measures the willingness of private agents to lend to the state (as sovereigns rarely lend to each other),

[5] As businesses and households are subject to similar incentives to borrow along the financial cycle, a further decomposition of the private sector is not asked for.

[6] After the financial crises, various measures have been taken to smooth government expenditure and prevent excess spending, e.g. the European stability and growth pact.

public sector credit demand is best understood to resemble the public sectors' needs for external finance. This might occur due to policy preference shifts or risk perception shifts when governments lever.

We hypothesize that the 2008 – 2012 public sector credit demand increase reflects the huge financing needs of governments to stabilize the Western economies by means of fiscal policy interventions. Figure A7 (Appendix G) depicts the idiosyncratic government credit components for all available government credit series. As becomes clear, excess increases in the idiosyncratic government spending in times of crises is hardly observed at the country-level. This is the case for Asian crisis, the dotcom bubble bust and the financial crisis. Moreover, correlation patterns with risk and leverage indicators are insignificant or negative throughout, pointing to increased public borrowing activity during times when the banking sector is deleveraging. Reconsidering the aggregate credit demand findings, we note that its properties seem to stem from public credit demand. Therefore, we conclude that government expenditures to fight crises and absorb global risk shocks tend to co-move on the global level. By contrast, the country-specific (i.e. factor-adjusted) government credit series may be understood as resembling national economic and social policies as well as (possibly) rent-seeking.

Private sector credit demand decelerates in times of crises, e.g. in 1999, 2008 and 2011 (third row on right hand side of Figure 1). These decelerations could reflect a weakened willingness of firms and households to invest. Interestingly, private sector credit demand increases about 1 – 2 years prior to crisis events (e.g. 1997-98 and 2010-11). Put differently, sizeable expansions of private sector credit demand seem to precede major financial crises. This is roughly in line with Schularick and Taylor (2012), who argue that credit volume growth predicts financial market crises. The factor sharply increases from 2012 onwards and decreases after 2015 until the end of the sample period.

Private sector credit demand exhibits the richest correlations patterns (see Figure 3). Borrowing decreases with rising asset price risk and risk aversion, and increases with bank leverage growth. Put differently, if the economy is booming, private agents tend to borrow, when bubbles burst, they tend to refrain from borrowing. The sectoral dimension has an economic interpretation: When households and businesses borrow in times of economic stability, we might infer that they do because of investment- and consumption-motives. Investments might have real growth effects in the future. Hence, increased global private credit demand might also increase productivity in the medium term.

3.3 Variance decompositions

We assess the relative importance of the credit factors in explaining movements of the variables in the system across all countries. For this purpose, we follow EGH and the literature on latent global co-movements in macroeconomic variables (e.g. Kose et al. (2003)) and focus on variance decompositions (see Appendix A, step 11). Figure 6 contrasts the shares of

variances in key financial aggregates explained by the credit and monetary policy factors in both models.

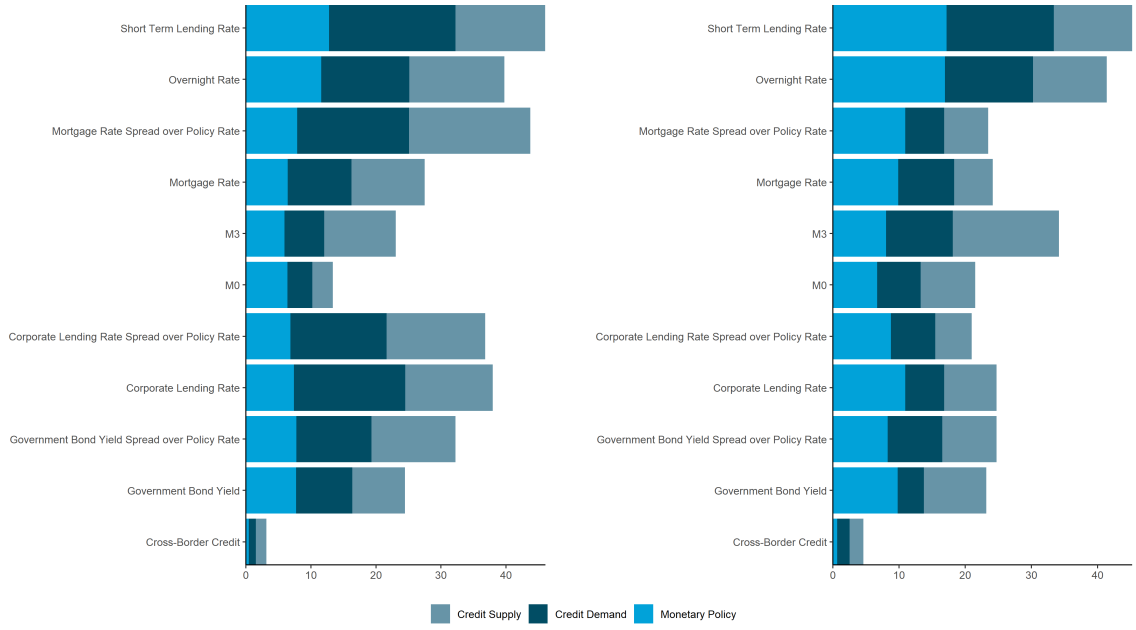

Figure 6: Explained shares of variance by aggregate credit (left) and credit composition model (right).

First of all, we make three key observations, namely (i) both models explain similar amounts of variance conditional on monetary policy, credit demand and credit supply on average, (ii) the aggregate credit model explains more variation in interest rate spreads, and (iii) the credit composition model explains more variation in monetary aggregates. We take the result in (i) as evidence that both models have a meaningful interpretation. The second finding (ii) is best understood to indicate that interest rate spreads can be largely traced back to sector-specific flows. This is in line with a sizeable literature arguing in favour of credit spreads as predictors of economic and financial stability at the aggregate level, e.g. Gilchrist et al. (2009). Finally, the result in (iii) seems to point at a higher relevance of global credit components to explain monetary aggregates. Figure 7 visualizes in more detail to which sector the explained variances can be attributed. As it turns out, monetary aggregates are largely explained by monetary policy and public sector credit supply.

We find that the credit supply components are, on average, more important for explaining variation in financial aggregates than the credit demand components. Regarding the private sector, the shares of variances explained by credit supply exceed those explained by credit demand for most variables (notable exceptions are the mortgage rate, M0 and the corporate lending rate spread). With respect to the public sector, the shares of variances explained by either credit supply or demand appear more balanced. This underlines the relative importance of public sector credit demand. Based on the variance decompositions, we cannot attribute a leading role to either of the supply factors. Both private and public sector credit supply

explain relatively large shares of variance. We elaborate on monetary policy in Appendix D.

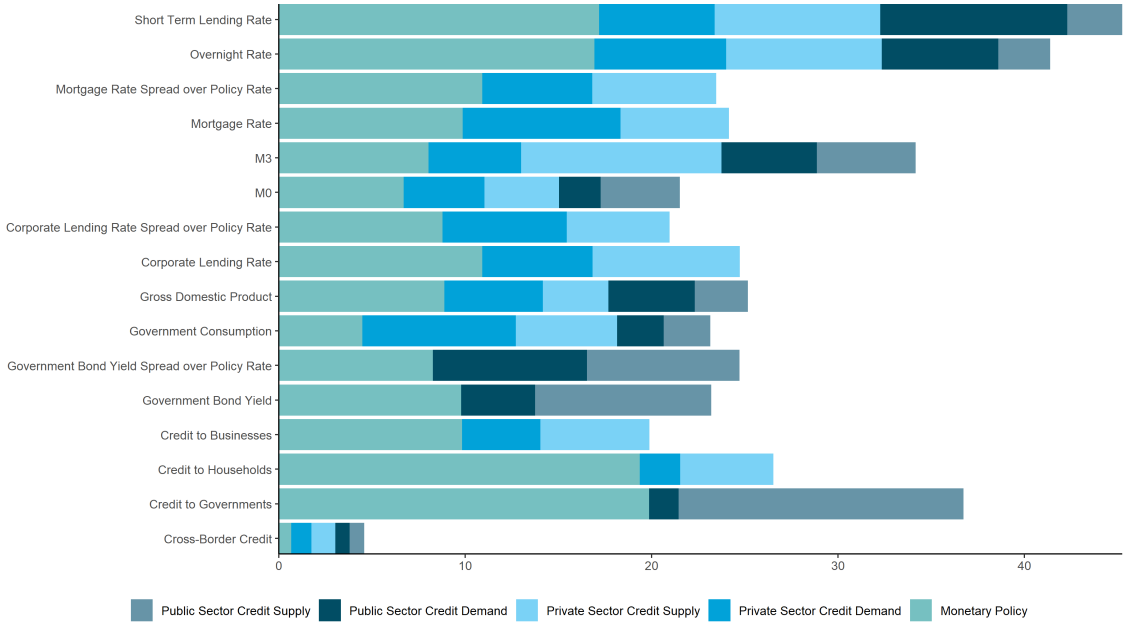

Figure 7: Explained shares of variance by credit composition model in detail

4 Robustness

We subject our models to various robustness checks.

4.1 Alternative orthogonalization schemes

To check to what extent the factors are contaminated with adverse information (e.g., other shocks), we subject them to orthogonalization routines that differ from the baseline specification presented in Section 3. Figure 8 shows the effect of applying the orthogonalization schemes given in Table 1 to the dynamic, non-orthogonalized factor trajectory estimates.

Scheme	Order of orthogonalization
baseline	private credit, public credit, monetary policy, share prices, inflation, output
O_1	private credit, public credit, monetary policy
O_2	public credit, private credit, monetary policy
O_3	monetary policy, private credit, public credit

Table 1: Alternative orthogonalization schemes (see step 9, Appendix A)

Our experiment reveals that the effect of not controlling for macroeconomic and share price factors yields slightly different estimates (O_1; compare red vs. orange lines in Figure 8). This is in line with EGH who perform a similar analysis.

Figure 8: Global credit cycles: Supply (demand) components are depicted in the left (right) hand side. Orange: baseline orthogonalization; red: O_1 – as baseline, without partialing out macroeconomic and share price factors; blue: O_2 – public sector partialed out before private sector and no partialing out of macroeconomic and share price factors; purple: O_3 – credit factors orthogonalized after monetary policy factor and no partialing out of macroeconomic and share price factors. For further notes see Figure 1.

We note that there are small differences when public factor estimates are subjected to orthogonalization in the first place and no macroeconomic and share price controls obtain (O_2; compare blue vs. orange lines in Figure 8). We also examine the effect of moving eventually shared information between credit and monetary policy factors into the credit instead of the monetary policy estimates (O_3; compare purple vs. orange lines in Figure 8). We observe that this changes the credit estimates, but only in terms of amplitude, not in sign. Hence, shared information monetary policy and credit factors do not have adverse effects on our estimates. Finally, we note that alternative orthogonalization schemes affect private sector estimates more than public sector estimates and demand estimates more than supply estimates. We emphasize with regard to O_2 and O_3 that the differences due to not partialing out macroeconomic and share price co-movements are larger than the differences from partialing out the public sector or monetary policy first. This underlines decent identification. To summarize, we conclude that our trajectories are sufficiently robust to changes in orthogonalization.[7]

[7]Figure A8 repeats the same exercise for the variance decomposition. Note that the macroeconomic and share price factors are not considered in these variance decompositions to avoid multi-collinearity. As can

4.2 Sub-sampling

To provide more evidence on the robustness of our variance decomposition results, we employ sub-sampling schemes across the time and the cross-sectional dimension. Note that our results are not fully comparable to those obtained by EGH without qualification, as we partial out a global factor prior to identification, whereas EGH partial out macroeconomic factors.

4.2.1 Advanced vs. emerging economies

We examine whether there are substantial differences in explained shares of variance for advanced and emerging economies in the credit composition model. Advanced and emerging economies differ in many respects, e.g. with regard to their exposure to global real and financial shocks. Their sensitivities might differ with respect to global liqudity components. As can be seen from comparing Tables A7 and A8, this is not the case: No systematic and noteworthy differences can be observed. We conclude that both credit and monetary policy factors are relevant on the global level.

4.2.2 EGH sample period

We estimate our aggregate credit model on the very same dataset, but we cut the sample at 2011Q2, such that we obtain an estimate of the period examined in EGH. Figure 9 juxtaposes the results with the factors obtained from EGH.

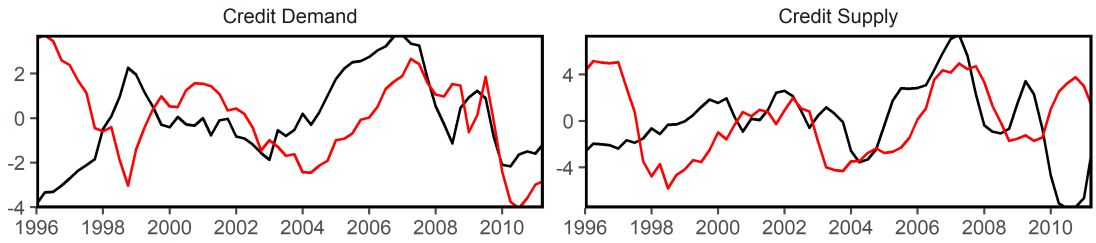

Figure 9: Aggregate credit model for 1996 – 2011 sample. EGH estimates in red. For further notes see Figure 1.

Ours and EGH's estimates are sizeably correlated, with $\hat{\rho} = 0.72$ in case of supply and $\hat{\rho} = 0.52$ for demand. If the observations after 2008 are dropped, these correlations increase to $\hat{\rho} = 0.73$ in case of supply and $\hat{\rho} = 0.81$ for demand. We present a comparison of both full sample models in Appendix E. Finally, we infer from Figure 10 that no relevant differences between the short sample model variance decomposition and results displyed in Figure 6 obtain.

be seen, the results from the variance decomposition shown in Figures 6 and 7 are robust to uphold our key conclusions. We note that results for monetary policy are hardly affected at all by orthogonalization, whereas the shares of explained variance by credit components fluctuate mildly, with few exceptions.

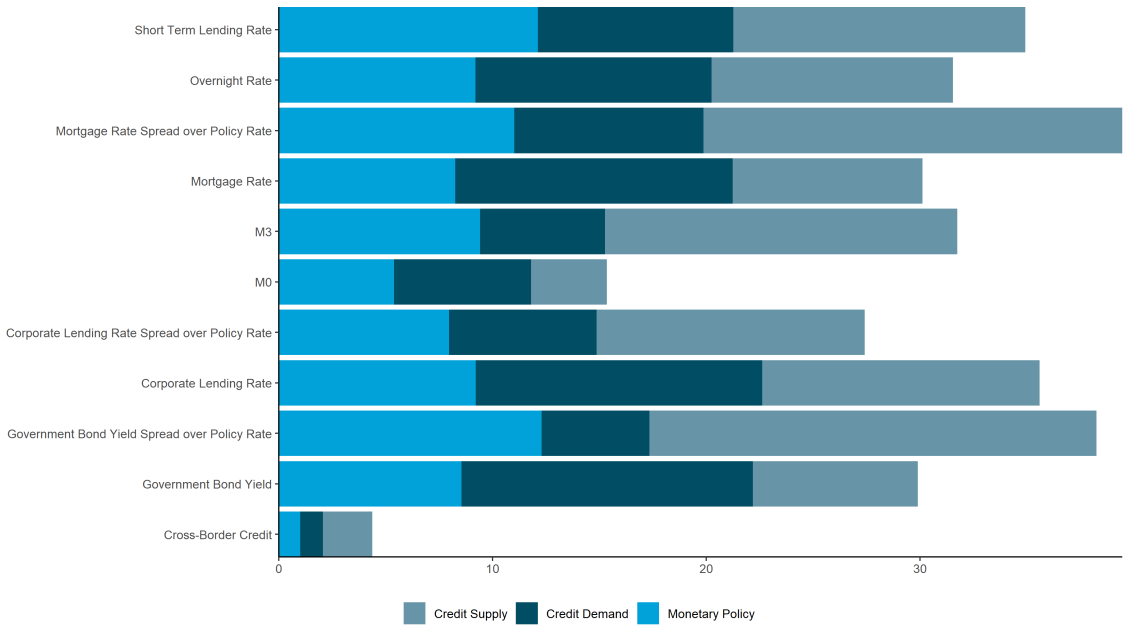

Figure 10: Explained shares of variance by aggregate credit short sample model

5 Conclusion

In generalizing the triad of global liquidity in the spirit of Eickmeier, Gambacorta, and Hofmann (2014) (i.e. monetary policy, aggregate credit supply and aggregate credit demand), we examine the credit composition of global liquidity by means a dynamic factor model that enables a decomposition of global credit demand and supply into flows directed to the public and private sectors. We extend the model of Eickmeier, Gambacorta, and Hofmann (2014) towards a dynamic state-space setting and identify global credit components by means of sign- and zero restrictions that develop from economic theory and recent empirical findings. Whereas the properties of the aggregate credit components in the triad model cannot be traced back to specific rationales, our global credit components explain substantial amounts of variance in financial and monetary indicators across the globe. We find that public and private agents substantially differ in their borrowing behaviour: Private entities borrow during boom-episodes of the business cycles, whereas public borrowing is particularly prevalent during episodes of economic slowdown. Moreover, global suppliers of credit follow distinct lending rationals. Whereas credit is supplied to public entities to hedge against losses in times of economic stress, credit is supplied to the private sector to maximize yields in times of low risk premia, economic stability and upswing. Against this background, the recent public sector credit expansions in the context of fighting the COVID-19 pandemic might substantially alter the credit composition of global liquidity. We expect a massive increase in public sector credit demand and supply and, albeit counteracting policies, fewer credit flowing into the private sector. Thus, modelling not only static, but dynamic effects of global credit composition shocks is a promising focus of further research.

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Appendix

A Appendix on estimation details

In this appendix, we provide a stepwise summary of (dynamic) factor extraction.

Y_t is the t-th column of the data matrix $\mathcal{Y}$, F_t is the t-th column of the matrix of all factors F, μ is a vector of intercepts, Θ is the factor loading matrix, U_t is the t-th column of the matrix of idiosyncratic components $\mathcal{U}$, with U_t following the normal distribution $U_t \sim \mathcal{N}(0, \Phi)$. In (3) Γ is the state loading matrix, ς_t is normally distributed white noise $\varsigma_t \sim \mathcal{N}(0, \Sigma)$. The covariance matrices Φ and Σ are positive-definite and diagonal of dimensions $N \times N$ and $J \times J$, respectively. Diagonality is not overly restrictive but required to fulfill central assumptions of the dynamic factor model. In particular, it is justified for Σ, as we require orthogonality for factor identification (see below, step 9; all co-movements are captured by the factors by construction, otherwise the model would be ill-specified; see Barhoumi et al. (2013) and Stock and Watson (2010)), and it is justified for Φ to avoid numerical instability (Doz et al. (2012) show that under the assumption of diagonality of Φ, the idiosyncratic processes are still consistently estimated). We impose zero-restrictions on Θ that are presented in Section 3.

In brief, the multi-step procedure consists of (i) the extraction of static factors for each of the variable groups described in Section 3 by means of principal component estimation (steps 1-4), (ii) dynamic system estimation (steps 5-9), (iii) uncertainty quantification (step 10), and (iv) variance decomposition (step 11). The estimation procedure involves the following steps in compact notation:

A.1 Identification of static factors

1. The data is grouped and normalized to fulfill the restriction $\mathcal{Y}'\mathcal{Y} = I$, where I is the identity matrix. This is necessary to identify the model (see Bai and Ng (2013) for details).
2. We extract the eigenvectors that belong to the largest eigenvalues of $\mathcal{Y}'\mathcal{Y}$. Rescaling these eigenvectors by N^{-1} yields the loading matrix denoted $\hat{\Theta}^{PC}$. Using these loadings, the matrix of static factors can be recovered up to an arbitrary rotation from the space $\hat{F}^{PC} = N^{-1}\hat{\Theta}^{PC\prime}\mathcal{Y}$ (Stock and Watson 2010), where N is large and T is fixed (Barhoumi et al. 2013).
3. We partial out the first principal component of all data, in order to avoid the modeling of a possibly non-stationary global factor. The initial static estimates of the variable-type factors are extracted from the variable groups (indexed by $s = 1, ..., S$) as the first J unrotated principal components. We impose that all principal components are mutually orthogonal (by means of linear regression) and have unit length, such that their rotations remain orthogonal.

4. To identify the structural component ζ_j to F_j, we rotate the obtained principle components with angles drawn uniformly from the interval $[0; \pi]$. For model admission, we restrict the loadings of the rotations on selected variables. These include (i) credit volumes, (ii) cross-border credit flows, the (iii) interest rates, and (iv) the spreads of the interest rates over the appropriate policy rate. From the set of rotations, we sequentially select the factors that satisfy the conditions shown in Tables A1 and A3 until we obtain 100 valid draws (as many as EGH). A condition is satisfied when the unweighted mean of all coefficients has the correct sign and at least 50% of the individual country coefficients have the correct sign. Following Fry and Pagan (2011) and EGH we then select the set of mutually orthogonal median target factors that is closest to the time domain median.

A.2 Identification of dynamic factors

5. The loadings of all initial estimates on the respective data are obtained by means of OLS regressions analogous to those described in step 4 and arranged accordingly in $\hat{\Theta}^{LS}$. To enhance the factors' interpretability and minimize the contribution of the non-structural component κ_j to F_j, we impose appropriate zero-restrictions on Θ ((see Section 2.2 and Appendix B)).
6. To estimate the initial idiosyncrasies $\hat{\mathcal{U}}$, we partial out $\hat{F}^{PC}$ from $\mathcal{Y}$ by means of linear regressions with $\hat{\mathcal{U}}^{LS}$ denoting the residuals of these regressions. The estimated variances of each idiosyncratic series are collected accordingly in $\hat{\Phi}^{LS}$.
7. Consider factor j. Its autoregressive dynamics $\gamma_j = \{\gamma_{j1}, \gamma_{j2}\}$, the respective intercept ${\hat{\mu_j}}^{LS}$, and the innovation variance of the factor ${\hat{\sigma}_j^2}^{LS}$ are obtained by means of second order linear autoregressions. The coefficients are stacked accordingly in the matrix $\hat{\Gamma}^{LS}$ (see (3)), and the individual factor innovation variances are collected in $\hat{\Sigma}^{LS}$. We restrict the coefficients $\gamma_{j,p}$ to lie within the AR(2) stationarity triangle by means of the restrictions proposed in Kim and Nelson (1999).
8. The Kalman filter is used to estimate the dynamic factors. This algorithm recursively minimizes the mean squared error of a linear projection of the states F on the data $\mathcal{Y}$.[8] Then, the Kalman smoother is used to exploit the entire sample information to obtain consistent estimates of the dynamic factors. The state-space system is initiated with the information obtained from the static model (Kim and Nelson 1999) setting $\mu = \hat{\mu}^{LS}$, $\Sigma = \hat{\Sigma}^{LS}$, $\Phi = \hat{\Phi}^{LS}$, $\Theta = \hat{\Theta}^{LS}$, and $\Gamma = \hat{\Gamma}^{LS}$. The (V)AR(2) factors at time $t = 1$ are initialized with their unconditional moments, that is mean zero and (vectorized) (co)variance $vec(H_{0|0}) = (I_{J^2} - \hat{\Gamma} \otimes \hat{\Gamma})^{-1} vec(\hat{\Sigma})$, with H_t being the covariance between the states and the data, and Γ as defined in (3). The unconditional mean of the AR(2) process $F_t = \mu + \gamma_1 F_{t-1} + \gamma_2 F_{t-2} + \epsilon_t$ is $\frac{\mu}{(1-\gamma_1-\gamma_2)}$. As in this case, $\mu = 0$ holds by construction, the unconditional mean is zero. Nevertheless, we have to initialize

[8] A technically rigorous presentation is given in chapter 13 of Hamilton (1994). Kim and Nelson (1999) provide a more intuitive formulation.

$\mu = 0$, as this is necessary for properly running the Kalman filter function. To improve upon computation time and numerical stability, we rely on the univariate approach to multivariate filtering by Koopman and Durbin (2000).

9. The dynamic factors are identified by means of the sign restrictions on the initialization, but they do not allow for a variance decomposition (step 11), as they are not necessarily orthogonal. Breitung and Eickmeier (2016) highlight that different orthogonalization schemes might yield different results. We use least squares regressions to partial out potential linear dependencies between the factors. We construct the orthogonalization schemes such that all non-credit and monetary policy factors are partialled out from the credit and the monetary policy factors.

A.3 Quantification of uncertainty

10. We employ the Monte Carlo procedure described in Hamilton (1994: p. 398) with modifications in order to account for the large size of the system, making uncertainty quantification computationally very demanding. Following Hamilton (1994), state estimation uncertainty comprises parameter uncertainty, filtering uncertainty, and model uncertainty. Unlike the original proposal, we do not randomly draw from the distribution of the parameters, but we sequentially repeat steps 5-8 for each of the valid 250 draws obtained in step 4. Hence, we draw from the identified distribution of all models of static factors, as their parameters belong to components that fulfill the sign-restrictions. Since the OLS estimator employed in step 6 is consistent, the parameter uncertainty is negligible for a sufficiently large number of draws. This procedure is computationally efficient compared with the procedure proposed by Hamilton (1994). The repeated estimation of the dynamic factors yields estimates of filtering uncertainty and model uncertainty. Accordingly, our uncertainty measure is not a confidence band in the classical sense, but rather a quantification of uncertainty across models, which can then be used (by normality of the factors) to obtain confidence intervals analytically.

A.4 Variance decompositions

11. Variance decompositions are convenient to assess the relative importance of the factors for explaining variation in country specific variables. We determine variance shares explained by each factor. Computing the share of explained variance by a factor is feasible by relating the product of the squared loadings of the respective series and the factor variance to the variance of the series, e.g., in case of an arbitrary factor j the share of explained variance for a series i is:

$$varshare_{i,j} = \frac{\theta_{i,j}^2 Var(F_j)}{Var(y_i)}, \tag{5}$$

where $\theta_{i,j}$ is the respective loading in Θ. Moreover, the factor variance $Var(F_j)$ is obtained from solving the Yule-Walker equations for an AR(2) process

$$Var(F_j) = \frac{(1-\gamma_{j,2})\sigma_j^2}{(1+\gamma_{j,2})[(1-\gamma_{j,2})^2 - \gamma_{j,1}^2]}, \tag{6}$$

where σ_j^2 is the innovation variance of factor j.

B Appendix on identification

In this appendix, we discuss identification schemes. Recall that (i) the sign restrictions are imposed on the means of the loadings and (ii) that there is no restriction placed on the interest rate spread loadings of the demand component.

B.1 Aggregate credit model

Table A1 presents the sign restrictions used to identify the aggregate credit model, whereas Table A2 depicts the respective zero-restrictions.

	LR & MR | GBY	LR-PR & MR-PR | GBY-PR	AC	CBC	OR
Credit Supply	≤ 0	≤ 0	≥ 0	≥ 0	
Credit Demand	≥ 0		≥ 0	≥ 0	
Monetary Policy	≤ 0	≥ 0	≥ 0	≥ 0	≤ 0

Table A1: Sign restrictions on factor loadings on the business lending rate (LR), government bond yield (GBY), mortgage rate (MR), interest rate spreads over the policy rate (PR), aggregate credit (AC), cross-border credit (CBC) and the overnight rate (OR). To reduce the computational burden we require either the private or the public sector to satisfy the sign restriction on the interest rates. As can be seen in Appendix F, this does not induce excess model uncertainty.

These applied restrictions develop from economic theory in the tradition of New Keynesian dynamic stochastic equilibrium (DSGE) modeling and recent empirical research. In the following, we briefly motivate the most essential restrictions. We design the zero restrictions along the following three lines of thought: (i) financial sector shocks spill over to the real economy, (ii) monetary policy shocks spill over to the real economy and inflation, and (iii) there are no spillovers between different parts of financial sectors. Regarding (i), we refer to a large body of recent literature that argues in favor of the existence of macro-financial spillovers on theoretical (Smets and Wouters 2007, Gilchrist et al. 2009) and empirical (Bassett et al. 2014) grounds. With respect to (ii), similar arguments have been put forth in the literature on the interrelations between monetary policy and the real economy (Barakchian and Crowe 2013, Gertler and Karadi 2015). Finally, regarding (iii) the financial-cycle literature has established that equity prices behave differently than house prices and credit, see e.g., Drehmann et al. (2012) (In fact, Borio (2014) claims that global financial cycles are most parsimoniously described in terms of credit and house price co-movements.). Thus, we model share prices separately.

	Credit	Monetary Policy	Share Prices	Inflation	Output
Corporate Lending Rate			0	0	0
Mortgage Rate			0	0	0
Government Bond Yield			0	0	0
Spread Government Bond Yield			0	0	0
Spread Corporate Lending Rate			0	0	0
Spread Mortgage Rate			0	0	0
House Prices			0	0	0
Short Term Lending Rate			0	0	0
Overnight Rate			0	0	0
M0			0	0	0
M3			0	0	0
Cross Border Credit			0	0	0
Aggregate Credit			0	0	0
Gross Domestic Product Gross Capital Formation Government Consumption Private Consumption					
Inflation	0		0		0
Share Prices	0			0	0

Table A2: Zero restrictions on Θ in dynamic factor estimation of the aggregate credit model

B.2 Credit composition model

In order to examine the sector specific financing conditions, we proceed by decomposing global aggregate credit demand and supply into global credit demanded by and supplied to the private and public sectors. To identify credit composition components, we use the sign restrictions shown in Table A3. Their motivation is analogous to those employed within the aggregate credit model. We include government bond yields and spreads of government bond yields over the policy rate to take account of (quasi) risk-free financing conditions. Moreover, Table A4 depicts zero-restrictions on the loading matrix Θ in dynamic estimation. These restrictions are motivated by means of similar considerations as those presented in the previous section.

	LR	MR	GBY	GBY-PR	MR-PR	LR-PR	CG	CH	CNFC	AC	CBC	OR
Public Sector Supply			≤ 0	≤ 0			≥ 0			≥ 0	≥ 0	
Public Sector Demand			≥ 0				≥ 0			≥ 0	≥ 0	
Private Sector Supply	≤ 0	≤ 0			≤ 0	≤ 0		≥ 0	≥ 0	≥ 0	≥ 0	
Private Sector Demand	≤ 0	≥ 0						≥ 0	≥ 0	≥ 0	≥ 0	
Monetary Policy	≤ 0	≤ 0	≤ 0	≥ 0	≥ 0	≥ 0				≥ 0	≥ 0	≤ 0

Table A3: Sign restrictions on loadings of the factors on the business lending rate (LR), government bond yield (GBY), mortgage rate (MR), interest rate spreads over the policy rate (PR), government credit (CG), household credit (CH), non-financial business credit (CNFC), aggregate credit (AC), cross-border credit (CBC), and the overnight rate (OR).

	Public Sector	Private Sector	Monetary Policy	Share Prices	Inflation	Output
Government Credit		0		0	0	0
Government Bond Yield		0		0	0	0
Spread Government Bond Yield		0		0	0	0
Business Credit	0			0	0	0
Household Credit	0			0	0	0
Corporate Lending Rate	0			0	0	0
Mortgage Rate	0			0	0	0
Spread Corporate Lending Rate	0			0	0	0
Spread Mortgage Rate	0			0	0	0
House Prices	0			0	0	0
Short Term Lending Rate				0	0	0
Overnight Rate				0	0	0
M0				0	0	0
M3				0	0	0
Cross Border Credit				0	0	0
Gross Domestic Product Gross Capital Formation Government Consumption Private Consumption						
Inflation				0		0
Share Prices	0	0			0	0

Table A4: Zero restrictions on Θ in dynamic factor estimation of the credit composition model

C Appendix on non-credit factors

In this appendix, we present the non-structurally identified factors from both models. Note that the sign is not identified and the standard deviation is normalized to unity.

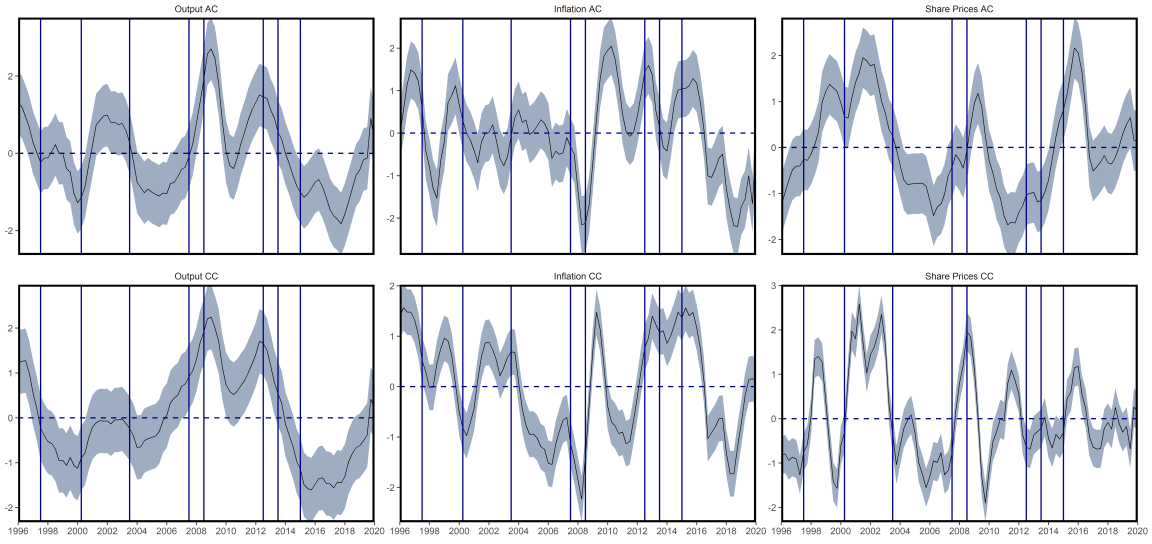

Figure A1: Non-credit factors for aggregate credit (AC) and credit composition (CC) models. For further notes, see Figure 1.

D Appendix on monetary policy factors

In this appendix, we show the different monetary policy factors. Figure A2 shows the monetary policy factors obtained from Eickmeier, Gambacorta, and Hofmann (2014), our aggregate credit model, and our credit composition model in Figure A2. An increase of the monetary policy factor indicates a tightening of monetary policy, whereas a decrease of the monetary policy factor points to accommodating monetary policy conditions. As can be seen from Figure A2, both the aggregate credit and the credit composition models yield almost identical monetary policy estimates. Taking estimation uncertainty into account (shaded blue areas), both estimates are not statistically different from each other.

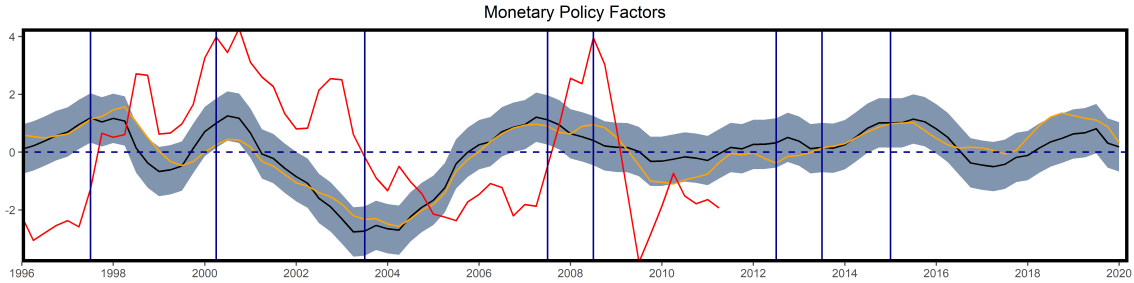

Figure A2: Comparison of our two monetary policy factors with the one obtained from Eickmeier et al. (2014) (red), our total credit model (black), and our credit composition model (orange). For further notes, see Figure 1.

Recall that the identification restrictions in both cases accord with the identification restrictions in EGH. According our estimates, monetary policy tightened at the beginning of the sample period and prior to the dotcom bubble burst. Between 2000 – 2004, monetary policy eased substantially, co-moving with the estimate of EGH. Prior to the financial turmoil monetary policy tightened. In this regard our estimates differ from EGH's, indicating a tightening of monetary policy about 2 – 3 years prior to the crash. After the 2008 crisis, monetary policy conditions remained on a plateau, only slightly increasing after the Fed 'taper tantrum' and the beginning of ECB's public sector purchase program.

E Appendix on comparison with EGH

In this appendix, we briefly elaborate on the (dis)similarities between our factors and those ('macro-purged') obtained from EGH in Figures A3 and A4.

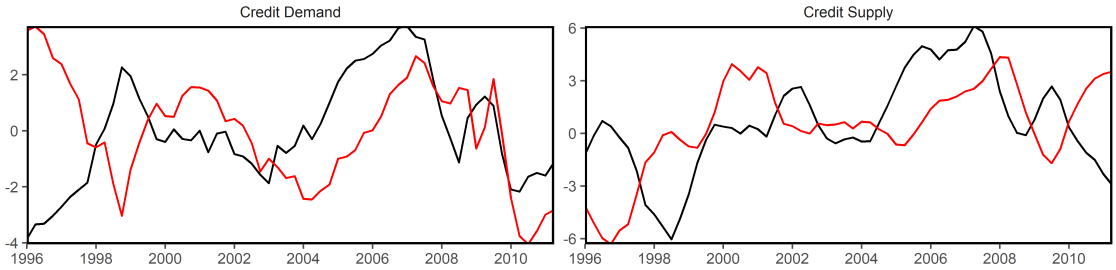

Figure A3: Comparison of aggregate credit model and EGH factors (in red)

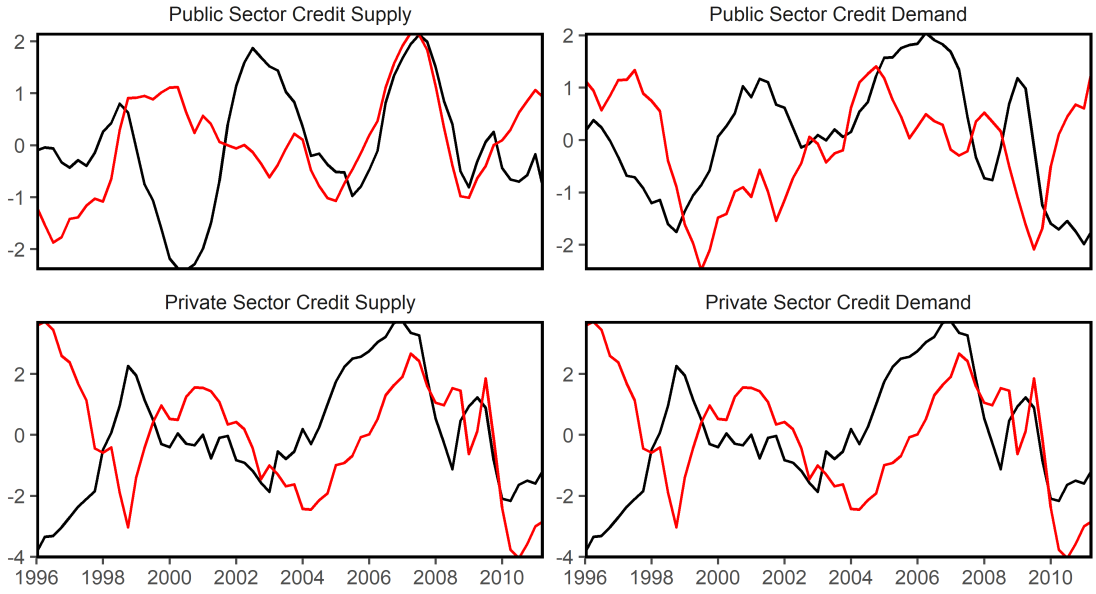

Figure A4: Comparison of credit composition model and EGH factors (in red)

F Appendix on static estimates

We present the raw static factors estimated in both models in Figures A5 and A6.

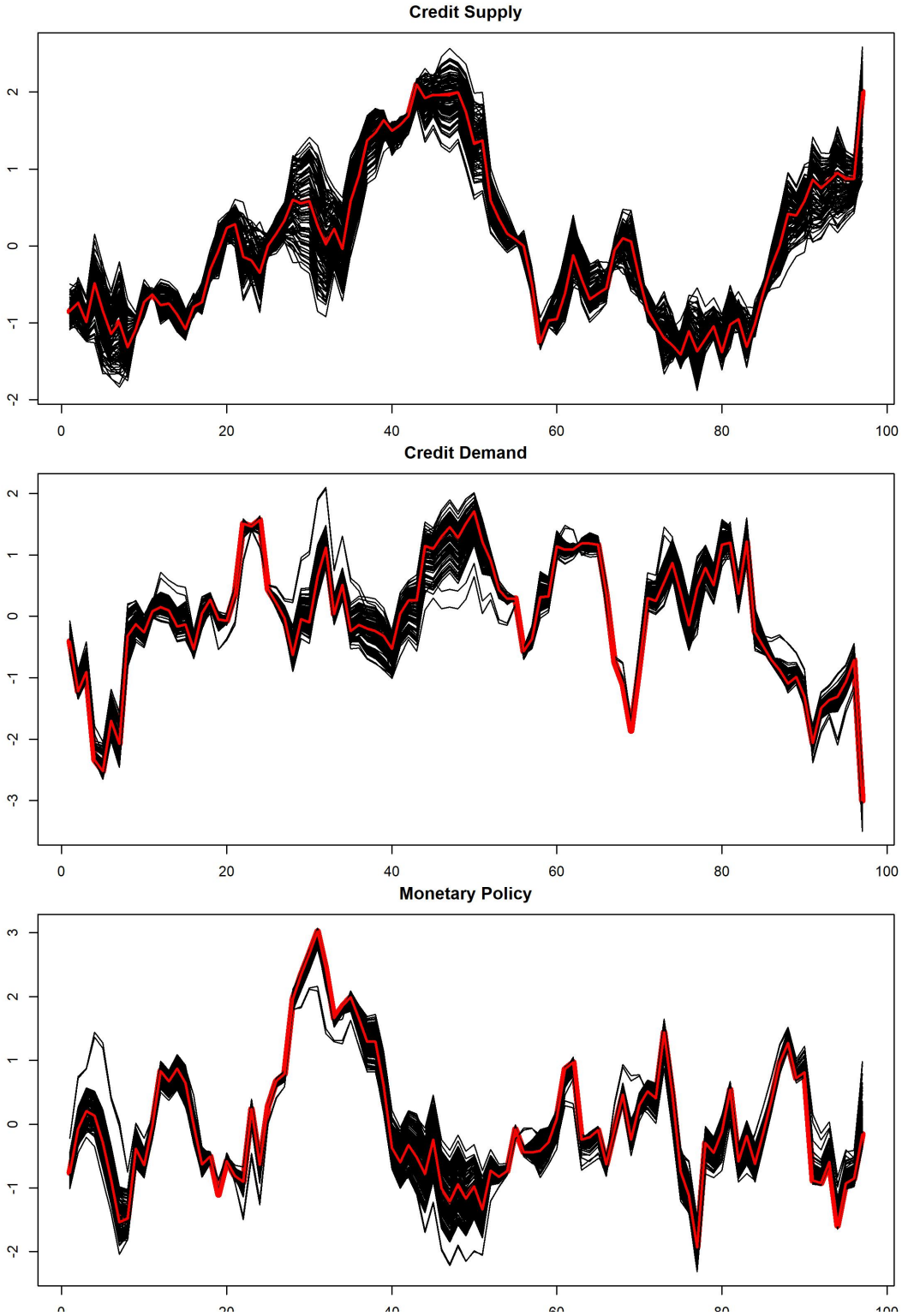

Figure A5: Static estimates of aggregate credit model. Median set in red

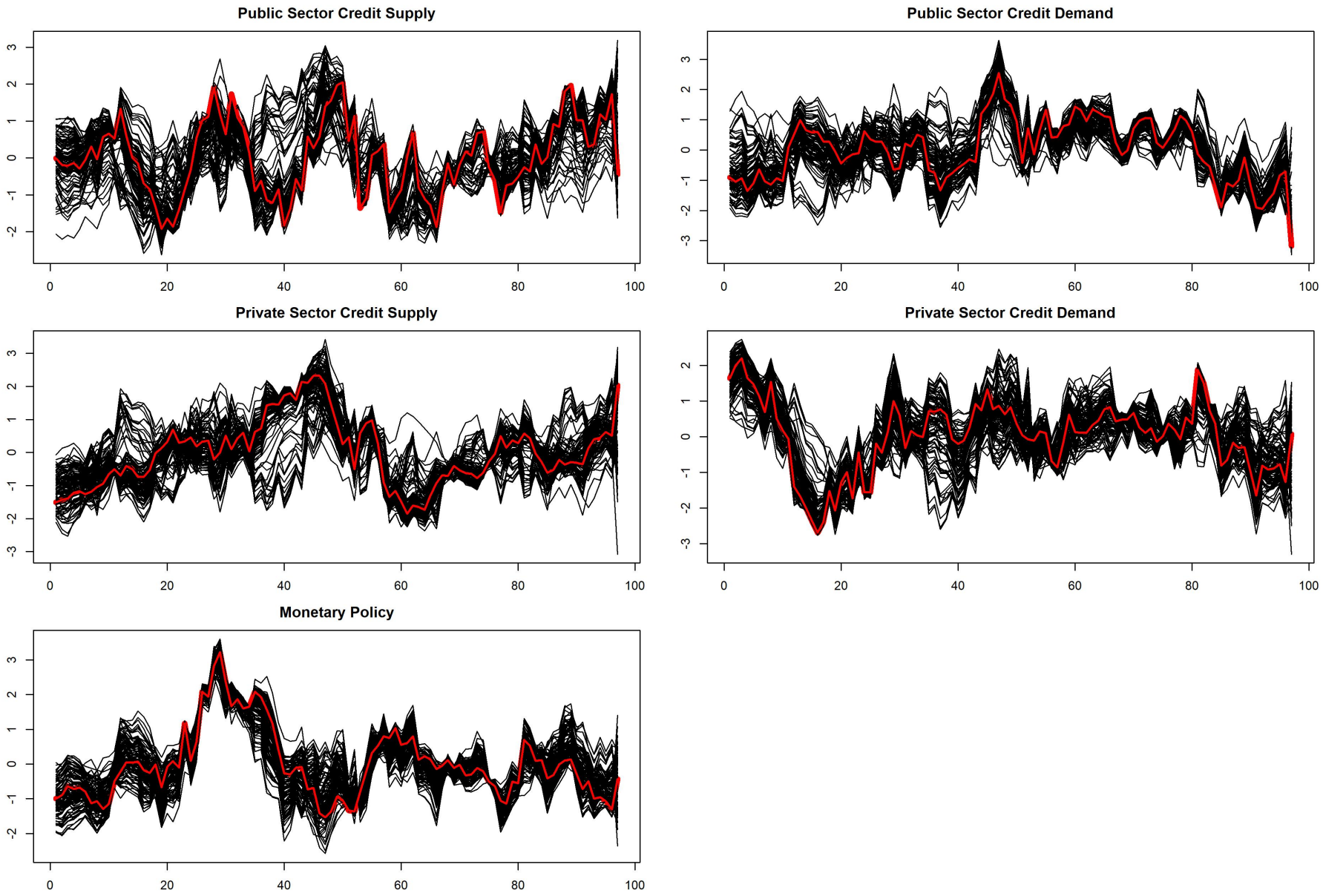

Figure A6: Static estimates of credit composition model. Median set in red

G Appendix on government credit historical decomposition

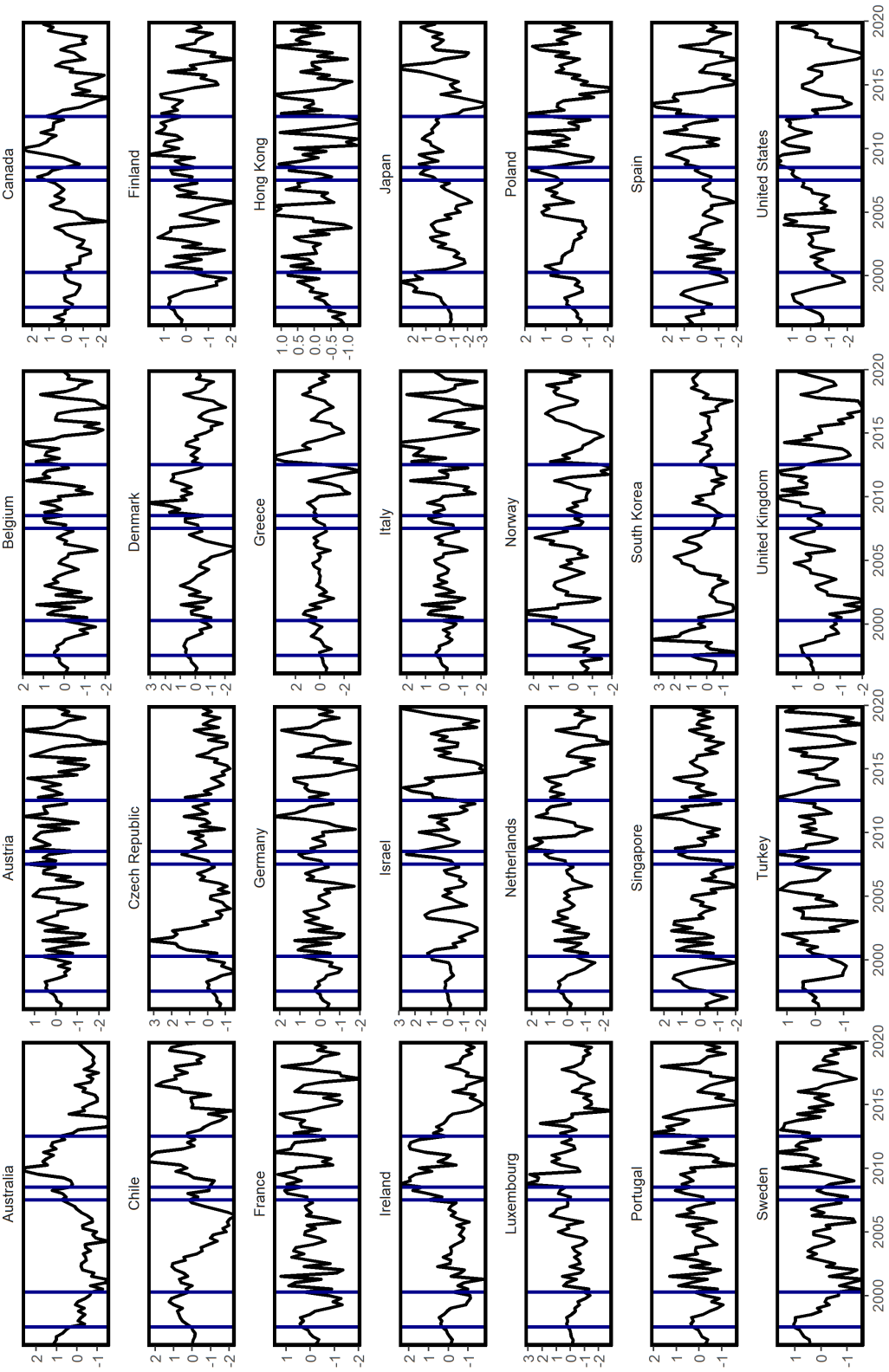

Figure A7: Idiosyncractic public credit components. Crises in international finance: Asian crisis (1997Q3), burst of dotcom bubble (2000Q2), financial turmoil (2007Q3), bankruptcy of Lehman Brothers (2008Q3), Mario Draghi's 'whatever it takes' in European banking and sovereign debt crisis (2012Q2).

H Appendix on variance decompositions

In this appendix, we provide extensive details on variance decompositions. Table A5 depicts explained shares of variance for the entire sample. Table A6 does so for each variable. Tables A7 and A8 show explained shares of variance for each variable in advanced and emerging economies, respectively. Figure A8 shows the results from the orthogonalization robustness check of Section 4.

	All	AE	EE
Expl. Var. Factors AC	30.9	30.4	31.9
Expl. Var. Idiosyncrasies AC	69.1	69.6	68.1
Expl. Var. Factors CC	32.0	31.1	33.7
Expl. Var. Idiosyncrasies CC	68.0	68.9	66.3

Table A5: Explained Variance in percent per variable in aggregate credit (AC) and credit composition (CC) models for the entire sample.

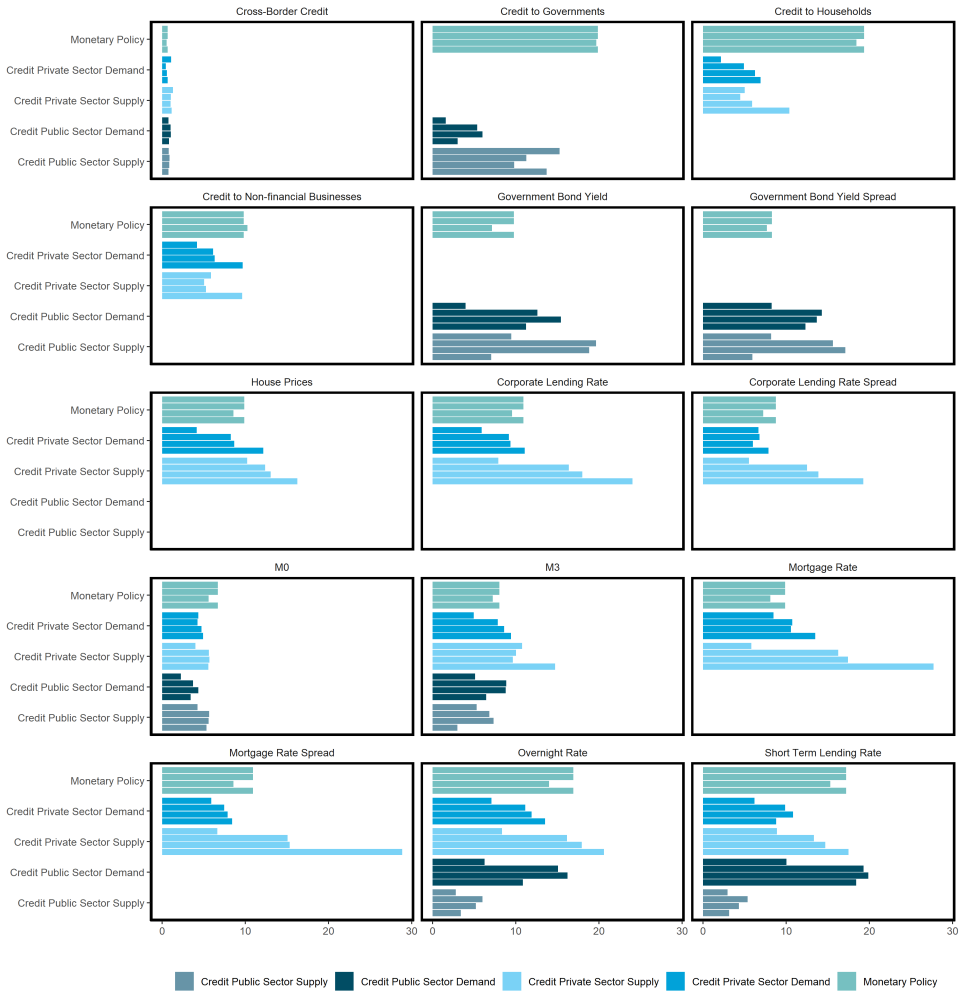

Figure A8: Comparison of explained shares of variance by credit composition model across different orthogonalization schemes. Share of explained variance for each variable for the following orthogonalization schemes from top to bottom: baseline, O_1, O_2, and O_3.

	CBC	CPI	GBY	GBYspread	GCONS	GDP	HP	INV	LR	LRspread	M0	M3	MR	MRspread	OR	PCONS	PPI	SP	STLR
Output AC					3.7	26.3		12.9								18.1			
Inflation AC		10.6			5.3	7.5		6.8								5.6	11.0		
Share Prices AC					12.1	9.3		8.9								9.2		8.4	
Credit Supply AC	1.6		8.1	12.9	5.7	5.2	9.2	4.2	13.5	15.2	3.2	11.0	11.3	18.7	14.7	5.6			13.8
Credit Demand AC	1.1		8.6	11.5	3.5	5.4	6.1	5.7	17.1	14.8	3.8	6.1	9.8	17.2	13.5	3.9			19.4
Monetary Policy AC	0.5	5.9	7.7	7.8	4.1	5.5	9.1	5.2	7.4	6.8	6.4	5.9	6.4	7.9	11.6	5.8	3.5	7.3	12.8
Expl. Var. Factors AC	3.2	16.5	24.4	32.2	34.4	59.3	24.4	43.7	38.0	36.8	13.3	23.0	27.5	43.7	39.8	48.1	14.5	15.7	46.0
Expl. Var. Idiosyncrasies AC	96.8	83.5	75.6	67.8	65.6	40.7	75.6	56.3	62.0	63.2	86.7	77.0	72.5	56.3	60.2	51.9	85.5	84.3	54.0
Output CC					6.2	22.8		12.8								21.4			
Inflation CC		15.7			4.8	10.8		8.8								4.7	34.2		
Share Prices CC					3.6	4.0		3.0								3.0		28.2	
Credit Public Sector Supply CC	0.8		9.4	8.2	2.5	2.8		3.0			4.2	5.3			2.8	4.5			2.9
Credit Public Sector Demand CC	0.8		4.0	8.3	2.5	4.6		4.5			2.2	5.1			6.2	4.6			10.0
Credit Private Sector Supply CC	1.3				5.4	3.5	10.2	4.0	7.9	5.5	4.0	10.8	5.8	6.6	8.4	3.4			8.9
Credit Private Sector Demand CC	1.1				8.2	5.3	4.2	7.5	5.9	6.7	4.3	5.0	8.5	5.9	7.1	5.3			6.2
Monetary Policy CC	0.7	9.0	9.8	8.3	4.5	8.9	9.9	7.4	10.9	8.8	6.7	8.0	9.9	10.9	16.9	5.4	3.7	8.3	17.2
Expl. Var. Factors CC	4.6	24.7	23.2	24.7	37.7	62.8	24.2	51.0	24.7	21.0	21.5	34.2	24.1	23.5	41.4	52.4	38.0	36.5	45.2
Expl. Var. Idiosyncrasies CC	95.4	75.3	76.8	75.3	62.3	37.2	75.8	49.0	75.3	79.0	78.5	65.8	75.9	76.5	58.6	47.6	62.0	63.5	54.8

Table A6: Explained Variance in percent per variable in aggregate credit (AC) and credit composition (CC) models for each variable. Variables include cross-border credit (CBC), consumer price index (CPI), long-term government bond yield (GBY), and its spread over the shadow policy rate (GBYspread), government consumption (GCONS), gross domestic product (GDP). house prices (HP), gross capital formation (INV), corporate lending rate (LR), and its spread over the shadow policy rate (LRspread), M0, M3, mortgage rate (MR), and its spread over the shadow policy rate (MRspread), overnight rate (OR), private consumption (PCONS), producer price index (PPI), share prices (SR), short-term lending rate (STLR).

	CBC	CPI	GBY	GBYspread	GCONS	GDP	HP	INV	LR	LRspread	M0	M3	MR	MRspread	OR	PCONS	PPI	SP	STLR
Output AC					3.3	34.7		16.8								21.2			
Inflation AC		10.3			6.4	6.0		6.5								3.7	13.9		
Share Prices AC					14.9	5.7		7.5								7.6		9.7	
Credit Supply AC	1.3		4.1	15.9	5.0	3.6	6.9	3.1	12.4	15.6	3.1	14.7	9.7	20.3	12.7	3.9			11.5
Credit Demand AC	1.1		7.9	12.9	4.0	4.3	6.5	3.3	15.0	17.8	2.9	4.9	8.9	19.3	13.9	2.7			22.1
Monetary Policy AC	0.5	5.4	6.6	5.4	4.3	4.1	10.3	4.4	5.5	7.1	6.5	3.7	5.0	6.3	10.7	5.3	3.8	5.7	11.5
Expl. Var. Factors AC	3.0	15.7	18.6	34.3	37.9	58.4	23.7	41.7	32.9	40.6	12.4	23.4	23.5	45.9	37.4	44.4	17.8	15.4	45.1
Expl. Var. Idiosyncrasies AC	97.0	84.3	81.4	65.7	62.1	41.6	76.3	58.3	67.1	59.4	87.6	76.6	76.5	54.1	62.6	55.6	82.2	84.6	54.9
Output CC					5.4	29.0		15.4								23.9			
Inflation CC		16.8			5.3	9.0		7.7								3.0	42.8		
Share Prices CC					4.5	3.9		1.8								2.3		29.2	
Credit Public Sector Supply CC	0.7		9.0	7.8	3.0	3.4		3.4			3.5	6.0			1.3	4.8			1.6
Credit Public Sector Demand CC	0.9		3.3	7.4	2.7	3.9		3.4			2.2	3.6			6.3	4.0			10.8
Credit Private Sector Supply CC	1.4				5.5	3.4	8.6	3.1	7.8	3.5	3.6	14.1	5.2	6.4	8.5	3.0			8.6
Credit Private Sector Demand CC	1.1				10.4	3.0	4.5	4.8	6.5	6.1	4.4	4.3	8.9	5.5	8.1	4.0			6.8
Monetary Policy CC	0.7	7.3	8.8	8.0	4.2	6.3	10.2	7.0	8.1	10.6	5.3	5.4	8.6	10.4	15.3	4.6	3.7	5.5	15.0
Expl. Var. Factors CC	4.9	24.2	21.1	23.1	41.0	61.8	23.3	46.6	22.4	20.1	19.0	33.3	22.7	22.3	39.4	49.5	46.5	34.7	42.8
Expl. Var. Idiosyncrasies CC	95.1	75.8	78.9	76.9	59.0	38.2	76.7	53.4	77.6	79.9	81.0	66.7	77.3	77.7	60.6	50.5	53.5	65.3	57.2

Table A7: Explained Variance in percent per variable in aggregate credit (AC) and credit composition (CC) models for each variable in advanced economies. For further notes see Table A6.

	CBC	CPI	GBY	GBYspread	GCONS	GDP	HP	INV	LR	LRspread	M0	M3	MR	MRspread	OR	PCONS	PPI	SP	STLR
Output AC					4.8	9.6		3.8								10.7			
Inflation AC		11.0			2.8	10.5		7.5								9.9	5.8		
Share Prices AC					5.3	16.5		12.1								13.2		6.6	
Credit Supply AC	3.0		17.1	6.2	7.2	8.5	16.3	6.8	15.2	14.4	3.2	5.5	16.4	13.4	17.3	9.6			18.8
Credit Demand AC	0.7		10.4	8.6	2.5	7.6	4.9	10.9	20.6	10.0	5.1	7.9	13.0	10.4	13.0	6.7			14.0
Monetary Policy AC	0.2	6.8	10.2	12.9	3.5	8.3	5.5	7.0	10.4	6.3	6.3	9.1	11.1	13.0	12.8	6.9	3.0	9.5	15.3
Expl. Var. Factors AC	4.0	17.9	37.8	27.7	26.1	60.9	26.7	48.2	46.1	30.7	14.6	22.5	40.5	36.8	43.0	57.0	8.8	16.1	48.1
Expl. Var. Idiosyncrasies AC	96.0	82.1	62.2	72.3	73.9	39.1	73.3	51.8	53.9	69.3	85.4	77.5	59.5	63.2	57.0	43.0	91.2	83.9	51.9
Output CC					7.9	10.5		7.0								15.6			
Inflation CC		13.7			3.6	14.6		11.2								8.8	19.0		
Share Prices CC					1.6	4.2		5.7								4.6		26.8	
Credit Public Sector Supply CC	1.2		10.5	9.0	1.3	1.8		2.2			5.3	4.3			4.9	4.0			5.7
Credit Public Sector Demand CC	0.4		5.5	10.2	2.0	6.1		7.0			2.4	7.4			6.2	6.2			8.4
Credit Private Sector Supply CC	0.6				5.2	3.7	15.1	6.1	8.0	8.7	4.6	5.9	7.9	7.5	8.2	4.3			9.5
Credit Private Sector Demand CC	0.8				3.1	9.9	3.0	13.5	5.0	7.6	4.2	6.0	7.0	7.3	5.6	8.5			4.9
Monetary Policy CC	0.4	11.9	12.0	8.9	5.2	14.0	8.8	8.2	15.4	5.9	8.5	11.9	14.2	12.6	19.1	7.3	3.9	12.1	21.8
Expl. Var. Factors CC	3.4	25.6	27.9	28.1	29.9	64.8	26.9	60.9	28.5	22.3	25.0	35.4	29.0	27.4	44.0	59.2	22.8	38.8	50.4
Expl. Var. Idiosyncrasies CC	96.6	74.4	72.1	71.9	70.1	35.2	73.1	39.1	71.5	77.7	75.0	64.6	71.0	72.6	56.0	40.8	77.2	61.2	49.6

Table A8: Explained Variance in percent per variable in aggregate credit (AC) and credit composition (CC) models for each variable in emerging economies. For further notes see Table A6.

I Appendix on variables and cross sectional entities

Advanced economies				
Australia	Austria	Belgium	Canada	Czech Republic
Denmark	Finland	France	Germany	Greece
Ireland	Israel	Italy	Japan	Korea
Luxembourg	Netherlands	New Zealand	Norway	Portugal
Singapore	Spain	Sweden	Switzerland	United Kingdom
United States				

Table A9: Advanced economies according to IMF (2019)

Emerging economies				
Argentina	Brazil	Chile	China	Colombia
Hong Kong	Hungary	India	Indonesia	Malaysia
Mexico	Poland	Russia	Saudi Arabia	South Africa
Thailand	Turkey			

Table A10: Emerging economies according to IMF (2019)

	N_{AC}	N_{CC}
Output	149	149
Inflation	80	80
Share Prices	40	40
Credit and Monetary Policy	445	530
Total N	714	799

Table A11: Number of series within groups of aggregate credit (AC) and credit composition (CC) models

Variable Group	Name of data	Source	Transformation
Consumption (CONS)	Private consumption expenditure, constant prices, seasonally adjusted	IMF IFS, Datastream	year on year differences
	Government consumption expenditure, constant prices, seasonally adjusted	IMF IFS, Datastream	year on year differences
Cross border credit (CBC)	Cross border credit claims to all sectors, FX and break adjusted change, all instruments from all reporting institutions, US Dollar	BIS locational banking statistics	year on year differences
	Cross border credit liabilities to all sectors, FX and break adjusted change, all instruments from all reporting institutions	BIS locational banking statistics	
Government credit (CG)	Credit to general government from all sectors, breaks adjusted, at market value, US-Dollar	BIS credit statistics	year on year differences
Household credit (CH)	Credit to households from all sectors, breaks adjusted, at market value, US-Dollar	BIS credit statistics	year on year differences
House prices (HP)	OECD real house price index, seasonally adjusted	Datastream	year on year differences
Inflation (I)	Consumer price index, not seasonally adjusted	Datastream	year on year differences
	Producer price index, not seasonally adjusted		
Interest rates (IR)	Long-term government bond yield (mostly ten year maturity)	Global financial data, Datastream	no transformation
	Money market rate (mostly prime lending rates)	Datastream	
	Overnight rate (mostly deposit & interbank lending rates)	Datastream, Eickmeier et al. (2014)	
	Business lending rate	Global financial data, Eickmeier et al. (2014)	
	Mortgage lending rate	Global financial data, Eickmeier et al. (2014)	
	Shadow policy rate	Krippner (2020)	
Investment (INV)	Gross capital formation, constant prices, seasonally adjusted	IMF IFS, Datastream	year on year differences
Money (M)	M0 current prices, not seasonally adjusted	Datastream, Global financial data	year on year differences
	M3 current prices, not seasonally adjusted		
Non-financial corp. credit (NFC)	Credit to non-financial corporations from all sectors, breaks adjusted, at market value, US-Dollar	BIS credit statistics	year on year differences
Output (O)	GDP, expenditure approach, constant prices, seasonally adjusted	IMF IFS, Datastream,	year on year differences
Share Prices (SP)	Nominal share price index, not seasonally adjusted	Datastream, Global Financial Data	year on year differences

Table A12: Variables and data sources

J Appendix on endorsement variables

Name	Source	Retrieved	Description	Time Period
European banks leverage	Miranda-Agrippino and Rey (2020)		Leverage of large EU banks. Higher values mean higher leverage.	1996Q1 – 2012Q3
Global asset price risk factor	Miranda-Agrippino and Rey (2020)	Miranda-Aggripino (2020)	Global asset price risk factor (inverted). Higher values imply higher risk premia.	1996Q1 – 2019Q4
Global risk aversion	Miranda-Agrippino and Rey (2020)	own calculations	Aggregate risk aversion for the extended sample (1975 – 2012). Higher values imply increased risk aversion by investors.	1996Q1 – 2019Q4
Global bank leverage	Miranda-Agrippino and Rey (2020)		Global bank leverage. Higher values mean increased leverage.	1996Q1 – 2012Q3
Systemic important bank leverage	Miranda-Agrippino and Rey (2020)		Global systemic important bank leverage. Higher values mean increased leverage.	1996Q1 – 2012Q3

Table A13: Details on endorsement variables