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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. Going beyond previous work, we decompose aggregate credit components into credit supply and demand flows directed at businesses, households and governments. We show that this decomposition enhances the understanding of global liquidity considerably. Whereas global government sector credit supply is best understood as a safe-haven lending factor from an investors perspective, lenders supply the businesses and households with credit to maximize profits along the financial cycle. Moreover, the government 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 liquidity 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 risk premia), have become prominent predictors of the business cyle and financial crisis (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 (business, household or government), matters for economic stability, as credit is not equally productive and stabilizing across sectors. In fact, reference to a sectoral dimension, i.e. the allocation of credit to the household, government and non-financial business sectors implies important repercussions for longer-term growth effects, financial stability, monetary policy leeway, and

[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).

the severity of recessions following credit booms. For example, by means of a calibrated dynamic stochastic equilibrium (DSGE) 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 (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 et al. 2014). A rich literature investigates 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“(BG) hypothesis, 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 et al. (2014). 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 set 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 credit-side determinants of global liquidity (i.e. sectoral supply and demand flows) to an integrated analysis. In specific, we estimate instruments for structural global credit components of businesses, households and governments. 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. To this end, we construct a factor model for a multitude of credit, interest and house price 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. We find that global credit composition components explain large shares of variance in international financial aggregates, in particular interest rates. Moreover, we extensively document that the prevalence of credit components varies across the financial cycle, characterized by financial sector risk and risk aversion. For instance, whereas household credit supply is high during financial cycle upswings, government credit supply increases in response to adverse innovations to the financial cycle.

A theoretical framework is presented in Section 2. The econometric specification and the identifying restrictions are outlined in Section 3. Empirical results are discussed in Section 4. Section 5 concludes. The Appendices contain document supplementary results and robustness properties of our estimates.

2 Theoretical considerations

In this section, we outline a heuristic framework to investigate global credit composition. More specifically, we discuss briefly sector-specific rationales to lend and borrow. Given that previous research has established that credit composition matters at the country level, it is likely to matter at the global level as well. Thus, taking an aggregate perspective as in Eickmeier et al. (2014) might conceal important properties of global credit flows. Our considerations are meant to motivate the sectoral decomposition as well as the identification restrictions presented in Section 3.3.

2.1 Global lenders' portfolio choice

Flows of cross-border credit (loans), securities (bonds and various kinds of asset backed securities) and house prices are the essence of global liquidity (Borio 2014). Following the framework of Miranda-Agrippino and Rey (2020), global banks and asset managers 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. Largely inspired by Miranda-Agrippino and Rey (2020), we next provide an intuition of lenders' decisions between lending either to private or government entities 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 (i.e. businesses and households) lending at higher yields. The remainder of the investment volume will be directed by each bank towards inter-bank credit (which we do not consider in this work) or credit supplied to non-financial businesses and households (i.e., the private sector). Thus, a sequence of innovations to aggregate lending can be decomposed as

$$\zeta^{aggregate}_{supply,t} = \zeta^{business}_{supply,t} + \zeta^{households}_{supply,t} + \zeta^{governments}_{supply,t},\ t \in \mathbb{N}, \tag{1}$$

where each ζ_t on the right-hand side is a zero-mean sequence of i.i.d. random variables, and each sectoral component ζ is determined by stochastic economic fundamentals such as sector characteristics, financial innovation, regulation, competition or a change in agents' risk disposition.

How lenders divide supplied credit volumes among business, household and government credit depends on the respective yields and risks as well as on the stance of monetary policy (for the role of monetary policy in a heterogeneous agent framework see Coimbra and Rey 2017, 2018). We presume this lending behaviour to imply a stable intertemporal credit market equilibrium with stationary leverage and debt-service ratios. This equilibrium might change once economic fundamentals are subject to shocks. For instance, if risk-appetite increases, financial intermediaries could shift lending towards the higher-yield sector. Eventually they engage in excess risk-taking, e.g., as a result of the concentration of risky assets. This may also occur, for instance, due to loose monetary policy (as it was the case prior to sub-prime mortgage crisis, see Justiniano et al. (2017)) or due to higher yields (i.e. mortage) securities.

High yields and decent profit opportunities imply that private sector lending (i.e. $\zeta^{business}_{supply,t}$ and $\zeta^{households}_{supply,t}$) is mainly active during upswing-episodes of the financial 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.[2] 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.

2.2 Borrowing behaviour of private and public agents

We first elaborate on risk taking behaviour and proceed with brief comments on the cyclicality of sectoral borrowing. Unlike the case of credit supply, we not only need to understand the decision problem of representative agents (global lenders), but of three representatives of rather distinct sectors (businesses, households and governments). Thus, aggregate borrowing can be written as

$$\zeta_{demand,t}^{aggregate} = \zeta_{demand,t}^{business} + \zeta_{demand,t}^{households} + \zeta_{demand,t}^{governments},\ t \in \mathbb{N}, \tag{2}$$

where each ζ_t on the right-hand side is a sequence of i.i.d. random variables, where as in the case of supply, each sectoral component ζ is determined by stochastic economic fundamentals such as sector characteristics, financial innovation, regulation and the like. We argue in favour of substantial heterogeneity in the equilibrium determinants of sectoral credit markets.

Borrowing by governments Unlike the private sector (businesses and households), the internal financing of the government sector is relatively stable due to tax revenues. Even though tax volumes might fluctuate over the business cycle, the government sector generates tax income from the *entire* distribution of households and businesses. Therefore, sovereign borrowing ($\zeta_{demand,t}^{governments}$) is motivated by many reasons that are not necessarily related to the state of the economy.[3] For example, some governments may expand their balance sheet by means of debt instruments due to a lack of internal financing. Moreover, democratic governments may partly make spending decisions in accordance with optimal re-election chances across the voting cycle. Thus, we cannot assume that governments make spending decisions only based on business and financial cycle considerations.

Borrowing by non-financial businesses Unlike governments, households generate internal finance through *specific* labor markets. Moreover, businesses often 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, whereas the government sector can guarantee a relatively stable stream of income to its lenders, making its securities relatively less risky to default, debt services of the private sector depend

[2] 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".

[3] 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.

more on the states of the financial cycle such that its securities are relatively more risky to default. With regard to borrowing behaviour over the financial 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).

Borrowing by households 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.

2.3 Instrumenting global credit composition shocks

Suppose, credit data is sampled for periods $t = 1,.,,,T$. Then, the structural innovations to $\{\zeta^{supply}\}_t^T$ and $\{\zeta^{demand}\}_t^T$ as defined in (1) and (2), respectively, are unobserved. Thus, our goal is to obtain an instrument for the series of structural innovations to credit demand and supply conditions. 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 serial correlation, we model dynamic estimates of global credit supply and demand components. For this purpose, we presume that each factor j allows for a representation

$$\overbrace{\underset{(1\times T)}{\left[F_{j,1}\ldots F_{j,t}\ldots F_{j,T}\right]}}^{F_j} = \overbrace{\underset{(1\times T)}{\left[\zeta_{j,1}\ldots \zeta_{j,t}\ldots \zeta_{j,T}\right]}}^{\zeta_j} + \overbrace{\underset{(1\times T)}{\left[\kappa_{j,1}\ldots \kappa_{j,t}\ldots \kappa_{j,T}\right]}}^{\kappa_j}, \tag{3}$$

where ζ_j are 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 with regard to the weighting scheme of κ_j, and only assume stationarity for each factor in levels. By assumption, a set of contemporaneous sign restrictions identifies ζ_j. We explicitly model the autoregressive dynamics in a state-space environment. By implication, the factors cannot be understood as series of pure structural shocks. Put differently, these shocks lack a strict structural interpretation. Nevertheless, the factors are highly correlated with the structural innovations by construction. Thus, they can be used as relevant instruments to assess the economic properties of the underlying exogenous credit shocks.

$$\overbrace{\underset{(1\times T)}{\left[F_{j,1}\dots F_{j,t}\dots F_{j,T}\dots\right]}}^{F_j} = \overbrace{\underset{(1\times T)}{\left[\zeta_{j,1}\dots\zeta_{j,t}\dots\zeta_{j,T}\dots\right]}}^{\zeta_j} + \overbrace{\underset{(1\times T)}{\left[\kappa_{j,1}\dots\kappa_{j,t}\dots\kappa_{j,T}\dots\right]}}^{\kappa_j}, \tag{4}$$

3 Data and methodology

In this section, we first describe the data. Subsequently, we provide an outline of the factor model.[4]

3.1 Data

To obtain instruments for exogenous supply and demand components for credit channeled towards non-financial businesses, households and governments, we construct a data-set along the lines of Eickmeier et al. (2014). In particular, we partial out other co-movements in financial and real-economy variables, such as investment or share 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 Eickmeier et al. (2014). Moreover, we constructed aggregate credit variables only for periods, for which all credit 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 A6 for details). Quarterly data have been taken whenever available. At the beginning of the sample period and mostly for emerging economies data is sparse. Missing data was interpolated by means of linear interpolation. 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). 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 Tables A6 and A7. Table A8 documents the number of series used in estimation.

3.2 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

[4] All computations have been performed in R.

has been initiated with the estimation of the global business cycle in Kose et al. (2003). All time series $y_i = (y_{i1}, y_{i2}, \ldots, y_{iT})'$, indexed by $i = 1, ..., N$, and sampled for 43 economies are organized by columns 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 T-dimensional row-vector of factor j. Likewise we interpret the matrix F to consist of J-dimensional rows F_t' such that F_t collects all factors at time t in one column.

The series-specific idiosyncrasies are denoted with $u_i = (u_{i1}, u_{i2}, \ldots, u_{iT})'$ 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 a simple Markov-chain Monte Carlo (MCMC) algorithm as well as precision sampling in the spirit of Chan and Jeliazkov (2009). As we deal with quarterly data, all factors are sampled as a vector-autoregression of order $p = 4$. Let Y_t denote an N-dimensional column vector comprising the sample information available for period t. The observation equation is given by

$$\underset{N\times 1}{\overbrace{\begin{bmatrix} y_{1t} \\ \vdots \\ y_{N,t} \end{bmatrix}}^{Y_t}} = \underset{(N\times J)}{\overbrace{\begin{bmatrix} \theta_{11} & \ldots & \theta_{1J} \\ \vdots & \ddots & \vdots \\ \theta_{1N} & \ldots & \theta_{JJ} \end{bmatrix}}^{\Theta}} \underset{(J\times 1)}{\overbrace{\begin{bmatrix} F_{1,t} \\ \vdots \\ F_{J,t} \end{bmatrix}}^{F_t}} + \underset{(N\times 1)}{\overbrace{\begin{bmatrix} u_{1,t} \\ \vdots \\ u_{N,t} \end{bmatrix}}^{U_t}}, \tag{5}$$

where, in case of the credit composition model, selected elements $\theta_{j,i}$ are set to zero. The state equation is a vector-autoregressive process of order $p = 4$, i.e.,

$$\underset{J\times 1}{\overbrace{\begin{bmatrix} F_{1,t} \\ \vdots \\ F_{J,t} \end{bmatrix}}^{F_t}} = \underset{J\times J}{\overbrace{\begin{bmatrix} \gamma_{11,1} & \ldots & \gamma_{1J,1} \\ \vdots & \ddots & \vdots \\ \gamma_{1J,1} & \ldots & \gamma_{JJ,1} \end{bmatrix}}^{\Gamma_1}} \underset{(J\times 1)}{\overbrace{\begin{bmatrix} F_{1,t-1} \\ \vdots \\ F_{J,t-1} \end{bmatrix}}^{F_{t-1}}} + \ldots + \underset{J\times J}{\overbrace{\begin{bmatrix} \gamma_{11,p} & \ldots & \gamma_{1J,p} \\ \vdots & \ddots & \vdots \\ \gamma_{1J,p} & \ldots & \gamma_{JJ,p} \end{bmatrix}}^{\Gamma_p}} \underset{(J\times 1)}{\overbrace{\begin{bmatrix} F_{1,t-p} \\ \vdots \\ F_{J,t-p} \end{bmatrix}}^{F_{t-p}}} + \underset{(J\times 1)}{\overbrace{\begin{bmatrix} \zeta_{1,t} \\ \vdots \\ \zeta_{J,t} \end{bmatrix}}^{\zeta_t}}. \tag{6}$$

In (5) 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 (6) 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 required to satisfy central identification assumptions of the dynamic factor model. In particular, it is justified for Σ, as we require orthogonality for factor identification following Bai and Wang (2015). Initially, the data is normalized to fulfill the restriction $\mathcal{Y}'\mathcal{Y} = I_N$, where I_N is the identity matrix of order N. From the normalized data, we partial out the first principal component of all data in order to avoid the modeling of a possibly non-stationary global factor, the first principle component of gross domestic product, consumer and producer price indices as well as private and government consumption in order to avoid modeling an output factor and the first principle component of share prices in order to avoid modeling a share price factor. The subsequent Gibbs sampling procedure involves iterating trough the following steps:[5]

1. We draw the factors from their conditional posterior distribution by means of precision sampling in the spirit of Chan and Jeliazkov (2009), exploiting the band-matrix structure of the precision matrix of the multivariate-normal conditional posterior distribution. Each draw is conditional on steps 2-6 as described below. In Appendix B we present a detailed treatment of this step.
2. We use least squares regressions to partial out potential linear dependencies between the factors. Breitung and Eickmeier (2016) highlight that different orthogonalization schemes might yield different results. Thus, we construct the orthogonalization schemes such that the order of the factors is (almost) random by generating random permutations of the factor indices $j = 1, ..., J$.
3. The loadings of all initial estimates on the respective data are drawn equation-by-equation and conditional on the previous steps from their conditional truncated normal posterior distribution and arranged accordingly in $\hat{\Theta}$. For the loading of factor j on variable i ($\theta_{i,j}$), we employ a vague truncated normal prior that has support over a range of plausible values with prior mean $\bar{\mu}_i \in \{-1, +1\}$ (in accordance with the negative or positive sign restriction; see Section 3.3) or $\bar{\mu}_i = 0$ if there is no restriction and variance $\bar{\psi}_i = 5^2$. The prior for the sign-restricted parameters is bounded from below by zero (if $\bar{\mu} = +1$) or bounded from above by zero (if $\bar{\mu} = -1$). The prior for the unrestricted parameters is normal, but not truncated.[6] The conditional posteriors are normal with the same truncation as the prior.
4. The innovation variances of each idiosyncratic series i along the diagonal of $\hat{\bar{\Phi}}$ are sampled equation-by-equation conditional on the previous steps from an inverse-Gamma distribution with shape $(\bar{a}+\frac{T}{2})$ and scale $(b+\frac{1}{2}G)$), where $a = 5, b = \dfrac{1}{100}$ and G denotes the sum of squared residuals of the observation equation. Thus, the idiosyncratic series innovation variance prior is fairly vague.
5. The innovation variances of each factor j along the diagonal of $\hat{\Sigma}$ are sampled equation-by-equation and conditional on the previous steps from an inverse-Gamma distribution with shape $(\bar{a} + \frac{T}{2})$ and scale $(b + \frac{1}{2}V)$, where $a = 5, b = \dfrac{1}{100}$ and V denotes the sum of squared residuals of the state equation. Thus, the factor innovation variance prior is fairly vague.
6. The vector-autoregressive parameters are sampled conditional on previous steps from their conditional multivariate-normal posterior. The prior loading for each factor j is normal with mean $\bar{\mu} = 0.1$ and has variance $\bar{\psi}_j = 100^2$ (i.e. the prior is vague). Put

[5] In setting up the sampling scheme, we roughly follow Chan et al. (2019).

[6] For the sake of exposition, we present the univariate case. Practically, the multivariate analogue is implemented, i.e. all factor loadings are sampled conditional on the remaining relevant factors. The prior is truncated multivariate-normal with prior mean vector $\bar{\mu}_i$ and prior variance matrix $\bar{\Psi}_i$, where i indexes the time series for which the factor loadings are obtained.

differently, the vector-autoregressive coefficients remain effectively unrestricted.

We obtain 50.000 draws and discard the first 20.000 as burn-in. By orthogonality, each factor can be separately identified. By separate identification, all factors are identified. As all factors are identified, the model is identified. Identification is ensured as Σ is diagonal and, by means of prior truncation, for all credit (monetary policy) factors all relevant credit volume (overnight rate) loadings are positive. Put differently, the identification conditions stated in Bai and Wang (2015) that (i) Σ is diagonal (to identify scale) and (ii) at least one loading is positive (to identify sign) are satisfied. Note that, while each draw necessarily yields orthogonal factors, the distributions of the individual factors are not necessarily independent for any finite number of draws. However, we emphasize that the median factors we obtain (see Figure 1) are only weakly correlated and no correlation coefficient is significantly different from zero at conventional significance levels.

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 given by

$$varshare_{i,j} = \frac{\theta_{i,j}^2 Var(F_j)}{Var(y_i)}, \tag{7}$$

where $\theta_{i,j}$ is the respective loading in Θ.

3.3 Identifying restrictions

In this section, we discuss identification restrictions. Table 1 presents the sign restrictions used to identify the aggregate credit and the credit composition models.

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 (government, business and household), whereas a credit demand factor indicates the change in credit *demanded* at the aggregate level or by the distinct sectors. 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 government, business and household sectors. The motivation of these restrictions is analogous to the restrictions 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 1 depicts zero-restrictions on the loading matrix Θ in dynamic estimation in order to disentangle sectoral credit components. We emphasize that the number of restrictions placed on individual factors is modest.[7] Moreover, we estimate the monetary policy component as motivated by the triad perspective on global liquidity of Eickmeier et al. (2014) to immunize the credit factors against potential contamination with monetary policy surprises. Finally, it is important to notice that the resulting factors have an ordinal scale, with higher values indicating favourable conditions for borrowers (credit demand) or lenders (credit supply).

	AC	CG	CNFC	CH	OR	GBY	LR	MR	GBY-PR	LR-PR	MR-PR
Aggregate Credit Supply	≥ 0					≤ 0	≤ 0	≤ 0	≤ 0	≤ 0	≤ 0
Aggregate Credit Demand	≥ 0					≥ 0	≥ 0	≥ 0			
Government Supply		≥ 0	0	0		≤ 0	0	0	≥ 0		
Government Demand		≥ 0	0	0		≥ 0	0	0			
Business Supply		0	≥ 0	0		0	≤ 0	0		≥ 0	
Business Demand		0	≥ 0	0		0	≤ 0	0			
Household Supply		0	0	≥ 0		0	0	≤ 0			≥ 0
Household Demand		0	0	≥ 0		0	0	≤ 0			
Monetary Policy	≤ 0	≤ 0	≤ 0	≤ 0	≥ 0	≥ 0	≥ 0	≥ 0	≤ 0	≤ 0	≤ 0

Table 1: Baseline sign and zero restrictions in aggregate credit (first two rows) and credit composition (row three to eight) models on aggregate credit (AC), government credit (CG), household credit (CH), non-financial business credit (CNFC), overnight rate (OR), government bond yield (GBY), the business lending rate (LR), mortgage rate (MR), interest rate spreads over the policy rate (PR).

4 Empirical analysis

In this section we undertake a structural interpretation of the extracted credit aggregates, and underline that a distinction of credit into flows directed to business, household and government sectors enhances the understanding of global financing conditions considerably.

For assigning economic interpretations to the factor information we rely on eyeball inspections of individual credit components and their prevalence across the financial cycle, variance decompositions, local projections for impulse response analysis and linear correlations between the factors and a variety of international financial indicators (see Appendix I for a full list). More specific and with regard to the latter, we assess correlation patterns between our credit component instruments and credit market indicators (e.g. US credit conditions), financial market indicators (e.g. VIX), global financial indicators and cross-border credit flows. Although we do not draw conclusions on potential causal effects from correlation exercises, we consider them to unravel economic states that are (un)favorable for enhancing global liquidity in total or in some of its important components.

[7] As dynamic estimates are correlated, we orthogonalize in the following order: government, household, business, monetary policy, where for a particular sector, the decision to order demand or supply first is randomized for each draw. Practically, the algorithm converges very fast, such that correlations between the factors are small or close to zero after a small number of draws.

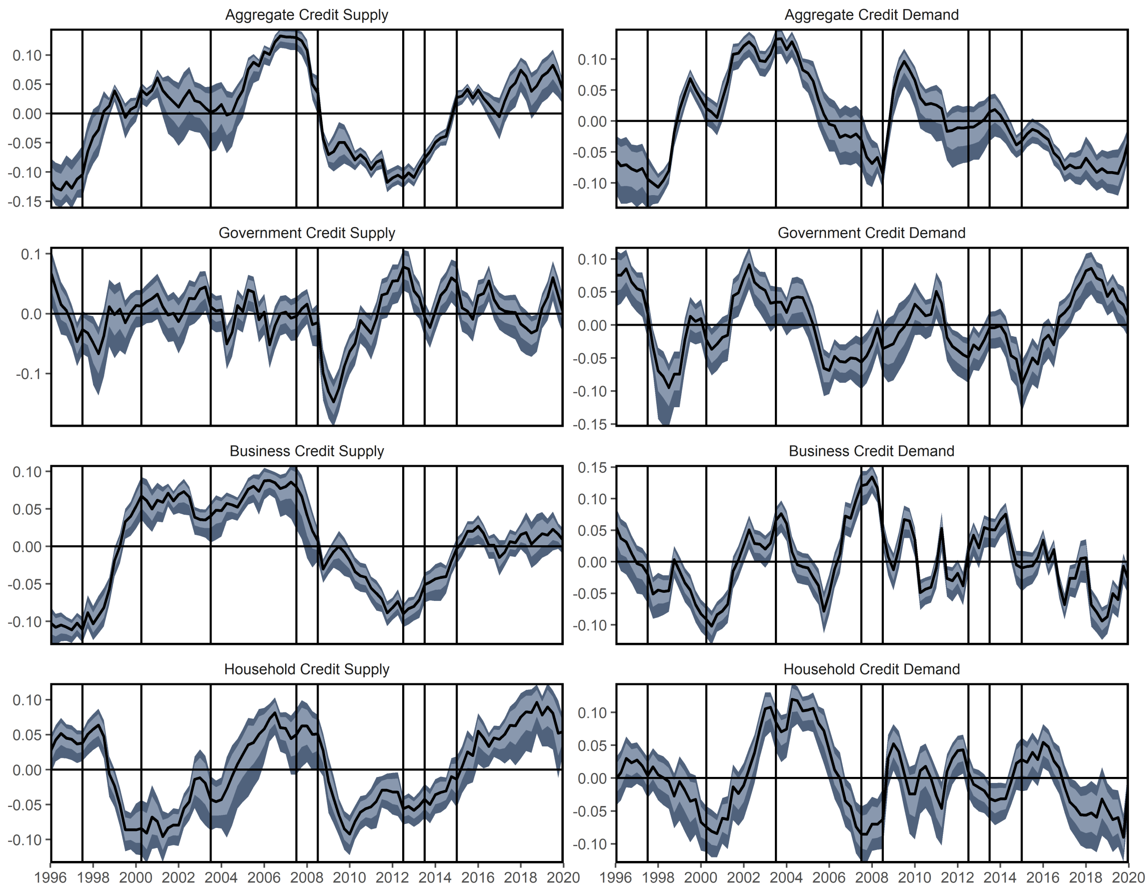

Figure 1: Global credit cycles: Supply (demand) components are shown in the left (right) hand side panel. From top to bottom: Aggregate credit, government sector credit, business and household credit. Black lines indicate the posterior medians. Shaded areas indicate 16 and 84 (inner) as well as 2.5 and 97.5 (outer) posterior percentiles. 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 government sector purchase program (2015Q1).

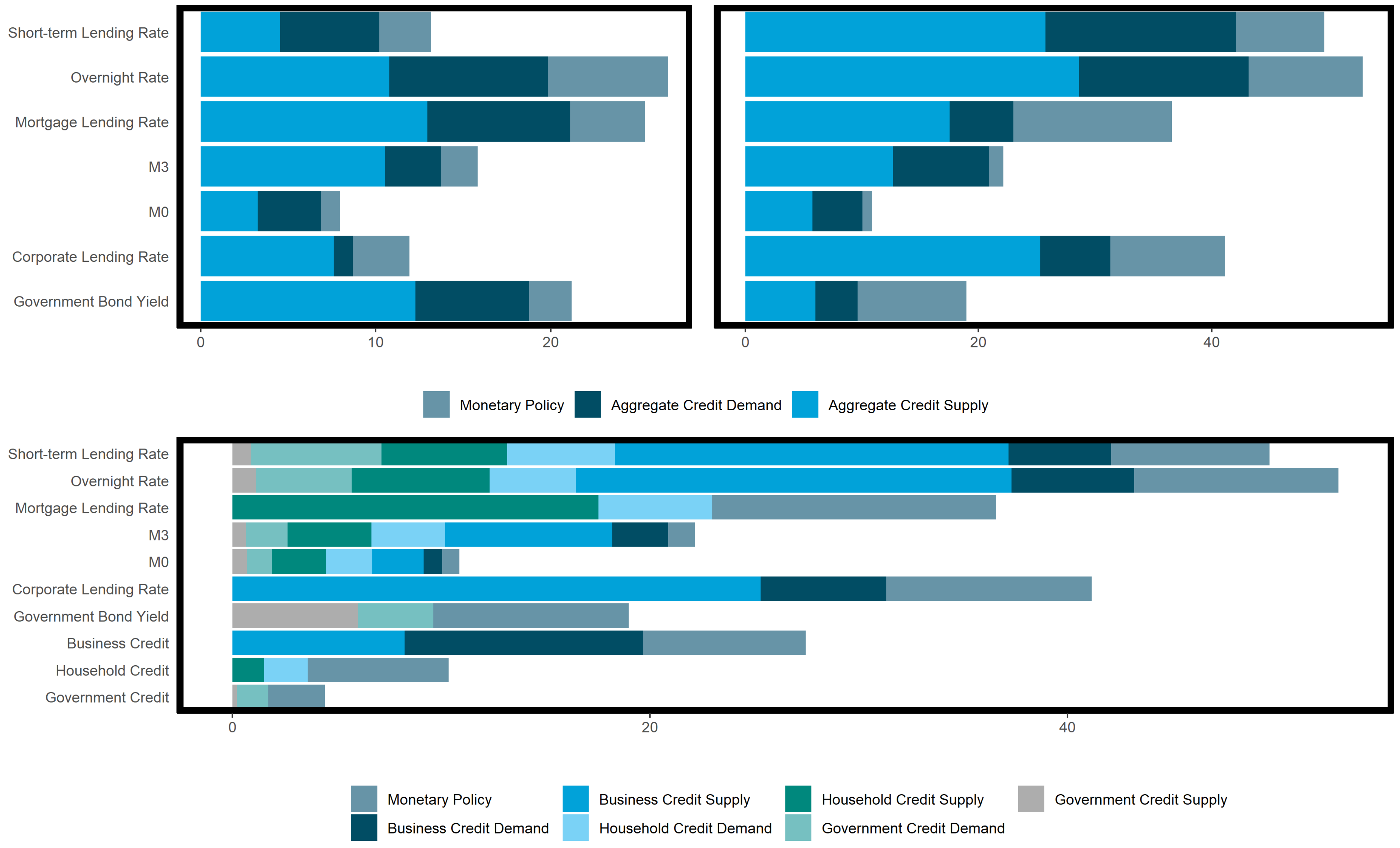

Figure 2: Explained average shares of variance for selected variables by aggregate credit (upper left panel) and credit composition model (upper right panel, same variables as in upper left panel) and credit composition model by sector (lower panel).

Estimates of dynamic credit components are shown in Figure 1 (respective robustness results are shown in Appendix D).Variance decompositions are shown in Figure 2. Correlation estimates are depicted graphically in Figures A1 (global financial indicators), A3 (European indicators) and A2 (US indicators). Local projection estimates are shown in Figures 3 and 4. The monetary policy estimates are shown in Appendix C.

4.1 Variance decompositions

We assess the relative importance of the credit factors in explaining movements of the variables averaged across all countries. For this purpose, we follow the literature on latent global co-movements in macroeconomic variables (e.g. Kose et al. (2003) and Eickmeier et al. (2014)) and focus on variance decompositions. Figure 2 contrasts the shares of variances in key financial aggregates explained by the credit and monetary policy factors in both models.[8]

We make three key observations. First of all, the credit composition model tends to explain larger shares of variance on average. In particular, we note that variation in interest rates is far better explained by the credit composition model. This is best understood as pointing to sectoral information that is concealed when taking an aggregate perspective on interest rates. Thus, the credit composition model substantially improves the understanding of important components of global liquidity flows. Secondly, credit components are, on average, more important for explaining country-specific financial aggregates than monetary policy. We find that credit components from both models unequivocally dominate monetary policy in terms of explaining global co-movements in financial aggregates. In the credit composition model, the relative contribution of monetary policy is smaller but this does not come as a surprise, as there are more credit components than in the aggregate credit model. Thirdly, credit supply is, on average, more important for determining international aggregates in comparison with credit demand. For instance, the lower panel of Figure 2 visualizes in more detail to which sector the explained variances can be attributed. As for the aggregate factor model, we find that the credit supply components are, on average, more important for explaining variation in financial variables in comparison with credit demand components. Moreover, it becomes apparent from the lower panel of Figure 2 that most sectoral credit components are important to explain global liquidity flows.

4.2 The aggregate credit perspective

We proceed with the analysis of an aggregate credit specification in the spirit of Eickmeier et al. (2014) to understand the economics behind aggregate credit. Recall for the following

[8]Appendices E and F show corresponding loading distributions per factor and variable for the aggregate and the credit composition model, respectively. Finally, for country-specific results, we refer to Appendix G. Tables A1, A2, A3, A4 and A5 document explained shares of variance for each variable in the entire sample, in advanced and in emerging economies, Asian, Euro-zone, and Latin American countries as well as for the US for the aggregate credit and the credit composition models, respectively. From these results we diagnose, on average, plausible factor loadings within all considered groupings of country specific estimates.

elaboration that conceptually, higher values of the aggregate credit supply indicate increased willingness (e.g., due to increased risk-taking or animal spirits) or improved opportunities to lend (e.g., due to deregulation or financial innovation).

According to theoretical considerations, lending to the business sector follows a profit maximization rationale along the financial cycle. Risk taking and leveraging characterize the financial cycle (Miranda-Agrippino and Rey 2020). For instance, a financial cycle upswing corresponds to increased leverage, higher credit flows and higher risky asset prices. Thus, correlations and local projections of financial credit supply with risk taking and leverage might provide insights into the link between credit supply and states of the financial cycle. Moreover, we remind the reader that financial cycles are usually twice as long (at least) than business cycles (Borio 2014).

4.2.1 Global aggregate credit supply

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 Eickmeier et al. (2014), we find that credit supply conditions improve at the beginning of the new millennium. After 2003 the global credit supply factor rises, possibly resembling the international flow of funds described by the SG or 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. Moreover, we observe that global credit supply conditions 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 and estimate local projections. We obtain five essential results: First, as displayed in Figure A1, aggregate credit supply is positively correlated with bank leverage measures across the world.[9] Similarly, aggregate credit supply is negatively correlated with the VIX index ($\hat{\rho} = -0.21$; see Figure A2) and a Euro-area sovereign systemic stress indicator ($\hat{\rho} = -0.70$; see Figure A3). Economically, this means that credit supply increases in times of financial cycle upswings. Second, aggregate credit supply deteriorates when responding to an impulse in global financial sector risk aversion and expands in response to a risk shock (see Figure 4), which is approximated by asset price risk and risk aversion components in the spirit of Miranda-Agrippino and Rey (2020). Economically, these findings are best understood to indicate that lenders increase credit supply in times of financial cycle upswings. Third, aggregate credit supply is highly positively correlated with cross-border

[9] $\hat{\rho} \in \{+0.27; +0.45; +0.49; +0.44\}$ for broker-dealer, systemic important global bank, a broader set of global banks and European bank leverage (see Figure A1).

credit flows. Recall that the loadings on cross-border credit supply flows remain unrestricted in our model, thus, this finding is not trivial.[10] Fourth, less credit is supplied when the European banking system is under stress.[11] This finding underlines that financial market risk and credit supply are inversely related, although we refrain from drawing conclusions regarding causality. Fifth, aggregate global credit supply expands in response to impulses in the US credit supply shocks of Adrian et al. (2014) and Jermann and Quadrini (2012) (see Figure 4). Economically, this means that global credit supply depends on US credit supply conditions. We note that this finding is ambiguous, as aggregate credit supply deteriorates in response to supply shocks obtained from Bassett et al. (2014) and Mumtaz et al. (2018).

4.2.2 Global aggregate credit demand

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). Other (structural) sources of demand type credit factors are collateral effects and (possibly) deteriorating lending standards, which are associated with non-decreasing lending rates and credit expansion. As displayed in the upper right hand side panel of Figure 1, aggregate credit demand was low prior to the Asian crisis, and temporarily expanded during the dotcom crisis. Interestingly, credit demand deteriorated to average levels prior to the US financial crisis of 2007/08. During the financial crisis, credit demand abruptly surged for about two years. This is likely to resemble the higher demands of businesses to bear vital expenses, and of governments to finance policies that were designed to absorb adverse economic shocks. In times of liquidity shortages, firms typically draw on credit lines or substitute bank credit with capital market finance (e.g. bonds). Subsequently the factor decreased until the end of the sample.

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 and impulse response profiles, 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.

[10] $\hat{\rho} \in \{+0.73; +0.75; +0.57; +0.66; +0.69; +0.36\}$ for global cross-border credit related to all sectors and banks, Eastern Asia non-bank cross border credit (see Figure A1) as well as cross-border credit volumes related to UK all sectors, UK banks, UK non-banks (see Figure A3).

[11] $\hat{\rho} \in \{-0.39; -0.34; -0.38; -0.59\}$ for the probability that two more or more large banks default in Spain, France, Greece and Italy, respectively (see Figure A3).

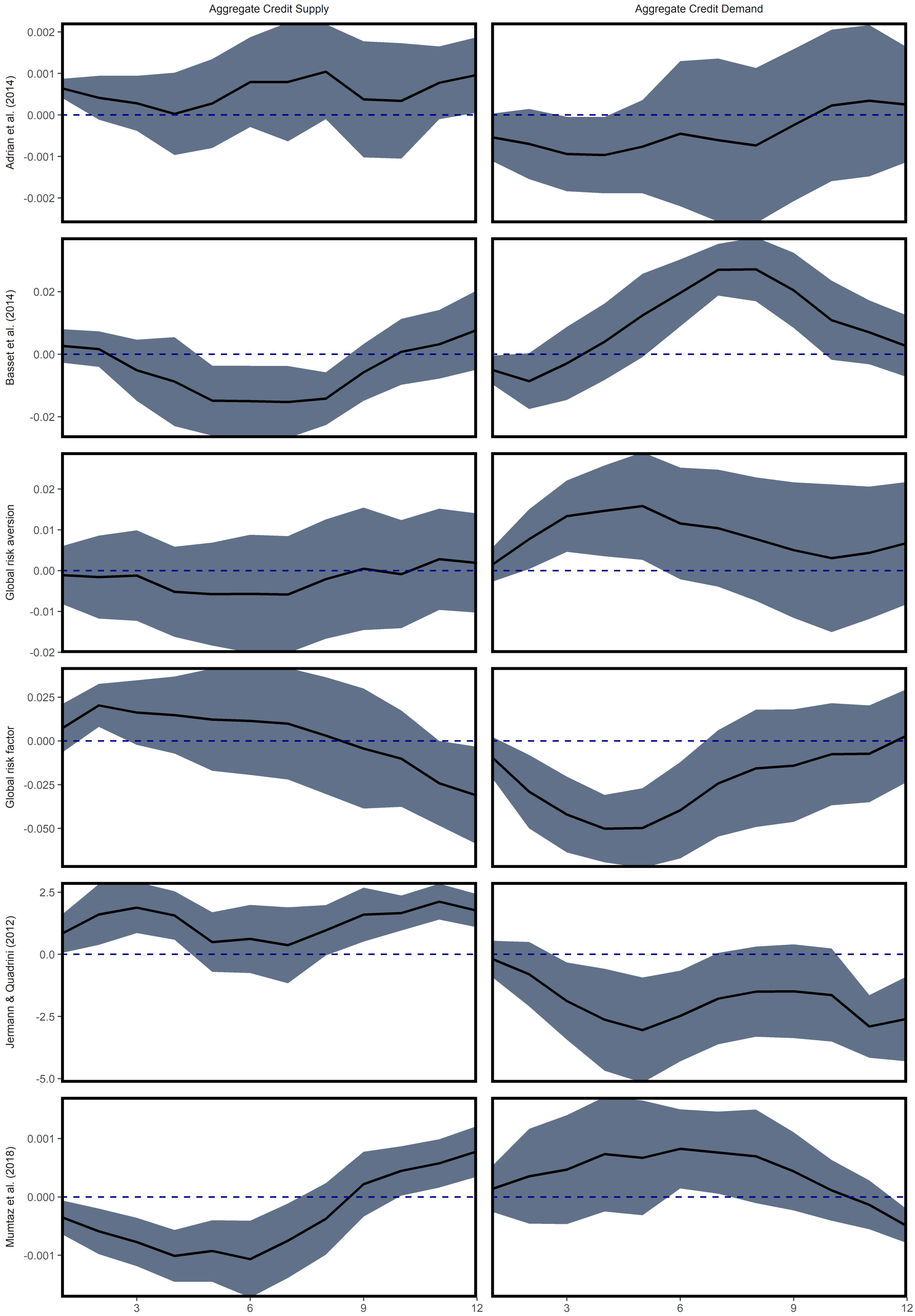

Figure 3: Local projections (Jorda et al. 2015, Adämmer et al. 2021) of identified global risk instruments from Miranda-Agrippino and Rey (2020) and identified US credit supply shocks over 12 quarters from Adrian et al. (2014), Bassett et al. (2014), Jermann and Quadrini (2012) and Mumtaz et al. (2018) on the credit factors. All aggregate credit factors and the respective shock (one by one) are included. Shaded areas indicate 95% confidence bounds.

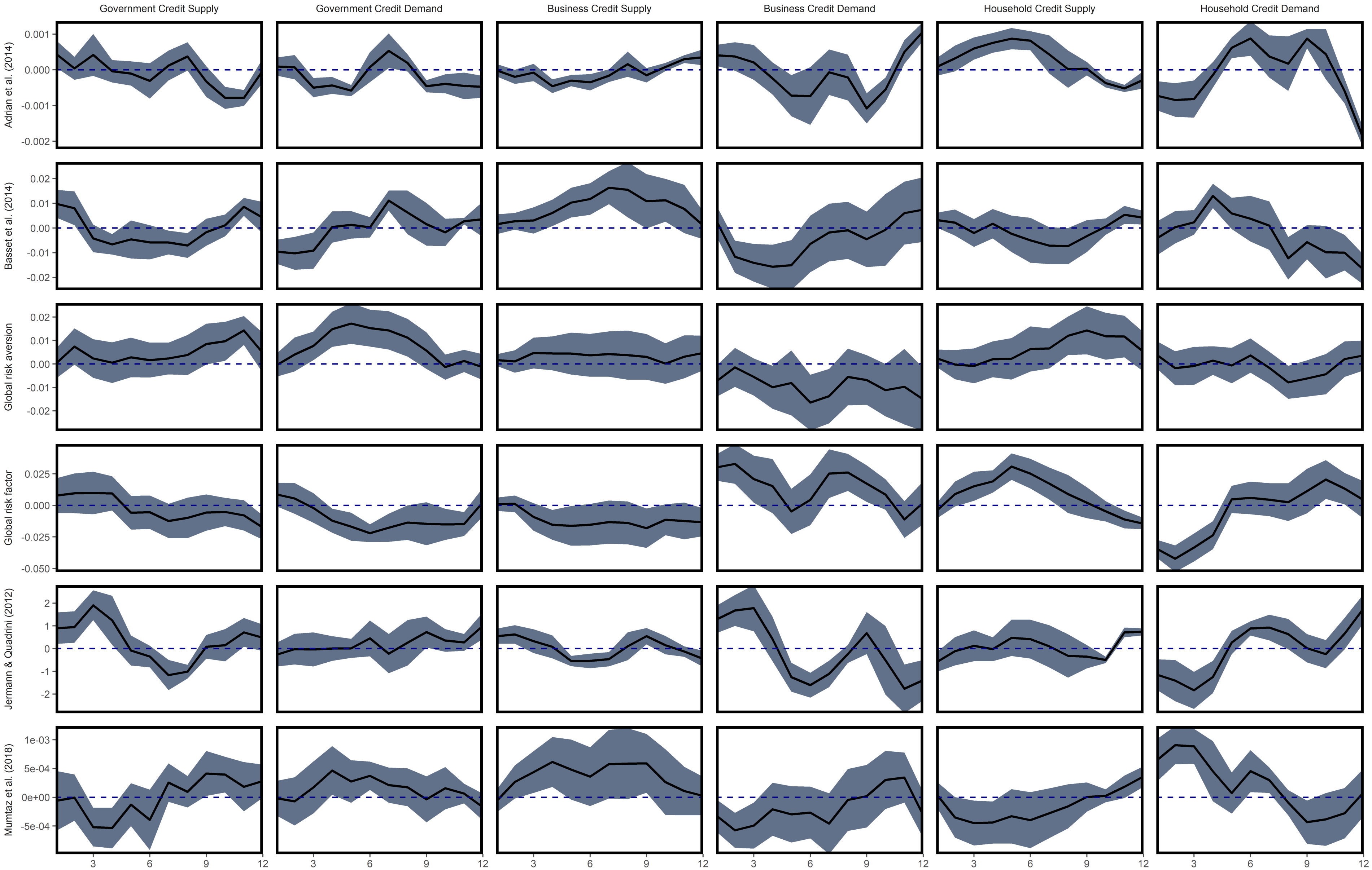

Figure 4: Local projections of identified global risk instruments on the credit factors. All credit compositions factors and the respective shock (one by one) are included. For further notes see Figure 3.

Correlation analyses (see Figures A1, A2 and A3) and local projections reveal, first of all, that global credit demand is positively correlated with financial market uncertainty and negatively correlated with (realized) financial market stress.[12] Secondly, correlations with leverage are negative throughout.[13] Finally, aggregate credit demand shrinks when responding to impulses in global risk, and expands after an impulse in global risk aversion (see Figure 3). This means that aggregate credit demand is high in times of global financial cycle downswings. Dependence on US credit market conditions (exemplified by Adrian et al. (2014), Bassett et al. (2014) and Jermann and Quadrini (2012)) seems negative (see Figure 3), which lends support to the financial-cycle downswing hypotheses, as the global financial cycle substantially hinges on US monetary policy Miranda-Agrippino and Rey (2020). Similar to aggregate credit demand, it is difficult to attribute these findings to agent-specific rationales due to aggregation.

4.3 Credit composition across the financial cycle

To unravel the underlying structural dependencies between heterogeneous borrowers and global lenders, we proceed by decomposing the credit components of global liquidity into government and private sectors for which plausible economic narratives are available. To gain a better understanding of which states of the financial cycle are favourable to sectoral credit components, we complement the findings from correlation analysis with local projections (see Figure 4).

4.3.1 Credit composition supply components

Analogous to the discussion of aggregate credit supply, we examine government and private sector credit supply flows.

Global government credit supply is depicted in the second row on the left hand side of Figure 1. Lending conditions fluctuate around the zero-line until the 2007 US financial turmoils, followed by a strong deterioration in 2007/08. The 2007 decrease in government 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. Subsequently, government credit supply expanded steadily until the taper tantrum events of 2013, fluctuating around the mean afterwards. In normal times, corporate bond and mortgage yields are higher than government bond yields, assuming same 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

[12] $\hat{\rho} \in \{+0.24; +0.25; +0.22; -0.39; -0.25; -0.24; -0.25\}$ for MSCI world realized volatility, (see Figure A1), VIX (see Figure A2), European sovereign financial stress (see Figure A3), respectively.

[13] $\hat{\rho} \in \{-0.43; -0.27; -0.37; -0.46; -0.37; -0.23; -0.24; -0.25\}$ for broker-dealer leverage, systemic important bank leverage, global bank leverage (see Figure A1), equity to asset ratio of very small, small, medium-sized and large US banks (see Figure A2) and European bank leverage change (see Figure A3), respectively.

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 high-rated 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 safe-haven conjecture is weakly supported by the local projections shown in Figure 4 (second column, esp. fourth and fifth row): An increase in risk aversion leads to a surge in government credit supply and an impulse in risk leads to a medium-term (albeit statistically insignificant) contraction in government credit supply (i.e. during a financial cycle downswing, when risk declines, government credit supply increases). Moreover, the safe-haven interpretation is strongly supported by negative correlations of global government credit supply and leverage,[14] and with volatility.[15] Thus, we infer that government credit supply expands during the downswing of the financial cycle (when risk aversion is high and agents deleverage).

Global business credit supply is low at the outset of the new millennium and tends to deteriorate in times of economic crises, e.g., during the US financial turmoils in 2007 (third row on left hand side of Figure 1). Interestingly, business credit supply exhibits a high degree of persistence. For instance, the recovery (reversion to mean) after the US financial crisis took almost a decade. 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 (which is in line with a longer financial cycle), deteriorating again and subsequently recovering until the end of the sample period. Local projections (see Figure 4) indicate that business credit supply decreases in response to impulses in risk shocks. Nevertheless, the response is sluggish and small. Economically, this means that business credit supply tends to deteriorate the closer the financial cycle is to its high peak. This seems plausible given the course of events prior to the US financial crisis. The positive medium-sized correlations with leverage indicators partly lend support to this hypothesis, indicating a positive *contemporaneous* relationship between business credit supply and leverage.[16] Moreover, the local projections show mostly positive and significant responses to US credit supply (see Figure 4, e.g. credit supply shocks of Bassett et al. (2014) (second row), Mumtaz et al. (2018) (sixth row)). These results can be understood to indicate that business credit supply co-moves with the US financial cycle. To summarize, global business credit increases in times of low (perceived) risk and leverage and seems co-determined by the US financial cycle.

[14] $\hat{\rho} \in \{-0.54; -0.44\}$ for systemic important bank and global bank leverage (see Figure A1).

[15] $\hat{\rho} \in \{-0.60; -0.35; -0.4\}$ for MSCI World realized volatility and global volatility (see Figure A1) and VIX (see Figure A2).

[16] $\hat{\rho} \in \{+0.28; +0.38; +0.49\}$ for systemic bank, global bank and European bank leverage (see Figure A1).

Global household credit supply (fourth row on left hand side of Figure 1) deteriorates prior to the dotcom crisis, but gains momentum after 2003, which coincides with the US and European mortgage credit expansion (Demyanyk and Van Hemert 2011, Justiniano et al. 2017). Interestingly, the factor stagnates about half a year before the US financial market crash in 2007 and deteriorates between 2008 and 2010. Interestingly, the factor reaches a plateau before the crisis fully develops. This might be caused by financial accelerator deceleration because of a lack of credit impulses. Afterwards, the factor recovers very slowly, reaching pre-crisis levels in 2019. Our local projections indicate that household credit supply increases in response to an impulse in global asset price risk and decreases in the medium term responding to risk aversion (see Figure 4, fifth column). Moreover, correlations with cross-border credit[17] and leverage[18] are positive. Strikingly, correlations with European financial system stress and bank default probability are negative, which is very well aligned with the mortgage and the European debt crisis.[19] Finally, global household credit supply responds positively to most US credit shocks (see Figure 4, sixth column, e.g. credit supply shocks of Adrian et al. (2014) (first row) and Jermann and Quadrini (2012) (third row)). Economically, this means that household credit supply is a key ingredient to a financial cycle upswing. This crucial insight is hidden when adopting the aggregate perspective.

4.3.2 Credit composition demand components

We now turn to the discussion of credit components demanded from global lenders by the government and private sectors.

Global government sector credit demand (second row on right hand side of Figure 1) is high at the beginning of the sample and deteriorates during the Asian crisis (and only slightly after the European stability and growth pact as been implemented in 1997Q2). Subsequently, the factor expands slightly above its mean level, but is low prior and during the financial crisis. Coinciding with the beginning of the ECB government sector purchase program, the factor steadily increases. Unlike government sector credit supply which measures the willingness of private agents to lend to the state (as sovereigns rarely lend to each other), government sector credit demand is best understood to resemble the government sectors' needs for external finance. This might occur due to policy preference shifts, risk perception changes when governments lever, fiscal co-movements in military spending, welfare spending, government borrowing constraints (e.g. European stability and growth pact) and the like. As

[17] $\hat{\rho} \in \{+0.45; +0.46; +0.25; +0.39; +0.39; +0.37\}$ for cross-border credit change in all sectors, cross-border credit change for banks, East-Asia cross-border credit flows, UK cross-border credit for all sectors, UK cross-border credit for banks, UK cross-border credit for non-banks (see Figure A1).

[18] $\hat{\rho} \in \{+0.34; +0.55; +0.36\}$ for broker-dealer leverage, systemic important bank leverage and global bank leverage (see Figure A1).

[19] $\hat{\rho} \in \{-0.23; -0.47; -0.35; -0.41; -0.17; -0.37; -0.34\}$ for European sovereign systemic stress and simultaneous default probability for two or more large banks for Germany, Spain, France, UK, Greece and Italy (see Figure A1).

the local projections show, US credit shocks hardly exert an influence on global government credit demand (see Figure 4, e.g. the shocks of Adrian et al. (2014) and Jermann and Quadrini (2012) (first and third rows)). This is in line with the conjecture that government credit demand is mainly determined by policy preferences, and not by the availability of credit. Moreover, risk (risk aversion) shocks reduce (increase) government credit demand (see Figure 4). Put differently, governments increasingly borrow when the global financial cycle is deteriorating. This is supported by negative correlations with leverage. We emphasize that government credit demand is the only demand factor with strongly negative correlations with leverage.[20] Finally, correlations with cross-border credit flows are not significantly different from zero, and there is no unambiguous link to the US credit market (see Figure 4).

Global business credit demand (third row on right hand side of Figure 1) is, in general, low during phases of relatively low global economic activity (e.g. Asian crisis, dotcom bubble burst or financial crisis), but peaks prior to crisis outbreaks (e.g. in 2007). Put differently, sizeable expansions of business credit demand seem to precede major financial crisis. This is roughly in line with Schularick and Taylor (2012), who argue that credit volume growth predicts financial market crisis. Note that business credit demand increases do not necessarily indicate higher liquidity demand by businesses. Similarly, increasing business credit demand values might indicate preference shifts in favour of external financing. Local projections show that business credit demand is mostly negatively (positively) affected by risk aversion (risk) shocks (see Figure 4). This can be taken as pointing to an enhanced demand for external finance by businesses in times of *perceived* stable financial conditions. This is supported by positive correlations with cross-border credit[21] and leverage.[22] We emphasize that business credit demand is the only demand factor that exhibits a significantly positive association with cross-border credit flows. There is no unambiguous link to the US credit market (see Figure 4).

Global household credit demand (fourth row on right hand side of Figure 1) slowly decreases from 1996 onwards until it reaches a local minimum during the dotcom bubble burst, indicating a possible preference shift from consumption and mortgage credit to saving. Subsequently, the factor increases until 2005 and decreases afterwards. Interestingly, household credit demand was fairly low prior to the US financial crisis, indicating that the US mortgage debt expansion was (at least at the global level) mostly fueled by the corresponding supply component. With the beginning of the financial crisis, household credit surges, possibly indicating household demand for debt-service. Afterwards, the factor fluctuates with relatively

[20] $\hat{\rho} \in \{-0.20; -0.46; -0.47; -0.31\}$ for broker-dealer leverage, systemic important bank leverage, global bank leverage and European bank leverage (see Figure A1).

[21] $\hat{\rho} \in \{+0.39; +0.36; +0.35; +0.28; +0.25; +0.36\}$ for cross-border credit change in all sectors, cross-border credit change for banks, East-Asia cross-border credit flows, UK cross-border credit for all sectors, UK cross-border credit for banks, UK cross-border credit for non-banks (see Figure A1).

[22] $\hat{\rho} \in \{-0.46; -0.47; -0.31\}$ for systemic important bank leverage, global bank leverage and European bank leverage (see Figure A1).

low volatility around the zero line. Household credit demand deteriorates instantaneously when risk increases (see Figure 4, fifth column, fourth and fifth row), but it is not correlated significantly with cross-border credit or leverage indicators. This might be interpreted to point to the limited relevance of this component. Most likely, global household borrowing is only relevant in times of crisis, when households have to meet obligations.

5 Conclusion

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 non-financial business, household and government sectors. We employ 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 cannot be traced back to specific rationales, our global credit composition 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 most likely supplied to government entities to hedge against losses in times of financial stress, credit is supplied to the private sector to maximize yields in times of low risk premia, economic stability and upswing. More specifically, household credit supply is fostered by risk shocks, i.e. increases in financial cycle upswings and bubble-buildings. Against this background, the recent government 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 government credit demand and supply and, albeit counteracting policies, fewer credit flowing into the private sector.

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Appendices

A Correlations with reduced-form indicators

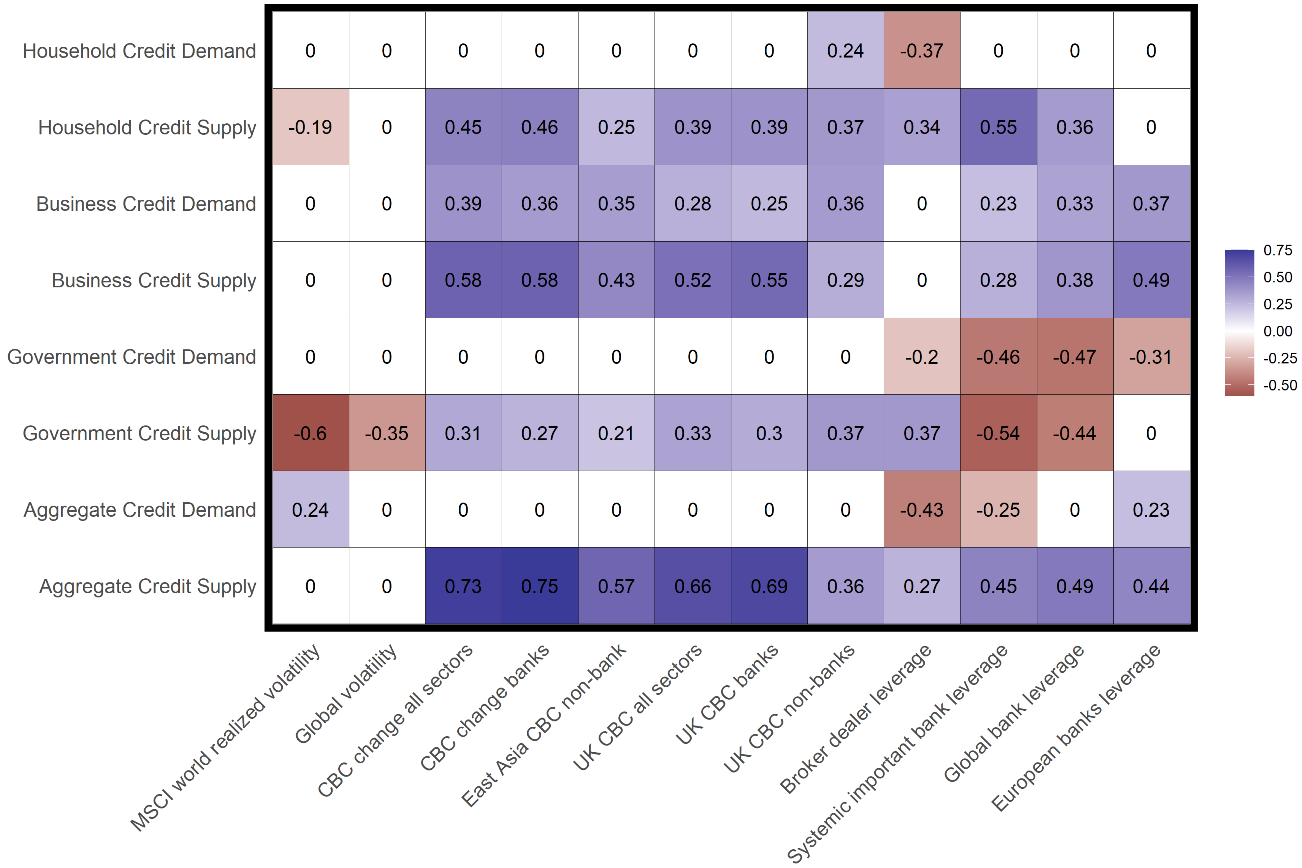

Figure A1: Heatmap for reduced-form credit models and international financial indicators. Corresponding to an approximate significance level of 10%, correlations that are less than a rule-of-thumb threshold of $1.65/\sqrt{T}$ in absolute value are set to zero. For the individual variables see Table A9.

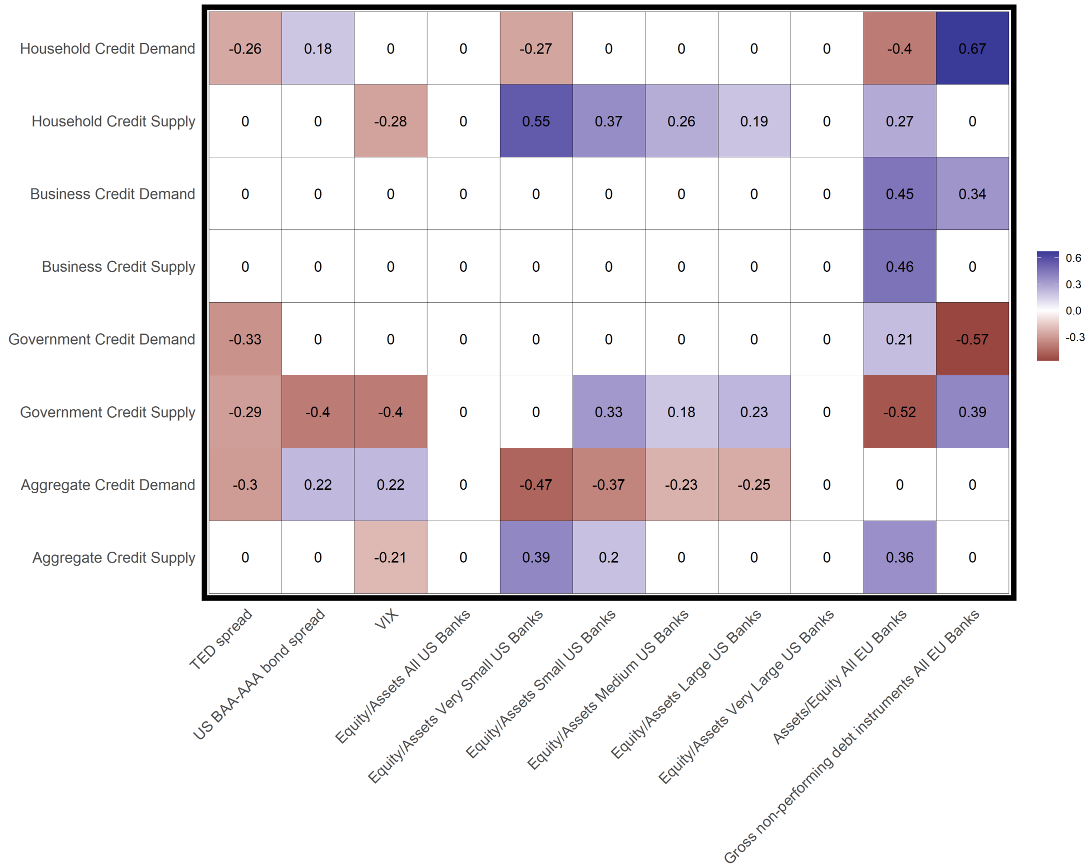

Figure A2: Heatmap for the credit models and US credit market indicators. For further notes see A1.

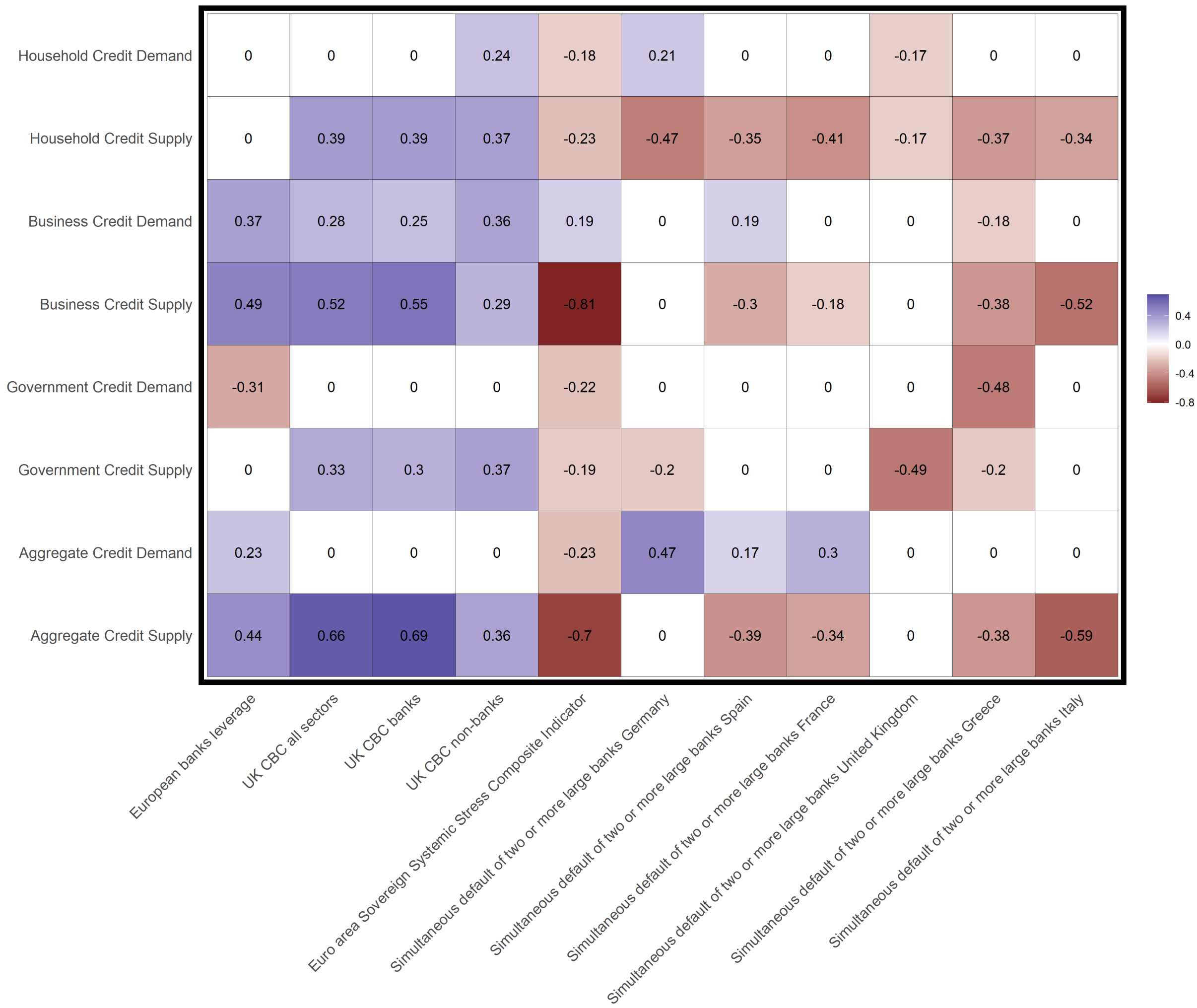

Figure A3: Heatmap for the credit models and European credit market indicators. For further notes see A1.

B Precision sampling implementation

Following Chan and Jeliazkov (2009), we formulate the state-space model in matrix form. This yields:

$$\mathcal{Y} = \Theta\mathcal{F} + \mathcal{U} \tag{8}$$

and

$$H_\Gamma \mathcal{F} = \epsilon, \tag{9}$$

where

$$H_\Gamma = \begin{bmatrix} I_K & 0 & 0 & 0 & 0 & 0 & \dots & 0 \\ -\Gamma_1 & I_K & 0 & 0 & 0 & 0 & \dots & 0 \\ -\Gamma_2 & -\Gamma_1 & I_K & 0 & 0 & 0 & \dots & 0 \\ -\Gamma_3 & -\Gamma_2 & -\Gamma_1 & I_K & 0 & 0 & \dots & 0 \\ -\Gamma_4 & -\Gamma_3 & -\Gamma_2 & -\Gamma_1 & I_K & 0 & \dots & 0 \\ 0 & -\Gamma_4 & -\Gamma_3 & -\Gamma_2 & -\Gamma_1 & I_K & \dots & 0 \\ \vdots & 0 & -\Gamma_4 & -\Gamma_3 & -\Gamma_2 & -\Gamma_1 & \ddots & 0 \\ \vdots & \ddots & \ddots & \ddots & \ddots & \ddots & \ddots & 0 \\ 0 & \dots & 0 & \dots & 0 & 0 & -\Gamma_4 & I_K \end{bmatrix}$$

with I_K denoting the $K \times K$ identity matrix. Then, under the assumption of normality of ϵ

$$\mathcal{F} \sim N\left(M, M^{-1}\left[I_T \otimes \{\Theta'\Psi^{-1}\}vec(\mathcal{Y})\right]\right)$$

where I_T is the identity matrix of order T and $M = H_\Gamma'(I_T \otimes \Sigma^{-1})H_\Gamma + (I_T \otimes \{\Theta'\Psi^{-1}\Theta\})$. As this distribution is available in closed form, we can draw from it directly.

C Monetary policy factors

Figure A4 shows the monetary policy factors from the aggregate credit and the credit composition models. Eventual and slight differences are due to the distinct sample information on credit data used for both models, (i.e. credit aggregates vs. credit component data. Recall that the factors only have an ordinal interpretation. We infer that both models yield decent and similar estimates of the true signal.

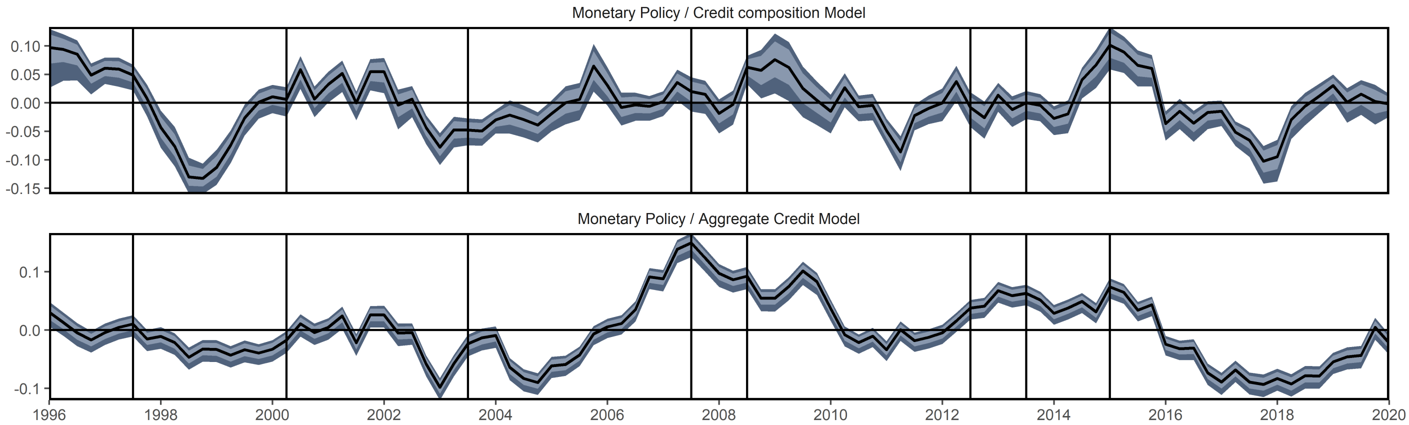

Figure A4: Monetary policy factors from credit composition (upper panel) and aggregate credit (lower panel) models. For further notes see Figure 1.

D Factor robustness to looser identification restrictions

Figure A5 shows the credit factors with (orange) and without (blue) prior truncation on the factor loadings (i.e. the restrictions presented in Section 3.3 hold for the medians of the loadings, but not for all individual loadings). We note that identification does not hinge on truncation, as the estimates are sufficiently similar, with government credit supply being a minor exception. Therefore, we infer that truncation is not overly restrictive. Recall that the factors only have an ordinal interpretation.

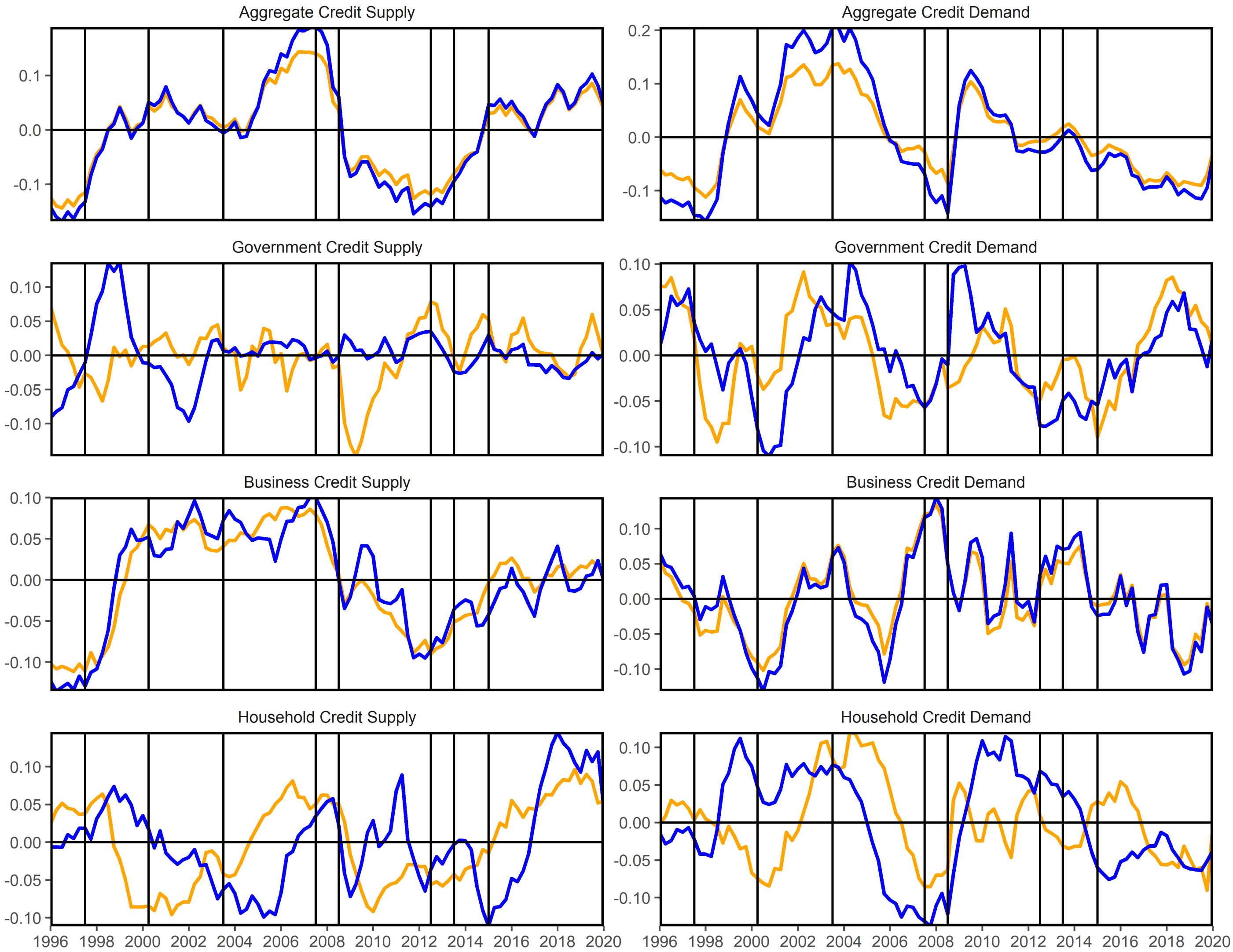

Figure A5: Credit factors from credit composition (upper two panels) and aggregate credit (lower six panels) models with (orange) and without (blue) truncation on the factor loadings. For further notes see Figure 1.

E Country-specific results - aggregate credit model

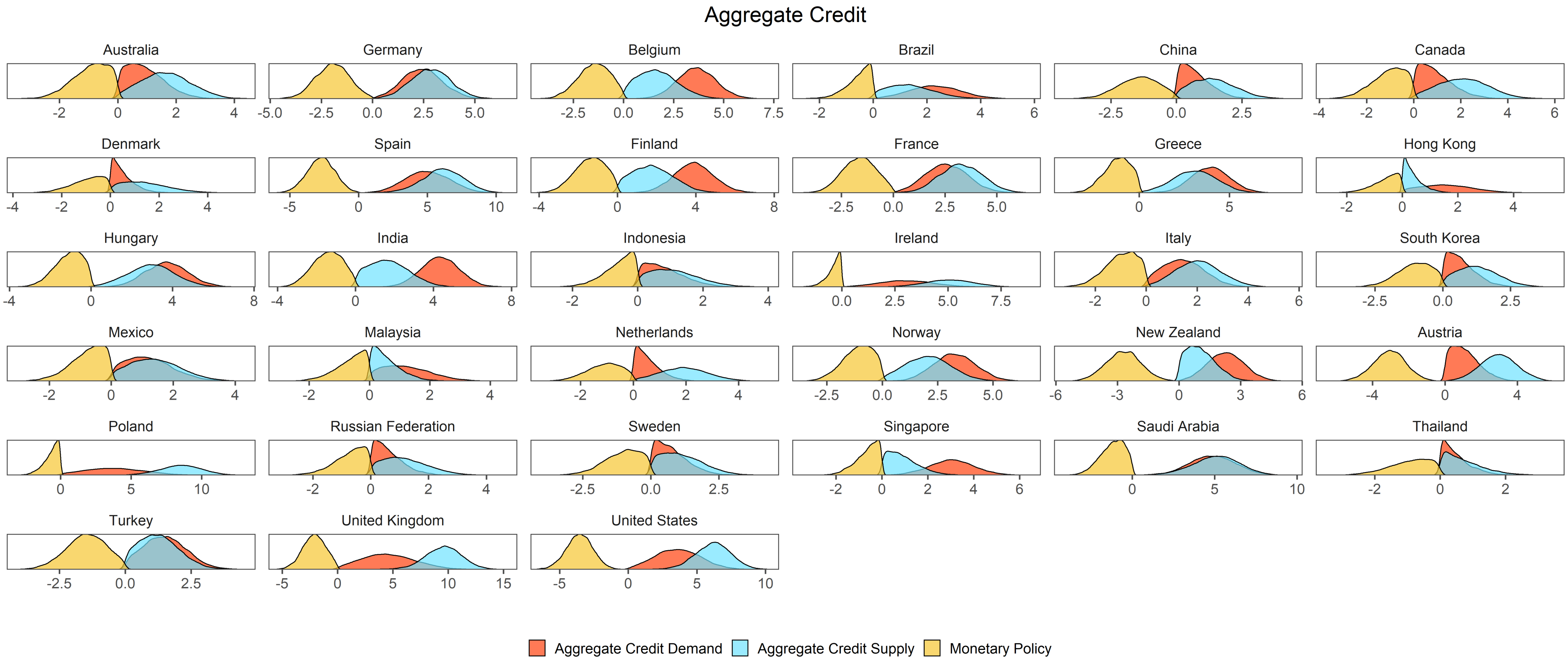

Figure A6: Country-specific loading posterior distributions for aggregate credit.

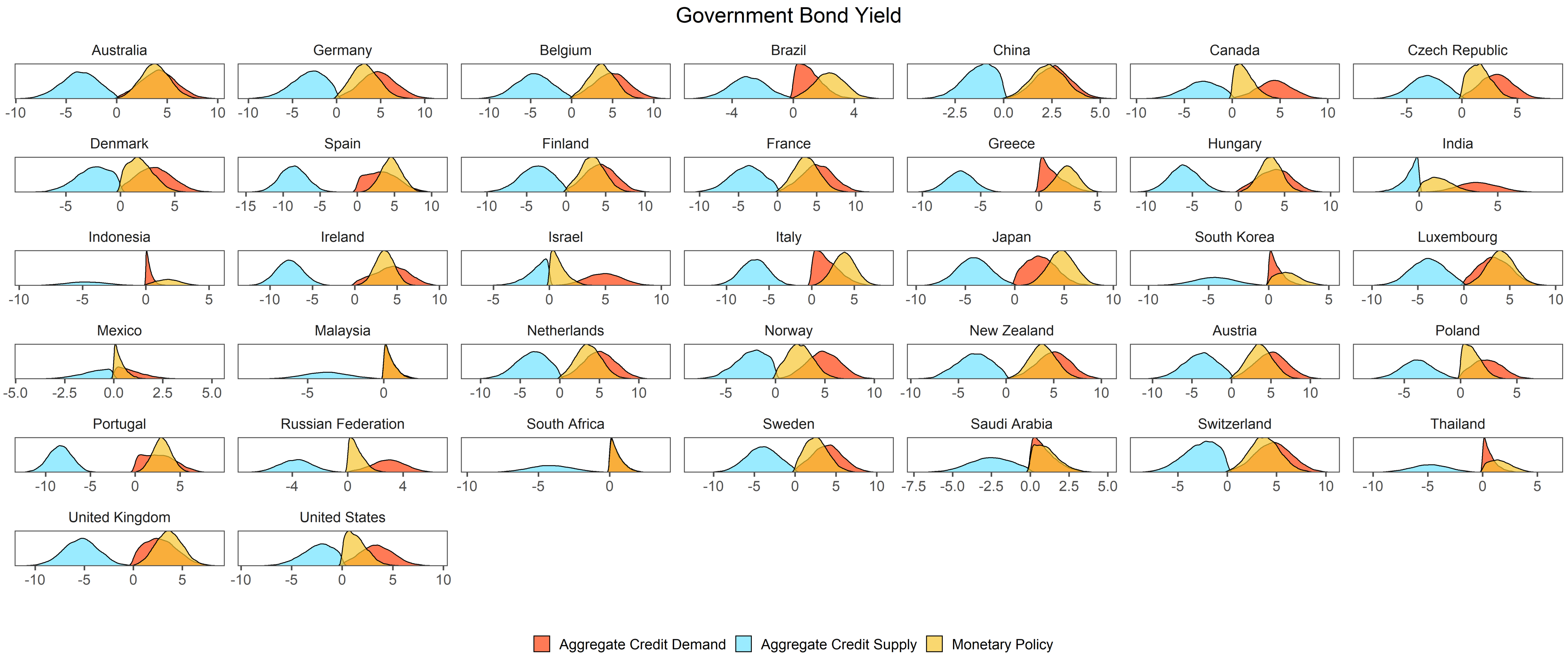

Figure A7: Country-specific loading posterior distributions for government bond yield (aggregate credit model).

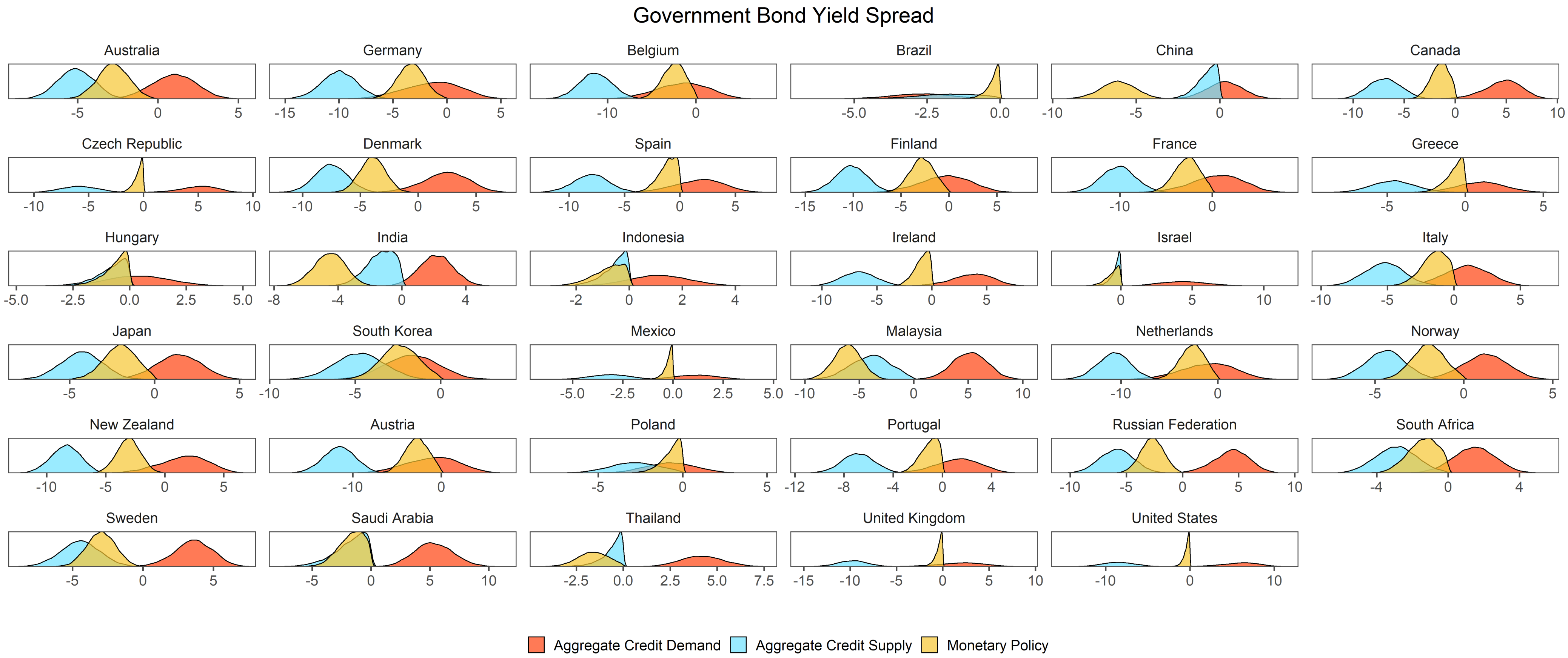

Figure A8: Country-specific loading posterior distributions for government bond yield spread (aggregate credit model).

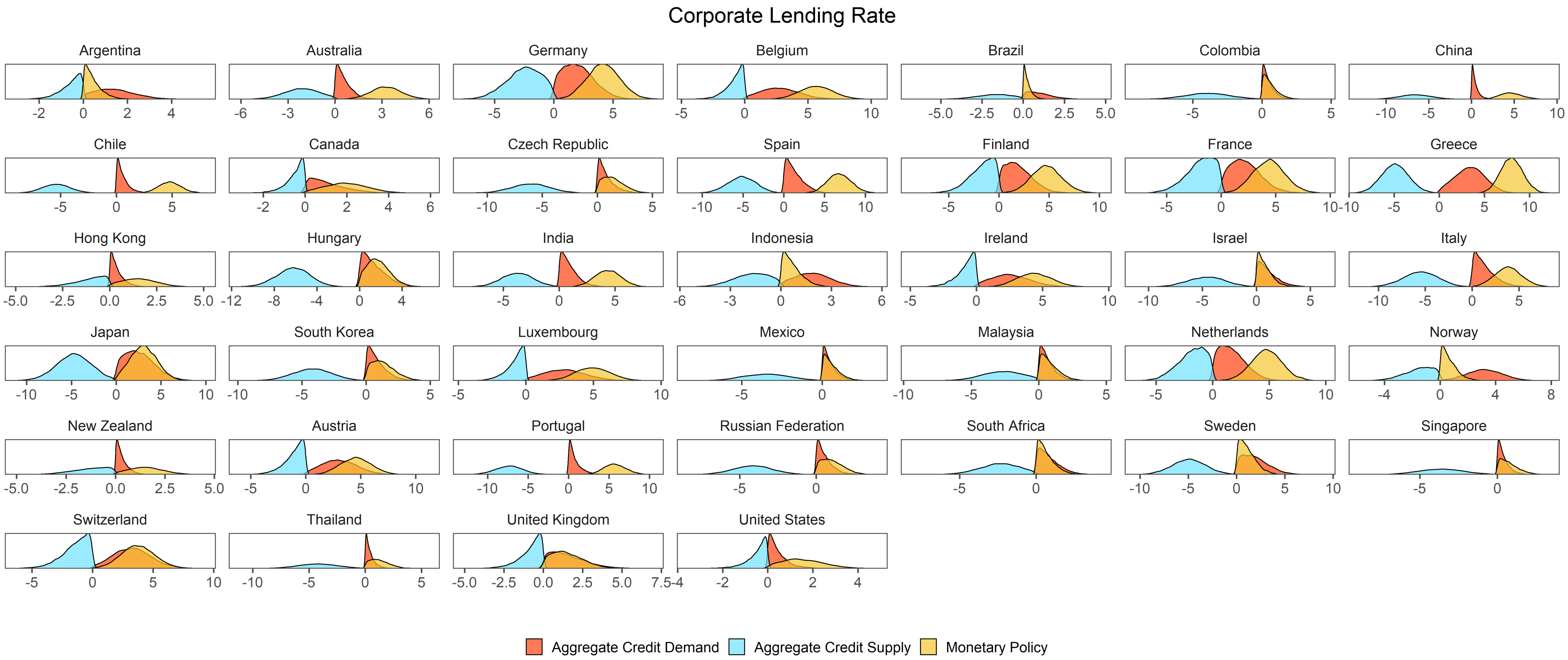

Figure A9: Country-specific loading posterior distributions for corporate lending rate (aggregate credit model).

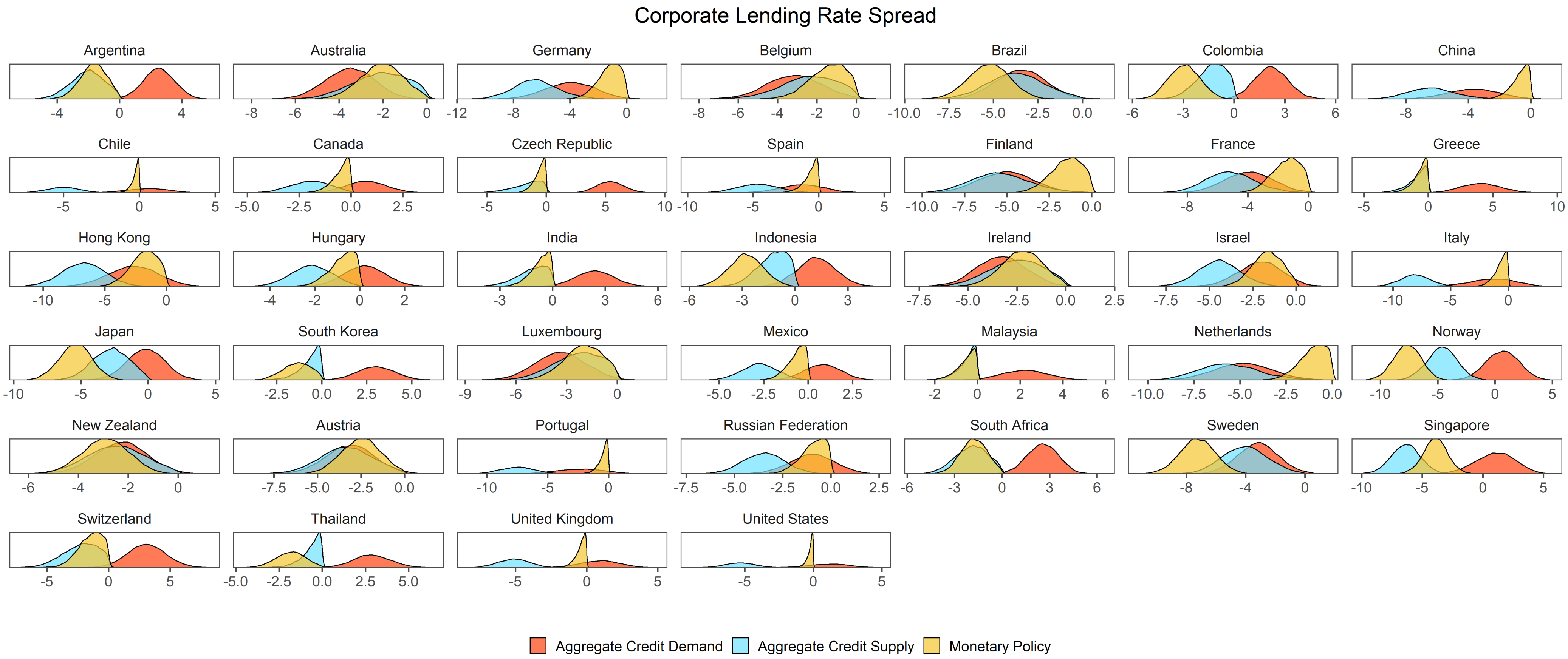

Figure A10: Country-specific loading posterior distributions for corporate lending rate spread (aggregate credit model).

Figure A11: Country-specific loading posterior distributions for mortgage rate (aggregate credit model).

Figure A12: Country-specific loading posterior distributions for mortgage rate spread (aggregate credit model).

F Country-specific results - credit composition model

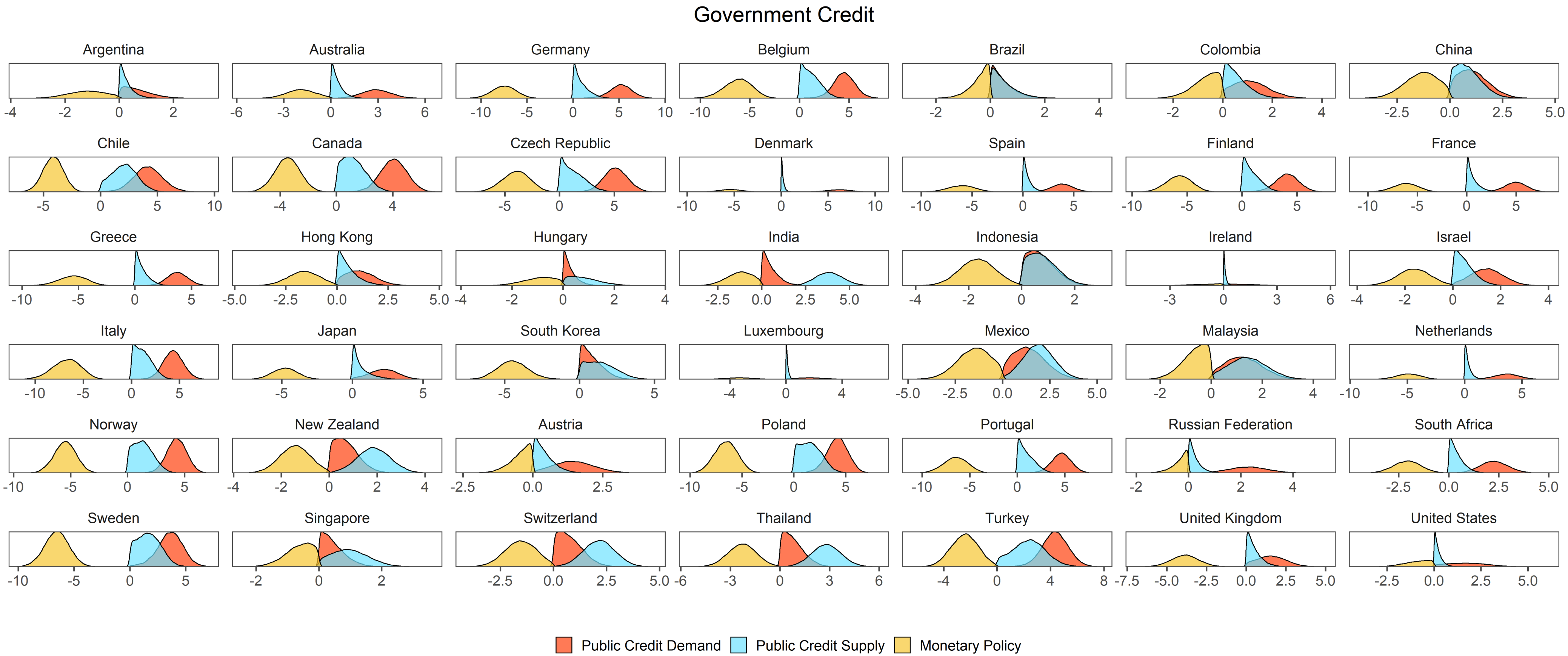

Figure A13: Country-specific loading posterior distributions for government credit (credit composition model).

Figure A14: Country-specific loading posterior distributions for business credit (credit composition model).

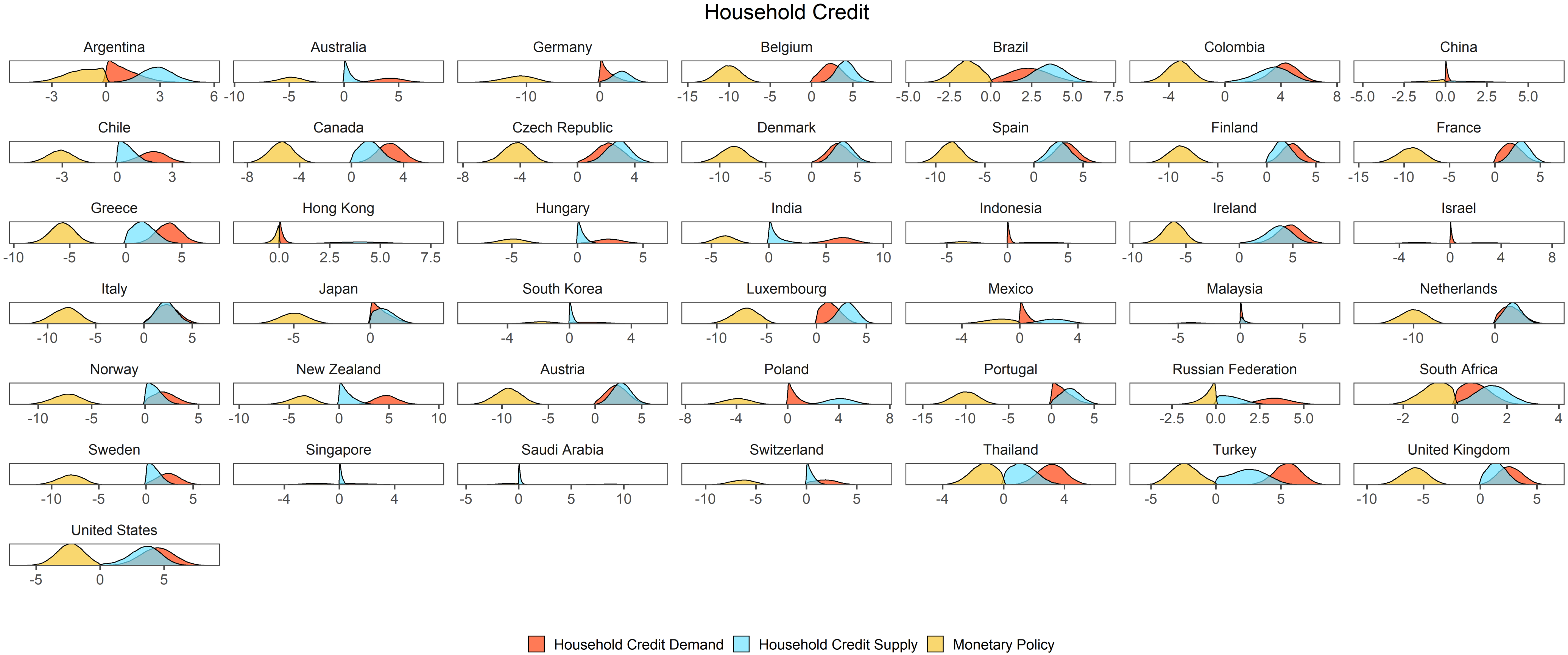

Figure A15: Country-specific loading posterior distributions for household credit (credit composition model).

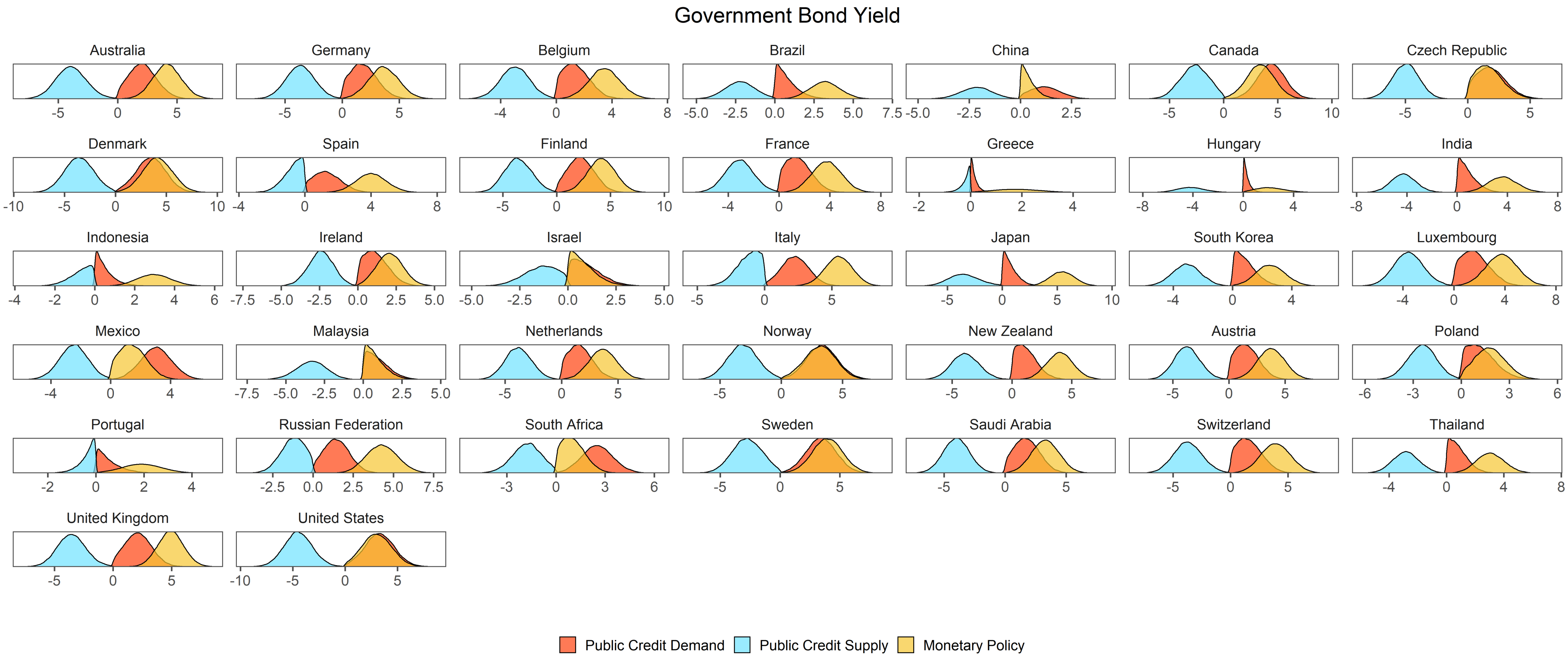

Figure A16: Country-specific loading posterior distributions for government bond yield (credit composition model).

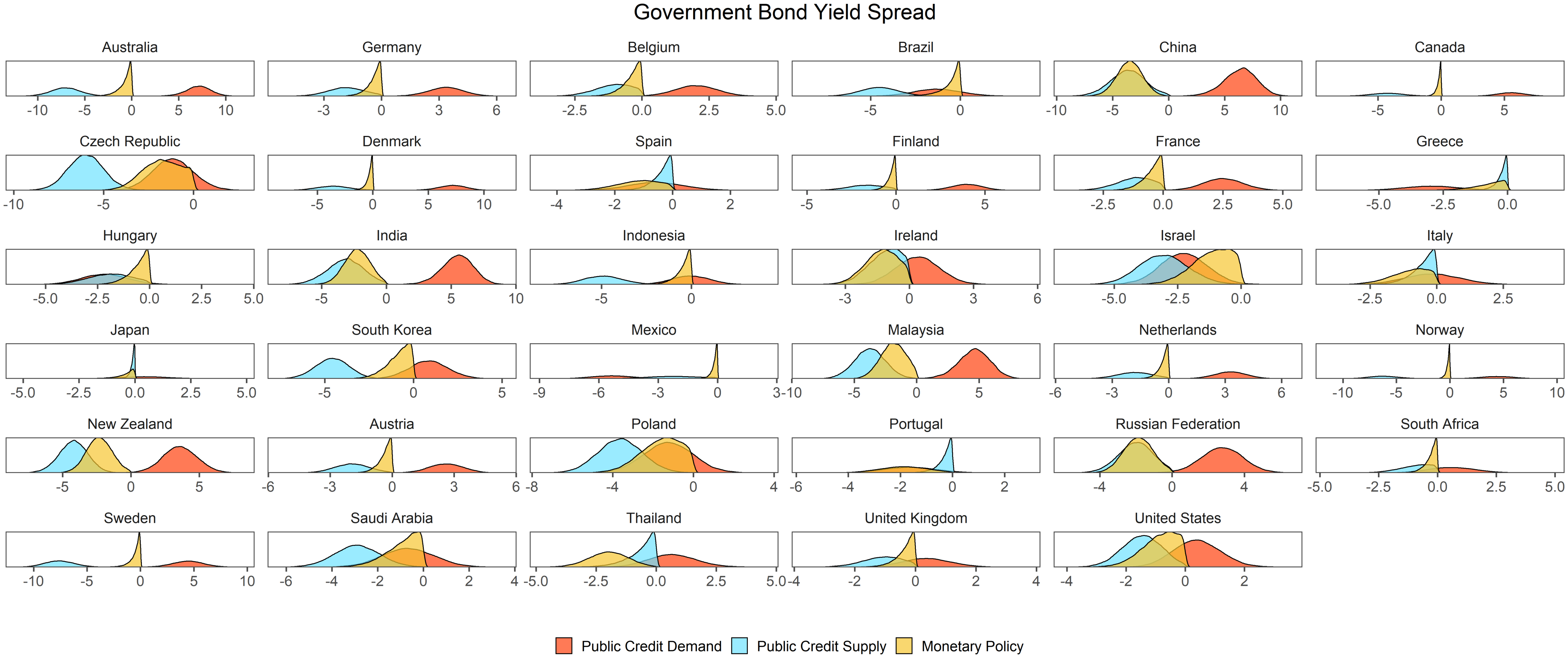

Figure A17: Country-specific loading posterior distributions for government bond yield spread (credit composition model).

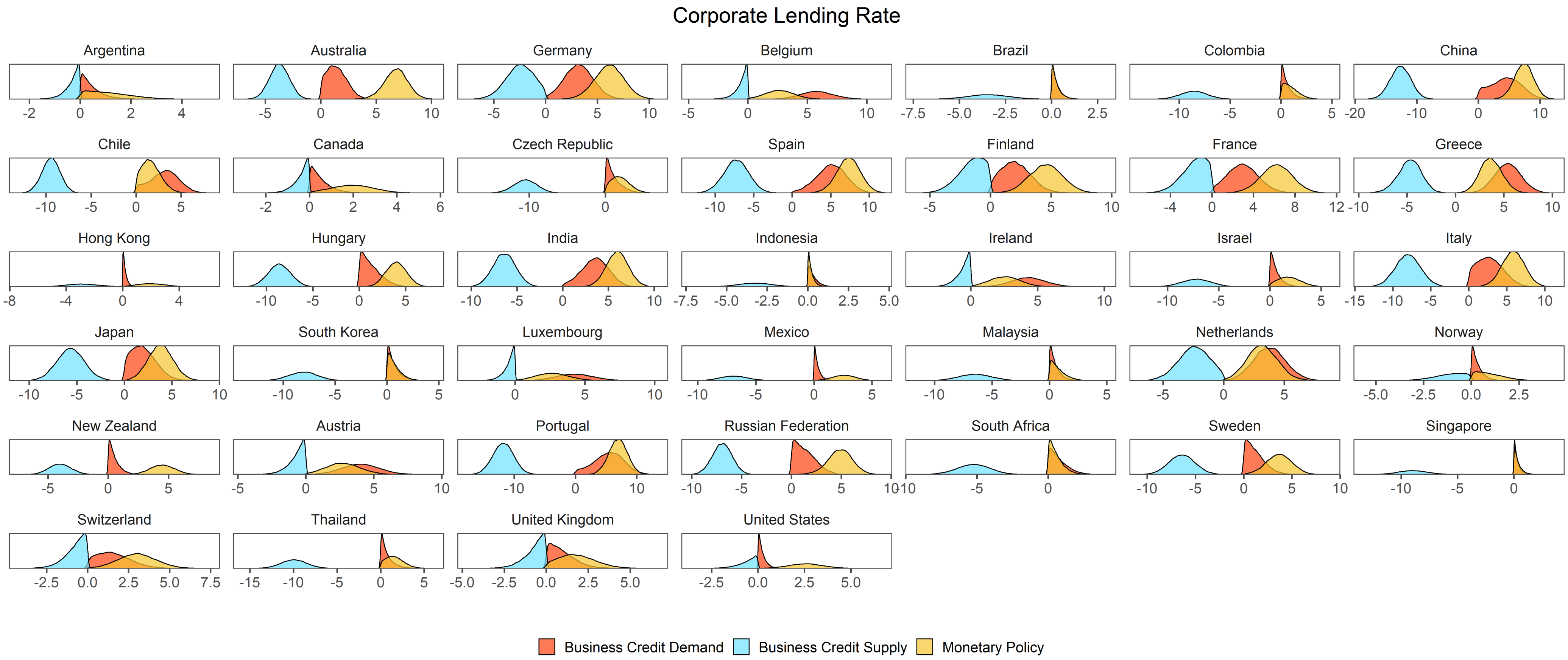

Figure A18: Country-specific loading posterior distributions for corporate lending rate (credit composition model).

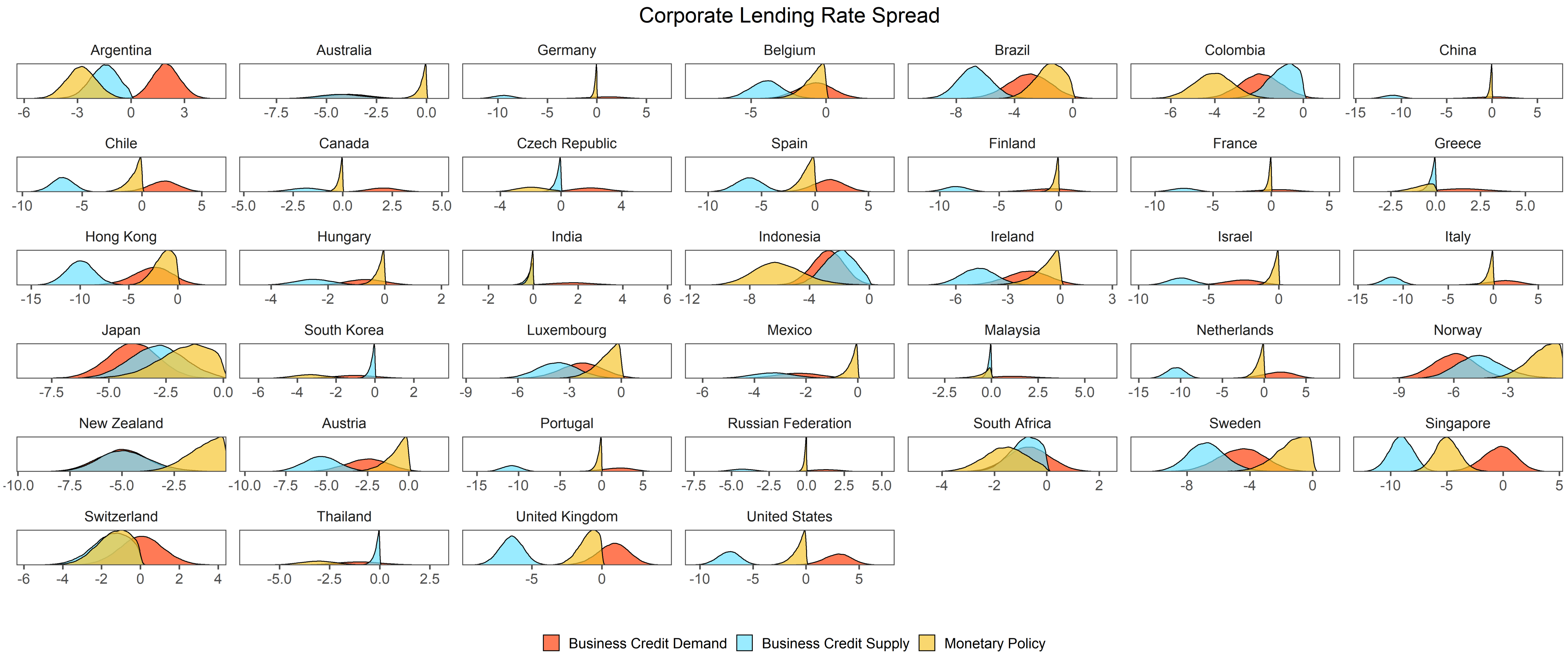

Figure A19: Country-specific loading posterior distributions for corporate lending rate spread (credit composition model).

Figure A20: Country-specific loading posterior distributions for mortgage rate (credit composition model).

Figure A21: Country-specific loading posterior distributions for mortgage rate spread (credit composition model).

G Appendix on variance decompositions

In this appendix, we provide extensive details on variance decompositions. Tables A1, A2, A3, A4 and A5 show explained shares of variance for each variable in the entire sample, in advanced and in emerging economies, Asian, Latin American, Euro-zone countries and US for the aggregate credit and the credit composition models, respectively.

We find that global credit flows (aggregate and decomposed) are more relevant in advanced economies compared with emerging economies for almost all financial variables (see Tables A1 and A3). The results documented in Tables A2, A4 and A5 offer interesting and plausible insights into the relevance of global credit components for country groups. Within the group of advanced economies the variation in US government bond yields and household credit volumes are more heavily determined by global credit than their Euro-zone counterparts, whereas the Euro-zone corporate lending rate and business credit volumes are heavily determined outside the Euro-zone (as opposed to almost complete domestic determination in the US counterparts). Moreover, it is interesting to note that corporate lending rates are also markedly determined by global credit components in Asia and Latin America. Overnight rates and short-term lending rates are almost throughout well explained by global credit components, but slightly more so in advanced economies (see Table A3). Interestingly, for the US global household credit demand and supply are most relevant for overnight and short-term lending rates, whereas in Asia, the Euro-zone and Latin America business credit supply is the single most important credit component for explaining overnight and short-term lending rates.

	CBC	GBY	GBYspread	HP	LR	LRspread	M0	M3	MR	MRspread	OR	STLR	AC
Entire sample:													
Aggregate Credit Demand	1.14	6.48	6.50	4.39	1.10	4.82	3.61	3.20	8.15	14.00	9.04	5.67	2.86
Aggregate Credit Supply	1.64	12.28	21.42	8.49	7.61	14.63	3.27	10.53	12.95	31.04	10.79	4.54	5.61
Monetary Policy	0.69	2.42	4.56	2.77	3.23	2.03	1.10	2.10	4.29	3.83	6.89	2.96	0.71
Explained by Factors	3.46	21.18	32.49	15.65	11.94	21.48	7.98	15.83	25.39	48.87	26.72	13.17	9.18
Explained by Idiosyncrasies	96.54	78.82	67.51	84.35	88.06	78.52	92.02	84.17	74.61	51.13	73.28	86.83	90.82
Advanced economies:													
Aggregate Credit Demand	1.33	6.14	2.66	5.38	1.62	6.21	2.64	2.07	9.12	10.50	2.89	2.94	3.76
Aggregate Credit Supply	2.10	9.77	22.50	9.09	7.12	18.96	2.38	13.00	14.14	32.03	2.70	3.79	7.79
Monetary Policy	0.86	2.53	0.99	3.18	4.69	2.49	0.95	1.35	5.54	3.73	4.06	3.99	1.07
Explained by Factors	4.28	18.44	26.15	17.66	13.43	27.65	5.97	16.43	28.79	46.26	9.65	10.72	12.62
Explained by Idiosyncrasies	95.72	81.56	73.85	82.34	86.57	72.35	94.03	83.57	71.21	53.74	90.35	89.28	87.38
Emerging economies:													
Aggregate Credit Demand	0.61	7.29	14.88	1.42	0.26	2.60	4.91	4.86	4.97	25.48	19.02	11.36	1.47
Aggregate Credit Supply	0.38	18.21	19.09	6.70	8.39	7.70	4.48	6.90	9.07	27.77	23.94	6.09	2.27
Monetary Policy	0.21	2.16	12.35	1.52	0.90	1.30	1.31	3.21	0.18	4.18	11.48	0.83	0.15
Explained by Factors	1.21	27.67	46.31	9.64	9.55	11.61	10.70	14.96	14.21	57.43	54.45	18.28	3.88
Explained by Idiosyncrasies	98.79	72.33	53.69	90.36	90.45	88.39	89.30	85.04	85.79	42.57	45.55	81.72	96.12

Table A1: Explained Variance in percent per variable in aggregate credit model for each variable. Variables include cross-border credit (CBC), long-term government bond yield (GBY), and its spread over the shadow policy rate (GBYspread), house prices (HP), 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), short-term lending rate (STLR) and aggregate credit (AC).

	CBC	GBY	GBYspread	HP	LR	LRspread	M0	M3	MR	MRspread	OR	STLR	AC
Asia:													
Aggregate Credit Demand	1.24	6.32	14.19	5.36	0.42	3.49	3.98	2.81	1.46	4.09	23.74	13.47	1.25
Aggregate Credit Supply	1.25	12.21	8.30	4.14	9.30	8.67	4.48	4.15	6.49	9.60	25.47	4.29	0.84
Monetary Policy	0.53	1.95	17.47	0.89	1.22	3.35	1.77	3.14	0.38	2.47	20.56	1.96	0.32
Explained by Factors	3.02	20.48	39.97	10.39	10.93	15.52	10.22	10.10	8.33	16.17	69.77	19.72	2.40
Explained by Idiosyncrasies	96.98	79.52	60.03	89.61	89.07	84.48	89.78	89.90	91.67	83.83	30.23	80.28	97.60
Euro zone:													
Aggregate Credit Demand	1.66	8.31	1.37	6.27	2.09	9.07	3.89	2.25	14.45	14.03	4.01	3.27	4.34
Aggregate Credit Supply	2.27	18.26	27.98	12.08	10.07	18.18	0.60	19.05	19.18	40.74	4.02	4.28	7.88
Monetary Policy	1.00	3.36	0.86	4.63	7.77	0.98	0.58	0.54	6.67	3.38	4.91	4.09	1.05
Explained by Factors	4.94	29.92	30.20	22.98	19.93	28.24	5.08	21.84	40.30	58.15	12.93	11.64	13.27
Explained by Idiosyncrasies	95.06	70.08	69.80	77.02	80.07	71.76	94.92	78.16	59.70	41.85	87.07	88.36	86.73
Latin America:													
Aggregate Credit Demand	0.26	1.59	5.28	0.71	0.17	1.66	2.05	11.10	5.50	50.03	14.33	5.96	0.78
Aggregate Credit Supply	0.42	12.22	12.88	2.44	4.03	6.50	4.96	10.70	3.23	37.79	11.21	5.83	0.53
Monetary Policy	0.17	3.99	0.04	2.29	0.75	1.59	0.08	3.46	0.05	4.09	0.97	1.07	0.06
Explained by Factors	0.85	17.80	18.20	5.45	4.94	9.75	7.09	25.26	8.78	91.91	26.52	12.86	1.37
Explained by Idiosyncrasies	99.15	82.20	81.80	94.55	95.06	90.25	92.91	74.74	91.22	8.09	73.48	87.14	98.63
US:													
Aggregate Credit Demand	0.83	4.46	14.68	2.27	0.03	1.11	13.97	0.99	3.16	18.27	6.09	7.66	4.46
Aggregate Credit Supply	1.64	2.46	34.33	3.56	0.05	26.66	17.32	0.40	0.99	43.25	6.18	7.27	16.08
Monetary Policy	0.44	0.44	0.03	6.35	0.42	0.02	7.34	0.43	0.77	0.03	0.32	0.05	2.85
Explained by Factors	2.90	7.36	49.04	12.18	0.49	27.79	38.64	1.82	4.92	61.56	12.59	14.98	23.38
Explained by Idiosyncrasies	97.10	92.64	50.96	87.82	99.51	72.21	61.36	98.18	95.08	38.44	87.41	85.02	76.62

Table A2: Explained Variance in percent per variable in aggregate credit model for each variable in Asia (China, India, Indonesia, Malaysia, Singapore), Euro zone (Austria, Belgium, Czech Republic, Finland, France, Italy, Ireland, Germany, Greece, Luxembourg, Netherlands, Poland, Portugal, Spain), Latin America (Argentina, Brazil, Chile, Colombia, Mexico) and US. Variables include cross-border credit (CBC), long-term government bond yield (GBY), and its spread over the shadow policy rate (GBYspread), house prices (HP), 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), short-term lending rate (STLR) and aggregate credit (AC).

	CBC	CG	CH	CNFC	GBY	GBYspread	HP	LR	LRspread	M0	M3	MR	MRspread	OR	STLR
Entire sample:															
Business Credit Demand	0.20			11.42				6.03	1.84	0.89	2.68			5.87	4.91
Business Credit Supply	0.30			8.24				25.29	13.94	2.47	8.00			20.87	18.86
Household Credit Demand	0.23		2.08				2.82			2.22	3.55	5.46	3.89	4.12	5.15
Household Credit Supply	0.34		1.52				3.50			2.58	4.02	17.52	6.65	6.61	6.03
Government Credit Demand	0.13	1.49			3.62	2.42				1.19	2.00			4.58	6.27
Government Credit Supply	0.10	0.21			6.01	2.24				0.71	0.64			1.13	0.87
Monetary Policy	0.19	2.71	6.76	7.79	9.35	0.41	0.71	9.84	0.89	0.82	1.27	13.60	0.67	9.78	7.59
Explained by Factors	1.49	4.42	10.36	27.46	18.98	5.07	7.03	41.17	16.68	10.88	22.15	36.59	11.21	52.98	49.68
Explained by Idiosyncrasies	98.51	95.58	89.64	72.54	81.02	94.93	92.97	58.83	83.32	89.12	77.85	63.41	88.79	47.02	50.32
Advanced economies:															
Business Credit Demand	0.20			13.73				9.07	2.35	0.84	2.23			5.35	4.82
Business Credit Supply	0.23			10.82				21.44	15.73	1.67	10.26			18.76	16.29
Household Credit Demand	0.12		2.22				3.35			2.66	1.49	5.23	4.20	4.71	6.19
Household Credit Supply	0.19		1.42				2.68			1.91	3.61	19.69	6.21	8.28	6.48
Government Credit Demand	0.11	1.95			4.77	2.17				1.01	1.41			5.53	7.81
Government Credit Supply	0.13	0.11			7.62	2.02				0.80	0.47			1.51	0.89
Monetary Policy	0.21	3.68	10.13	11.79	12.28	0.23	0.76	13.71	0.38	0.84	1.11	17.39	0.40	13.24	10.61
Explained by Factors	1.19	5.75	13.77	36.33	24.67	4.41	6.79	44.22	18.47	9.73	20.57	42.31	10.82	57.39	53.10
Explained by Idiosyncrasies	98.81	94.25	86.23	63.67	75.33	95.59	93.21	55.78	81.53	90.27	79.43	57.69	89.18	42.61	46.90
Emerging economies:															
Business Credit Demand	0.18			7.66				1.16	1.02	0.97	3.35			6.72	5.10
Business Credit Supply	0.48			4.07				31.46	11.08	3.54	4.68			24.30	24.22
Household Credit Demand	0.54		1.86				1.22			1.63	6.57	6.22	2.85	3.17	2.99
Household Credit Supply	0.74		1.67				5.97			3.49	4.61	10.40	8.09	3.90	5.08
Government Credit Demand	0.20	0.75			0.89	2.96				1.44	2.85			3.04	3.06
Government Credit Supply	0.04	0.38			2.21	2.72				0.58	0.90			0.52	0.81
Monetary Policy	0.14	1.14	1.61	1.30	2.42	0.82	0.55	3.65	1.70	0.79	1.51	1.17	1.57	4.15	1.30
Explained by Factors	2.32	2.26	5.15	13.03	5.51	6.50	7.75	36.28	13.81	12.44	24.47	17.78	12.50	45.81	42.56
Explained by Idiosyncrasies	97.68	97.74	94.85	86.97	94.49	93.50	92.25	63.72	86.19	87.56	75.53	82.22	87.50	54.19	57.44

Table A3: Explained Variance in percent per variable in credit composition model for each variable. Variables include cross-border credit (CBC), general government credit (CG), household credit (CH), non-financial business credit (CNFC), long-term government bond yield (GBY), and its spread over the shadow policy rate (GBYspread), house prices (HP), 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) and short-term lending rate (STLR).

	CBC	CG	CH	CNFC	GBY	GBYspread	HP	LR	LRspread	M0	M3	MR	MRspread	OR	STLR
Asia:															
Business Credit Demand	0.10			7.50				2.08	1.96	1.15	2.97			6.47	5.35
Business Credit Supply	0.20			0.69				41.38	14.16	1.30	5.37			27.15	21.06
Household Credit Demand	0.16		1.43				3.71			0.26	0.94	6.67	4.33	1.89	3.33
Household Credit Supply	0.27		0.71				2.30			3.34	2.20	5.59	5.92	3.07	6.27
Government Credit Demand	0.19	0.22			0.25	3.02				2.40	3.29			3.63	4.81
Government Credit Supply	0.02	0.47			3.33	2.54				0.54	0.69			1.76	1.57
Monetary Policy	0.23	1.18	1.64	1.22	5.52	0.80	0.63	5.77	2.58	1.36	2.76	1.03	2.71	7.21	1.72
Explained by Factors	1.17	1.87	3.79	9.41	9.09	6.35	6.64	49.23	18.71	10.35	18.21	13.30	12.97	51.18	44.10
Explained by Idiosyncrasies	98.83	98.13	96.21	90.59	90.91	93.65	93.36	50.77	81.29	89.65	81.79	86.70	87.03	48.82	55.90
Euro zone:															
Business Credit Demand	0.17			15.62				15.87	1.32	0.55	1.36			4.19	4.30
Business Credit Supply	0.16			12.54				21.49	22.69	1.91	13.66			22.19	22.44
Household Credit Demand	0.13		1.54				2.93			4.28	3.05	7.66	3.63	3.40	4.98
Household Credit Supply	0.25		2.31				2.68			1.39	4.52	24.89	6.01	9.57	3.56
Government Credit Demand	0.13	2.57			1.94	1.39				0.48	1.58			6.41	7.89
Government Credit Supply	0.19	0.08			6.00	1.40				0.25	0.35			0.88	0.43
Monetary Policy	0.32	5.18	13.87	15.09	9.51	0.46	0.77	19.80	0.22	0.36	0.64	20.01	0.36	16.63	16.05
Explained by Factors	1.35	7.82	17.72	43.25	17.45	3.25	6.38	57.16	24.23	9.23	25.15	52.56	10.00	63.28	59.64
Explained by Idiosyncrasies	98.65	92.18	82.28	56.75	82.55	96.75	93.62	42.84	75.77	90.77	74.85	47.44	90.00	36.72	40.36

Table A4: Explained Variance in percent per variable in credit composition model for each variable in Asia (China, India, Indonesia, Malaysia, Singapore) and Euro zone (Austria, Belgium, Czech Republic, Finland, France, Italy, Ireland, Germany, Greece, Luxembourg, Netherlands, Poland, Portugal, Spain). Variables include cross-border credit (CBC), general government credit (CG), household credit (CH), non-financial business credit (CNFC), long-term government bond yield (GBY), and its spread over the shadow policy rate (GBYspread), house prices (HP), 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) and short-term lending rate (STLR).

	CBC	CG	CH	CNFC	GBY	GBYspread	HP	LR	LRspread	M0	M3	MR	MRspread	OR	STLR
Latin America:															
Business Credit Demand	0.22			6.17				0.41	1.40	1.53	2.45			3.70	3.68
Business Credit Supply	1.10			0.96				21.71	7.57	7.83	4.18			13.64	20.56
Household Credit Demand	1.22		1.48				0.33			4.52	9.71	8.54	2.35	5.31	5.12
Household Credit Supply	1.39		2.54				5.59			4.32	5.88	9.09	13.05	3.59	2.97
Government Credit Demand	0.16	0.64			2.49	2.35				0.62	2.65			4.96	5.83
Government Credit Supply	0.02	0.21			1.79	2.12				0.30	0.65			0.08	0.09
Monetary Policy	0.06	0.69	1.11	0.81	2.36	0.02	1.25	0.77	1.08	0.52	1.08	0.30	1.71	0.58	0.26
Explained by Factors	4.17	1.55	5.14	7.94	6.64	4.49	7.16	22.89	10.04	19.64	26.60	17.93	17.10	31.84	38.50
Explained by Idiosyncrasies	95.83	98.45	94.86	92.06	93.36	95.51	92.84	77.11	89.96	80.36	73.40	82.07	82.90	68.16	61.50
US:															
Business Credit Demand	0.06			0.03				0.02	1.55	1.85	0.03			16.04	16.03
Business Credit Supply	0.29			1.11				0.16	11.30	2.58	1.40			2.54	2.49
Household Credit Demand	0.01		7.15				3.22			0.51	0.02	0.55	2.55	17.04	14.55
Household Credit Supply	0.25		5.17				0.01			10.64	0.34	7.89	25.20	14.08	16.26
Government Credit Demand	0.02	0.51			16.77	0.02				0.74	1.07			2.57	2.44
Government Credit Supply	0.01	0.00			23.62	0.23				6.50	0.33			0.03	0.09
Monetary Policy	0.07	0.14	1.71	3.73	15.51	0.10	0.48	3.18	0.05	0.40	0.05	17.92	0.06	3.44	1.51
Explained by Factors	0.70	0.66	14.03	4.88	55.90	0.35	3.71	3.35	12.90	23.22	3.24	26.36	27.81	55.73	53.38
Explained by Idiosyncrasies	99.30	99.34	85.97	95.12	44.10	99.65	96.29	96.65	87.10	76.78	96.76	73.64	72.19	44.27	46.62

Table A5: Explained Variance in percent per variable in credit composition model for each variable in Latin America (Argentina, Brazil, Chile, Colombia, Mexico) and US. Variables include cross-border credit (CBC), general government credit (CG), household credit (CH), non-financial business credit (CNFC), long-term government bond yield (GBY), and its spread over the shadow policy rate (GBYspread), house prices (HP), 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) and short-term lending rate (STLR).

H Appendix on variables and cross sectional entities

Variable Group	Name of data	Source	Transformation
Consumption (CONS)	Private consumption expenditure, constant prices, seasonally adjusted Government consumption expenditure, constant prices, seasonally adjusted	IMF IFS, Datastream IMF IFS, Datastream	year on year differences 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 Cross border credit liabilities to all sectors, FX and break adjusted change, all instruments from all reporting institutions	BIS locational banking statistics BIS locational banking statistics	year on year differences
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 Producer price index, not seasonally adjusted	Datastream	year on year differences
Interest rates (IR)	Long-term government bond yield (mostly ten year maturity) Money market rate (mostly prime lending rates) Overnight rate (mostly deposit & interbank lending rates) Business lending rate Mortgage lending rate Shadow policy rate	Global financial data, Datastream Datastream Datastream, Eickmeier et al. (2014) Global financial data, Eickmeier et al. (2014) Global financial data, Eickmeier et al. (2014) Krippner (2020)	no transformation
Investment (INV)	Gross capital formation, constant prices, seasonally adjusted	IMF IFS, Datastream	year on year differences
Money (M)	M0 current prices, not seasonally adjusted M3 current prices, not seasonally adjusted	Datastream, Global financial data	year on year differences
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 A6: Variables and data sources

Argentina	Austria	Australia	Belgium	Brazil	Canada
Colombia	China	Chile	Czech Republic	Denmark	Finland
France	Germany	Greece	Hong Kong	Hungary	India
Indonesia	Ireland	Israel	Italy	Japan	Luxembourg
Malaysia	Mexico	Netherlands	New Zealand	Norway	Poland
Portugal	Russian Federation	Singapore	South Africa	South Korea	Spain
Sweden	Saudi Arabia	Switzerland	Thailand	Turkey	United Kingdom
United States					

Table A7: Included economies.

	N_{AC}	N_{CC}
Output	165	165
Inflation	82	82
Share Prices	40	40
Credit and Monetary Policy	489	583

Table A8: Number of series within groups of aggregate credit (AC) and credit composition (CC) models

I Appendix on endorsement variables

Name	Source	Retrieved	Description	Time Period	Figure
Adrian et al. (2014) credit shock	Adrian et al. (2014)		Adjusted broker dealer leverage based credit shock proxy. Higher values mean loosening credit supply conditions.	1968Q1 – 2009Q4	A2
Assets / Equity EU banks	European Central Bank		Higher values mean higher European bank equity multiplier.	1996Q1 – 2020Q1	A3
Bassett et al. (2014) credit supply	Bassett et al. (2014)	Mumtaz et al. (2018)	Denotes the lending conditions survey based (controlled for demand and general state of the economy influences) bank sector supply shock. We invert the indicator to simplify interpretation. Thus, higher values indicate an expansionary credit supply shock.	1996Q1 – 2010Q4	A2
Broker dealer leverage	Miranda-Agrippino and Rey (2020)		Leverage of US broker dealers. Higher values mean higher leverage.	1996Q1 – 2012Q3	A1
East Asia cross border credit non-bank	Miranda-Agrippino and Rey (2020)		Higher values mean higher cross-border credit flows for non-bank entities in East-Asia.	1996Q1 – 2012Q3	A1
European banks leverage	Miranda-Agrippino and Rey (2020)		Leverage of large EU banks. Higher values mean higher leverage.	1996Q1 – 2012Q3	A3
Equity/Assets US very small banks	FRED		Total Equity to Total Assets, Banks with Total Assets up to $300M. Higher values mean higher leverage.	1996Q1 – 2020Q1	A3
Equity/Assets US small banks	FRED		Total Equity to Total Assets, Banks with Total Assets from $300M to $1B. Higher values mean higher leverage.	1996Q1 – 2020Q1	A3
Equity/Assets US medium-size banks	FRED		Total Equity to Total Assets, Banks with Total Assets from $1B to $10B. Higher values mean higher leverage.	1996Q1 – 2020Q1	A3
Equity/Assets US large banks	FRED		Total Equity to Total Assets, Banks with Total Assets from $10B to $20B. Higher values mean higher leverage.	1996Q1 – 2020Q1	A3

Equity/Assets US very large banks	FRED		Total Equity to Total Assets, Banks with Total Assets over $20B. Higher values mean higher leverage.	1996Q1 – 2020Q1	A3
Êuro-zone sovereign systemic stress indicator	European Central Bank		Stress indicator of Carlos Garcia-de Andoain (2018). Higher values mean higher systemic stress on sovereign bond markets.	1996Q1 – 2020Q1	A3
Gilchrist and Zakrajsek (2012) bond spread	Gilchrist and Zakrajsek (2012)	Gilchrist (2020)	The 'GZ spread' is a corporate bond spread measure, based on a large panel of below investment grade US corporate bonds. Larger spreads are linked to less favorable financing conditions, due to, i.a., larger risk premia and heightened default risk	1996Q1 – 2016Q2	A2
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 (i.e. the factor is inverted).	1996Q1 – 2019Q4	A1
Global bank leverage	Miranda-Agrippino and Rey (2020)		Leverage of a global sample of commercial banks. Higher values mean higher leverage.	1996Q1 – 2012Q3	A1
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	A1
Gross non-performing debt instruments EU banks	European Central Bank		Gross non-performing debt instruments in % of total gross debt instruments. Higher values mean higher non-performing value.	1996Q1 – 2020Q1	A3
Jermann and Quadrini (2012) credit supply	Jermann and Quadrini (2012)	Mumtaz et al. (2018)	Credit supply shock derived as innovations to the financial conditions index by Jermann and Quadrini (2012). Higher values mean beneficial credit supply shock.	1996Q1 – 2010Q2	A2
MSCI world realized volatility	Miranda-Agrippino and Rey (2020)	Datastream, own calculations	MSCI stock index realized volatility. Higher values mean increased volatility	1996Q1 – 2020Q1	A1

Mumtaz et al. (2018) news shock	Mumtaz et al. (2018)		Denotes a textual measure of credit supply similar to their approach to model changes in uncertainty. We invert the indicator to simplify interpretation. Thus, higher values indicate an expansionary credit supply shock.	1996Q1 – 2012Q4	A2
Simultaneous default of two or more large banks France	European Central Bank		Higher values mean higher probability of default of two or more large banks in France.	1996Q1 – 2020Q1	A3
Simultaneous default of two or more large banks Germany	European Central Bank		Higher values mean higher probability of default of two or more large banks in Germany.	1996Q1 – 2020Q1	A3
Simultaneous default of two or more large banks Greece	European Central Bank		Higher values mean higher probability of default of two or more large banks in Greece.	1996Q1 – 2020Q1	A3
Simultaneous default of two or more large banks Italy	European Central Bank		Higher values mean higher probability of default of two or more large banks in Italy.	1996Q1 – 2020Q1	A3
Simultaneous default of two or more large banks Spain	European Central Bank		Higher values mean higher probability of default of two or more large banks in Spain.	1996Q1 – 2020Q1	A3
Systemic important bank leverage	Miranda-Agrippino and Rey (2020)		Leverage of a global sample of other financial institutions. Higher values mean higher leverage.	1996Q1 – 2012Q3	A1
TED spread	FRED		Higher values mean higher European inter-bank market stress.	1996Q1 – 2020Q1	A2
UK cross border credit all sectors	Miranda-Agrippino and Rey (2020)		Higher values mean higher cross-border credit flows for all sectors in UK.	1996Q1 – 2012Q3	A3
UK cross border credit banks	Miranda-Agrippino and Rey (2020)		Higher values mean higher cross-border credit flows for banks in UK.	1996Q1 – 2012Q3	A3
UK cross border credit non-banks	Miranda-Agrippino and Rey (2020)		Higher values mean higher cross-border credit flows for non-banks in UK.	1996Q1 – 2012Q3	A3

US BAA-AAA spread	FRED		Higher values mean higher US bond market risk.	1996Q1 – 2020Q1	A2
VIX	FRED		Implied volatility of the S&P 500. Higher values mean increased volatility.	1996Q1 – 2020Q1	A2

Table A9: Details on endorsement variables