The importance of credit demand for business cycle dynamics

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This version: October 17, 2023
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Abstract

During 2020, liquidity demand by firms may have helped to stabilize the economy and ward off longer-run negative effects of the Corona recession. Nonetheless, the empirical macroeconomic literature is so far silent on the effect of credit demand shocks on aggregate fluctuations. This paper fills this gap. I identify a structural credit demand equation together with credit supply, aggregate supply, demand and monetary policy in a Bayesian structural VAR. The model combines informative priors on structural coefficients and multiple external instruments to achieve identification. As an additional novelty, I construct a new granular instrument for credit demand shocks from regional mortgage origination. I find that credit demand is quite elastic with respect to contemporaneous macroeconomic conditions, while credit supply is relatively inelastic. I identify an extremely large expansionary credit demand shock in 2020Q1, which pushed the US economy towards a sustained recovery, helping to avoid a stagflationary scenario in 2022. Furthermore, I document that credit demand shocks mostly drove the boom prior to financial crisis, while credit supply shocks were responsible during the crisis itself. Thus, both shocks matter for aggregate fluctuations, albeit at different times.

Keywords: Credit-driven business cycles, Granular instrument, Bayesian SVAR, Proxy VAR
JEL-Classification:

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1 Introduction

In the second quarter of 2020, the US (like many other countries around the globe) was in a severe recession due to supply-side and demand-side frictions caused by the Corona pandemic. GDP fell to around 11 percentage points below potential. At the same time, year-on-year real credit growth increased to 5.3%, higher than any quarter between 2008 and today. Such an expansion of credit during a recession differentiates the Corona pandemic from other recessions such as the financial crisis, which was marked by a slowdown of credit growth. The finance literature already notes that credit developments in 2020 can be explained by a stark increase of liquidity demand by firms (Acharya and Steffen; 2020; Li et al.; 2020). However, credit demand remains conspicuously absent from the existing empirical macroeconomic literature, which looks at the interaction between credit markets and aggregate macroeconomic developments through the lens of credit supply or unspecified credit market fluctuations.[1] This paper fills this gap.

To do so, I explicitly differentiate between credit demand and credit supply in a Bayesian structural VAR. The two credit market equations complement a common 3-variable macro model along the lines of Baumeister and Hamilton (2018). The econometric approach uses prior information on (semi-)elasticities and prior knowledge on the impact effect of shocks to directly estimate the structural form of the model (Baumeister and Hamilton; 2015). I extend this general idea even further, incorporating prior information on multiple structural shocks coming from multiple external instruments.[2] Thus, my approach makes use of many – if not most – sources of existing prior knowledge to facilitate the identification of the structural VAR model.

As my baseline, I include three instruments. The first two are standard in the literature: high frequency monetary policy surprises controlling for central bank information

[1] A non-exhaustive list of the former strand can be found in Gambetti and Musso (2017); Mumtaz et al. (2018), while the latter strand relates, for example, to Meeks (2012); Stock and Watson (2018); Furlanetto et al. (2019); Boivin et al. (2020).

[2] This approach is similar to the analysis of Nguyen (2019), who focuses on a single instrument in his paper. There have been several alternative approaches to combine traditional identification with external instruments in Bayesian VAR models (see, e.g. Caldara and Herbst; 2019; Arias et al.; 2021; Giacomini et al.; 2021; Braun and BrÃ¼ggemann; 2023). However, these do not offer the flexibility and transparency of our proposed approach.

effects (Miranda-Agrippino; 2016) for monetary policy shocks and the financial conditions index of Jermann and Quadrini (2012) for credit supply shocks. Additionally, I construct a new granular instrument (Gabaix and Koijen; 2020) for aggregate credit demand shocks. Specifically, I use microeconomic data on mortgages together with a broad set of controls to obtain a measure of unexpected idiosyncratic US county-level mortgage demand shifts. The granular nature of counties implies that shocks in large counties have an outsized and measurable effect on the national level. I find that the size-weighted national aggregate of county-level shocks – the so-called granular instrument – is about as informative as the credit supply instrument for the identification of the model.

The model provides three main results with respect to credit supply and demand. First, it indicates that credit demand is much more elastic than credit supply with respect to all variables but inflation. This implies that changes in macroeconomic conditions ceteris paribus result in shifts of the credit market equilibrium along the credit supply curve. This finding corroborates a narrative whereby endogenous shifts of credit demand explain a large share of the development on credit markets (Mian and Sufi; 2011). However, I also find a substantial role of credit demand shocks. These shocks are orthogonal to aggregate demand shocks, which I identify separately in our model. Thus, they are not related to changes in credit demand for consumption purposes (to name just one example). Instead, they might stem from changes in the liquidity needs of firms (as in the beginning of the Corona crisis, see Acharya and Steffen (2020); Li et al. (2020)) or unpredicted shifts in the mortgage demand of households as in our granular instrument. On average, credit demand shocks are nearly as important for business cycle dynamics as credit supply shocks. Credit supply and demand shocks jointly explain around 50% of the variation in output and interest rates, and 60%-80% of variation in credit market outcomes (loan growth and loan interest spreads). The contribution of credit demand shocks has been most influential during the Corona crisis, where a single expansionary credit demand shock in 2020Q2 helped the US economy to avoid a stagflation by dampening inflation in 2020 and by facilitating a faster recovery. The boom-bust cycle around the financial crisis offers a more nuanced picture: credit demand shocks mostly contributed to the boom before financial crisis, while credit supply shocks were the dominant force during the crisis. I link these findings to crucial differences in the impulse-response functions (Bernanke and Blinder; 1988). Expansionary credit supply shocks create an immediate boom. Credit demand shocks trigger a short recession on impact, but result in a more sustained boom period 1-2 years in the future.

In the following, I present the three main contributions of the paper step by step. In section 2, I construct the new granular instrument for credit demand shocks. Section 3 shows how to combine the instrument with a large set of additional prior information to identify a Bayesian structural VAR. The results of this model, in particular the distinctive features of credit demand and supply, are presented in section 4, before I conclude.

2 A new granular instrument for credit demand shocks

In order to disentangle credit demand and credit supply at the US level, I first develop a new granular instrument for credit demand shocks (Gabaix and Koijen; 2020) based on county-level mortgage data between 1996Q1 and 2016Q4. Mortgage data are attractive because they are the single most important component of aggregate credit (which I define as loans to households and nonfinancial corporations). On average they account for 68% (43%) of household (total) loans. They also feature very similar dynamics to aggregate credit growth, see Figure A.2 in Appendix B. Last, a complete dataset of all US mortgages is freely available at very disaggregated levels due to the Home Mortgage Disclosure Act. Our instrument draws value from the fact that US county sizes are highly unequal. Thus, shifts to local mortgage demand curves in large counties potentially have aggregate effects. I use a panel regression which controls for all other determinants of local mortgage market outcomes, leaving shifts of mortgage demand as the only structural explanation of the regression residuals.[3] Potential shocks resulting in these unpredicted shifts of local mortgage demand encompass, among others, local labor market shocks or unexpected changes to local zoning regulations.

[3]Opposed to estimations that maximize data fit, our residuals are not "measures of ignorance", because I explicitly do not control for contemporaneous changes in credit demand.

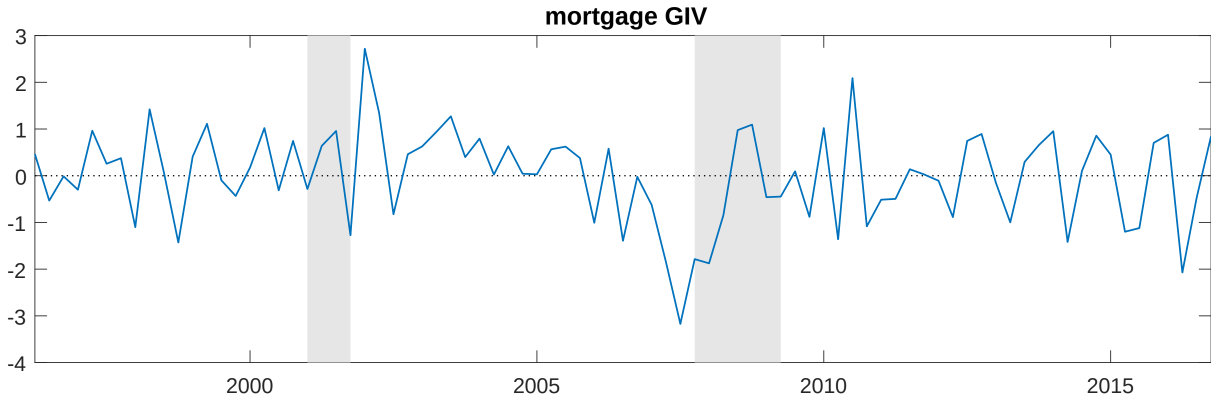

Figure 1: Granular instrument for credit demand

Figure 1 plots the time series of the granular mortgage demand instrument for the US. If relevant, the instrument would suggest that the credit demand curve experienced substantial shifts after the dot-com recession and before the financial crisis. The positive shocks after the dot-com recession may be explained by the fact that this recession was much more local than larger recessions (Baumeister et al.; 2022), allowing for a quick recovery in the worst-affected regions. The negative shifts before the financial crisis support the narrative that subprime borrowers with adjustable-rate mortgages were hit hard by rising interest rates between 2003 and 2007, triggering an unexpectedly large number of foreclosures.

The following subsections explain in more detail the panel regression I use to estimate regional mortgage demand shifts, and the features of the data I exploit to construct a granular instrument from the residuals of that regression.

2.1 Regional shifts of mortgage demand

In a first step, I obtain regional mortgage demand shifts as residuals from a panel regression of county-level mortgage origination. In this regression, I control for all influences other than county-level credit demand shocks which might affect credit market outcomes as described by our mortgage origination data. These influences include, in particular, predictable shifts of local mortgage demand curves, but also the local effects of alternative contemporaneous shocks. In particular, I run the following regression:

$$\frac{L_{it}}{\bar{L}_i} = X_{i,t-1}\beta + \alpha_i + \gamma_t + \kappa_i\eta_t + \sum_b w_{bi\tau}\lambda_{b\tau} + \epsilon_{it} \tag{1}$$

The endogenous variable L_{it} measures mortgage origination by county i and quarter t. I remove seasonal variation at the county level and express the data relative to their county-specific mean $\bar{L}_i$. The data are available through the Home Mortgage Disclosure Act, which provides single-loan data. While publicly available data only contain yearly time stamps, Neil Bhutta reports county-quarter level aggregates on his website using confidential time stamps. He restricts the sample to the 500 counties with the highest mortgage origination volume in any given year, covering around 90% of total US mortgage origination.[4]

From a theoretical perspective, mortgages are an important component of a household budget constraint. Moreover, mortgage amounts are limited by a borrowing constraint, which is a function of household credit worthiness and collateral value (see, for example, Iacoviello and Neri; 2010). These considerations inform the set of (lagged) explanatory variables $X_{i,t-1}$, which intend to capture all predictable changes of credit demand. In the baseline regression, I combine data from three different sources. First, I cover labor market outcomes through average weekly wages, total quarterly wages, the number of employed people and the number of establishments from the Quarterly Census of Employment and Wages (QCEW) by the Bureau of Labor Statistics (BLS). Second, I supplement this using income per capita and population dynamics from the Bureau of Economic Analysis (BEA). Third, house-price indices collected by the Federal Housing Finance Agency (FHFA) describe changes in household wealth.[5] Additionally, I remove the first principal component η_t with county-specific loadings κ_i (Gabaix and Koijen; 2020). There are at least two types of regional variation captured by this variable. First,

[4] For the original data and their description, see `https://sites.google.com/site/neilbhutta/data`. The definition implies that the county composition changes from year to year. The original dataset contains a total of 615 different counties. I exclude 45 counties due to low data availability (mostly because they are only present in the data for a single year). Appendix A contains additional data descriptions and robustness checks.

[5] In a robustness check, I also control for different measures of creditworthiness provided by Fannie Mae and Freddie Mac (FMFM) from 2000 onwards. Data from FHFA and FMFM are available at the 3-digit zip-code level. Appendix A describes how I transform these to the appropriate county-level data.

it accounts for local differences in the endogenous reaction of credit demand to aggregate developments, which may for example arise from differences in local wealth distributions (Favilukis et al.; 2017). Second, it captures the regionally different effects of national shocks. Important examples are credit supply shocks originating from changes in national regulation (Loutskina and Strahan; 2015), or international trade shocks with differential regional effects (Autor et al.; 2013).

County fixed effects α_i control for systematic county-level differences in mortgage origination, while aggregate (national) shocks are captured through time fixed effects γ_t. I also control for bank-level credit supply shocks through bank-year fixed effects $\lambda_{b\tau}$. I assume that the effect of bank-level shocks have on developments in county i depend on the market share of bank b in county i. The publicly available HMDA data allow us to calculate market shares $w_{bi\tau}$ at a yearly level.[6]

2.2 Exploiting granularity to construct the credit demand instrument

In a second step, idiosyncratic regional shocks $\hat{\epsilon}_{it}$ are aggregated to the national level. In this aggregation, idiosyncratic variation would cancel largely out if the 570 US counties in our sample were equal in size. However, this is not the case. Instead, Los Angeles county (the single largest county) accounts for around 5% of US mortgage originations in every single year, and the 10 largest counties combined are responsible for around 20% of US mortgages.[7] Indeed, the estimate for the Pareto rate is around 0.5 for the counties in our quarterly sample, pointing to a particularly heavy-tailed distribution of county sizes. This means idiosyncratic shocks to large counties are important for aggregate fluctuations (Gabaix; 2011).

Gabaix and Koijen (2020) show that granularity of the data is a sufficient condition for the validity of granular instruments at the national level. The granular credit demand

[6]This approach to isolate credit demand is similar to using bank-time fixed effects in a loan-level dataset (Khwaja and Mian; 2008). The scaling by market shares implies that shocks to bank b only affects counties where b has a nonzero market share. That is, I implicitly assume that the choice of banks *where* to operate is independent of *how strongly* to operate.

[7]Figure A.1 in Appendix A plots the cumulative distribution of county sizes.

instrument z_t^{cd} shown in Figure 1 is computed as the difference between the size-weighted and an equal-weighted mean of idiosyncratic regional shocks $\hat{\epsilon}_{it}$:[8]

$$z_t^{cd} = \underbrace{\sum_i \bar{L}_i \hat{\epsilon}_{it}}_{\text{size-weighted mean}} - \underbrace{\sum_i \frac{1}{N} \hat{\epsilon}_{it}}_{\text{equal-weighted mean}} . \tag{2}$$

3 Bayesian inference in a model of credit supply and demand

I model credit supply and demand as two equations of a Bayesian structural VAR (Baumeister and Hamilton; 2015). The original model identifies the full structural model via prior distributions on structural model parameters (i.e., elasticities and semi-elasticities). I extend this approach by including additional information from external instruments, one of them being the new granular instrument introduced above.

3.1 Data selection

Our structural VAR combines a model of credit supply and demand with a commonly used 3-variable macro model. Thus, it is a quarterly model with the following five variables: output gap (y_t), inflation (π_t), nominal shadow interest rates (i_t), growth rates of private debt (b_t) and spreads between loan interest rate and shadow rates (ω_t). These variables form the vector of endogenous variables $\mathbf{y}_t = (y_t, \pi_t, i_t, b_t, \omega_t)'$. I use shadow rates from Lombardi and Zhu (2018), which are based on a factor model of variables associated with a broad set of Fed policy instruments, properly capturing unconventional policy decisions by the Fed during the financial crisis and the Corona recession. In 2020Q2 and 202Q3, the shadow rate drops to -5.0% and -8.3%. From an empirical perspective, this is consistent with the unprecedented pace of bond-buying programs by the Fed. Theoretically, it matches a usual policy response to a recession as deep as during 2020.[9]

[8] In the baseline, I use average mortgage origination as weights s_i. The granular instrument is robust to the inclusion of additional controls in equation (1) and use of different weighting schemes in equation (2).

[9] I am grateful to Marco Lombardi for providing me with an update of his shadow rates. An alternative would be the Wu-Xia shadow rate, which is based on yield curves. This series is at 0.5 and 0.2 in 2020Q2

The model is identified with data from 1972Q1 to 2019Q4, while I evaluate it with data until 2023Q1. This ensures that the outsized shocks during the Corona pandemic do not distort the estimation. Results are robust if I use alternative identification periods: data prior to the financial crisis (1972-2008Q3); excluding only the immediate Corona recession (2020Q1-2020Q2); all data from 2020Q1 to 2023Q1. They remain also robust if I weigh observations in 2020Q1 to 2020Q2 by one tenth (Baumeister and Hamilton; 2019; Lenza and Primiceri; 2022) to counteract the much larger size of shocks in these three quarters. Results are also robust to using Wu-Xia shadow rates instead.

3.2 Model description

The five model equations are a Philipps curve (denoted by uppercase "s"), an aggregate demand equation ("d"), a monetary policy rule ("m"), a credit supply function ("cs") and a credit demand function ("cd"). All equations are feature contemporaneous dependencies (i.e., elasticities and semi-elasticities) and depend on $m = 4$ lags of the endogenous variables and a constant, combined in the vector $\mathbf{x}_{t-1} = \left(\mathbf{y}_{t-1}^{'}, \mathbf{y}_{t-2}^{'}, \ldots, \mathbf{y}_{t-m}^{'}, 1\right)^{'}$. Unexpected shifts of structural relationships are denoted by a structural shock u_t^*:

$$y_t = k^s + \alpha^{s,\pi}\pi_t + \alpha^{s,b}b_t + \alpha^{s,\omega}\omega_t + [\mathbf{b}^s]' \, \mathbf{x}_{t-1} + u_t^s \tag{AS}$$

$$y_t = k^d + \beta^{d,\pi}\pi_t + \beta^{d,i}i_t + \beta^{d,b}b_t + \beta^{d,\omega}\omega_t + \left[\mathbf{b}^d\right]' \mathbf{x}_{t-1} + u_t^d \tag{AD}$$

$$i_t = k^m + (1-\rho)\left[\psi^y y_t + \psi^\pi \pi_t + \psi^b b_t + \psi^\omega \omega_t\right] + [\mathbf{b}^m]' \, \mathbf{x}_{t-1} + u_t^m \tag{MP}$$

$$b_t = k^{cs} + \gamma^{cs,y}y_t + \gamma^{cs,\pi}\pi_t + \gamma^{cs,i}i_t + \gamma^{cs,\omega}\omega_t + [\mathbf{b}^{cs}]' \, \mathbf{x}_{t-1} + u_t^{cs} \tag{CS}$$

$$b_t = k^{cd} + \delta^{cd,y}y_t + \delta^{cd,\pi}\pi_t + \delta^{cd,i}i_t + \delta^{cd,\omega}\omega_t + \left[\mathbf{b}^{cd}\right]' \mathbf{x}_{t-1} + u_t^{cd}. \tag{CD}$$

To sharpen identification, I employ three external instruments: First, our own granular credit demand instrument z_t^{cd}, available from 1994Q2 to 2016Q4. Second, informationally robust monetary policy surprises, z_t^m, are provided by Miranda-Agrippino (2016) for the period 1990Q1 to 2009Q4. Third, the financial conditions index of Jermann and Quadrini (2012) serves as instrument for credit supply shocks z_t^{cs} between 1984Q2 and 2010Q2. I

and 2020Q3, which is *higher* than the actual Fed funds rate.

replace missing instrument values by zero.[10] External instruments have been introduced to structural VAR analysis in a frequentist fashion (Stock and Watson; 2012; Gertler and Karadi; 2015). However, their use has been mostly constrained by the following three disadvantages. First, the overwhelming number of applications used one external instrument to identify impulse-response functions to a single structural shock, leaving the rest of the model unidentified. Mertens and Ravn (2013) and Mertens and Montiel Olea (2018) extend frequentist identification to the case of $q > 1$ instruments for q structural shocks, albeit at the need of several additional zero restrictions in the model. The second potential problem has long come from weak (i.e., irrelevant) instruments, which has only recently been addressed by Montiel Olea et al. (2021). The third major disadvantage of the frequentist approach is that instrument validity is imposed dogmatically. As an alternative, instruments can be added to a Bayesian VAR. This has several advantages over the frequentist model. First, weak instruments are less of a problem (Caldara and Herbst; 2019). Second, additional information can be used to deal with the case of multiple instruments, and potentially identify the full structural model (?Giacomini et al.; 2021). Third, there is no need to assume instrument validity as long as the external instrument is not the only source of information in the corresponding structural equation (Nguyen; 2019).

In Bayesian SVARs, instruments are directly included in the VAR model. This has the advantage that instruments also inform the reduced-form VAR coefficients. Instruments can be included by adding additional instrument equations to the model (Caldara and Herbst; 2019; Arias et al.; 2021). However, this is counterintuitive because instruments are – in essence – external information on the structural model equations. I follow this principle and include them as exogenous variables in the VAR (Nguyen; 2019).[11] To do this, I formulate instrument equations that link the structural shocks directly to the instrument:

[10] Our main results are robust to the choice of alternative monetary policy and credit supply instruments.

[11] Paul (2020) shows for frequentist VAR models that the two-step estimator is equivalent to including the instrument as an exogenous variable in the VAR.

$$
\begin{aligned}
u_t^m &= \chi^m z_t^m + v_t^m \\
u_t^{cs} &= \chi^{cs} z_t^{cs} + v_t^{cs} \\
u_t^{cd} &= \chi^{cd} z_t^{cd} + v_t^{cd}
\end{aligned}
\tag{3}
$$

Using $\mathbf{u}_t = \mathbf{C}\mathbf{z}_t + \mathbf{v}_t$ to replace the vector of structural shocks, the full model can be expressed as a structural VAR in matrix notation

$$
\begin{aligned}
\mathbf{A}\mathbf{y}_t &= \mathbf{B}\mathbf{x}_{t-1} + \mathbf{C}\mathbf{z}_t + \mathbf{v}_t \\
\iff [\mathbf{A} \quad -\mathbf{C}] \begin{bmatrix} \mathbf{y}_t' & \mathbf{z}_t' \end{bmatrix}' &= \mathbf{B}\mathbf{x}_{t-1} + \mathbf{v}_t \\
\mathbf{v}_t &\overset{\text{i.i.d.}}{\sim} \mathcal{N}(0, \mathbf{D}).
\end{aligned}
\tag{4}
$$

The lagged structural coefficients are combined in $\mathbf{B} = \begin{pmatrix} \mathbf{b}^s & \mathbf{b}^d & \mathbf{b}^m & \mathbf{b}^{cs} & \mathbf{b}^{cd} \end{pmatrix}'$. The shocks $\mathbf{v}_t$ are assumed to follow a normal distribution with mean zero and variance $\mathbf{D}$. The combined matrix of structural contemporaneous coefficients and instrument coefficients $[\mathbf{A} \quad -\mathbf{C}]$ is defined as

$$
[\mathbf{A} \quad -\mathbf{C}] = \left[\underbrace{\begin{matrix}
1 & -\alpha^{s,\pi} & 0 & -\alpha^{s,b} & -\alpha^{s,\omega} \\
1 & -\beta^{d,\pi} & -\beta^{d,i} & -\beta^{d,b} & -\beta^{d,\omega} \\
-(1-\rho)\psi^y & -(1-\rho)\psi^\pi & 1 & -(1-\rho)\psi^b & -(1-\rho)\psi^\omega \\
-\gamma^{cs,y} & -\gamma^{cs,\pi} & \gamma^{cs,i} & 1 & -\gamma^{cs,\omega} \\
-\delta^{cd,y} & -\delta^{cd,\pi} & -\delta^{cd,i} & 1 & -\delta^{cd,\omega}
\end{matrix}}_{\mathbf{A}} \;
\underbrace{\begin{matrix}
0 & 0 & 0 \\
0 & 0 & 0 \\
-\chi_t^m & 0 & 0 \\
0 & -\chi_t^{cs} & 0 \\
0 & 0 & -\chi_t^{cd}
\end{matrix}}_{-\mathbf{C}} \right].
$$

3.3 Bayesian inference using different sources of information

Equation (4) implies that instrument coefficients $\mathbf{C}$ can be treated identical to structural contemporaneous coefficients $\mathbf{A}$. This is advantageous because the findings of Baumeister and Hamilton (2015) on the posterior distribution of structural parameters extend to this case.

Proposition 1. *If* $\mathbf{B}$ *and* $\mathbf{D}$ *follow a normal-inverse prior distribution, and if residuals are normally distributed, the posterior distribution of the model in equation* (4) *can be* *written as*

$$p\left(\mathbf{A},\mathbf{B},\mathbf{C},\mathbf{D}|\mathbf{Y}_T,\mathbf{Z}_T\right)=p\left(\mathbf{A},\mathbf{C}|\mathbf{Y}_T,\mathbf{Z}_T\right)\prod_{i=1}^{n}\left[\gamma\left(d_{ii}^{-1};\kappa_i^*,\tau_i^*\right)\phi\left(\mathbf{b}_i;\mathbf{m}_i^*,d_{ii}\mathbf{M}_i^*\right)\right].$$

Appendix C contains a proof of proposition 1, including a complete specification of the different parts of the posterior distribution. Importantly, the proposition shows that the posterior distribution $p\left(\mathbf{A},\mathbf{C}|\mathbf{Y}_T,\mathbf{Z}_T\right)$ can be sampled independently from $\mathbf{B}$ and $\mathbf{D}$, as it depends only on the data and prior distributions, which I specify in the following. The Appendix also provides a description of the Metropolis-Hastings algorithm used to sample from $p\left(\mathbf{A},\mathbf{C}|\mathbf{Y}_T,\mathbf{Z}_T\right)$, and reports convergence statistics.

3.4 Prior information on structural contemporaneous coefficients

The prior distributions for all structural contemporaneous parameters are summarized in Table 1. In nearly all cases (with the exception of interest rate smoothing ρ), I use Student t prior distributions. All priors have 3 degrees of freedom and in most cases a scale of 0.4, as in Baumeister and Hamilton (2018). I deviate from the scale only in cases where the existing literature shows particularly strong agreement (scale of 0.1) or disagreement (scale of 1). The following focuses in particular on the credit supply and credit demand equation, since coefficients in the three other equations mostly follow Baumeister and Hamilton (2018).

3.4.1 Priors on the credit supply and credit demand equation

The **credit demand curve** should be downward sloping, implying a negative sign for $\delta^{cd,\omega}$. Both theory and empirical estimates offer values in the range of $[-2,-1]$. Cúrdia and Woodford (2016) and Christiano et al. (2010) calibrate the elasticity to be -1.5 and -1.3, respectively.[12] Empirical estimates based on microeconomic data confirm these calibrations: DeFusco and Paciorek (2017) estimate a value between -1.5 and -2 using

[12]The elasticities from Cúrdia and Woodford (2016) are derived under linear intermediation costs and an intertemporal elasticity of substitution of 0.5. Their baseline model uses an intertemporal elasticity of substitution 6.25 (on average across households), which would imply model parameters that are unreasonably high for practical purposes.

Table 1: Priors for structural contemporaneous coefficients

Parameter	Meaning	Prior mode	Prior scale	Sign restrictions
	Student t distribution with 3 degrees of freedom			
$\alpha^{s,\pi}$	Effect of π on supply	2.00	0.4	$\alpha^{s,\pi} \geq 0$
$\alpha^{s,b}$	Effect of b on supply	0.80	1	
$\alpha^{s,\omega}$	Effect of ω on supply	-0.60	0.4	$\alpha^{s,\omega} \leq 0$
$\beta^{d,\pi}$	Effect of π on demand	0.75	0.4	
$\beta^{d,i}$	Effect of i on demand	-1.00	0.4	$\beta^{d,i} \leq 0$
$\beta^{d,b}$	Effect of b on demand	1.00	1	
$\beta^{d,\omega}$	Effect of ω on demand	-1.90	0.4	$\beta^{d,\omega} \leq 0$
ψ^{y}	Fed response to y	0.5	0.4	$\psi^{y} \geq 0$
ψ^{π}	Fed response to π	1.5	0.4	$\psi^{\pi} \geq 0$
ψ^{b}	Fed response to b	0.00	0.4	
ψ^{l}	Fed response to ω	0.00	0.4	
$\gamma^{cs,y}$	Effect of y on credit supply	0.10	0.1	$\gamma^{cs,y} \geq 0$
$\gamma^{cs,\pi}$	Effect of π on credit supply	0.00	0.4	
$\gamma^{cs,i}$	Effect of i on credit supply	-0.75	0.4	
$\gamma^{cs,\omega}$	Effect of ω on credit supply	0.20	1	$\gamma^{cs,\omega} \geq 0$
$\delta^{cd,y}$	Effect of y on credit demand	-0.20	0.4	
$\delta^{cd,\pi}$	Effect of π on credit demand	0.80	0.4	
$\delta^{cd,i}$	Effect of i on credit demand	-0.50	0.4	
$\delta^{cd,\omega}$	Effect of ω on credit demand	-1.50	0.4	$\delta^{cd,\omega} \leq 0$
$\chi^{m}, \chi^{cs}, \chi^{cd}$	Instrument coefficients	0	0.4	
	Beta distribution with $\alpha = 2.6$ and $\beta = 2.6$			
ρ	Interest rate smoothing	0.5	0.2	$0 \leq \rho \leq 1$

exogenous changes in nonconforming loan limits for mortgages purchased by Fannie Mae and Freddie Mac, while Karlan and Zinman (2019) uses random variations of interest rates on small business loans in Mexico to identify an elasticity of -1.1. An outlier is the DSGE-model fitted to European data by Gerali et al. (2010), which sets the elasticity to around -3. I restrict $\delta^{cd,\omega}$ to be negative, set the prior mode to -1.5. This assigns a prior probability of 15% for values of $\delta^{cd,\omega}$ below -2. For the interest rate elasticity of credit demand $\delta^{cd,i}$ there is conflicting evidence in the theoretical literature (Christiano et al.; 2010; Fiore and Tristani; 2013), and empirical estimates do not provide evidence to support either position. Therefore, I set the prior mode to zero. The modes of the remaining parameters in the credit demand curve, $\delta^{cd,y}$ and $\delta^{cd,\pi}$, are set to -0.2 and 0.8, respectively (Cúrdia and Woodford; 2016).

The **credit supply equation** in equation (CS) expresses loan growth depending on loan interest spreads and macroeconomic conditions. I would expect the semi-elasticity of loans to be positive. Christiano et al. (2010) calibrates $\gamma^{cs,\omega}$ around 0.1, consistent with empirical estimates that lie between 0.05 and 0.2 (Berger and Udell; 2004). However, Cúrdia and Woodford (2016) argues that the elasticity may be much higher if I account for intermediation costs. To reflect the considerable uncertainty, I choose a Student t prior distribution for $\gamma^{cs,\omega}$ with mode 0.2 and scale 1, which I restrict to be positive. For the elasticity of credit supply to risk-free interest rates $\gamma^{cs,i}$, the empirical literature provides strong evidence that it should be negative and in the range $[-1.5, 0]$, as lower interest rates impair bank profitability and thus loan supply (Jiménez et al.; 2012; Becker and Ivashina; 2014; Abadi et al.; 2023). I set the prior mode for $\gamma^{cs,i}$ to -0.75. For the output elasticity of credit supply $\gamma^{cs,y}$, I restrict the prior to be positive. Christiano et al. (2010), for example, argue that credit supply should shift outwards with expectations of a future boom.[13] The very precise estimates of Jiménez et al. (2012) inform a prior mode of 0.1 and a small scale of 0.1. For the last parameter in the credit supply function, the elasticity of credit supply to inflation $\gamma^{cs,\pi}$, there is no conclusive evidence in the

[13]In most theoretical macroeconomic models, current outcomes depend on expectations of future developments. As in Baumeister and Hamilton (2018), I assume that an AR(1)-process with an AR-coefficient of 0.75 provides a decent approximation of most macroeconomic time series (see also Doan et al.; 1984). I use this coefficient to replace expectations whenever I derive priors from theoretical model equations.

literature. Therefore, I center the prior distribution around 0.

3.4.2 Priors on aggregate supply, aggregate demand and the monetary policy rule

Abstracting from the possible role of loan growth and loan interest spreads, the remaining three equations are standard in the literature. Accordingly, I use the same prior distributions as Baumeister and Hamilton (2018) for $\{\alpha^{s,\pi}, \beta^{d,\pi}, \beta^{d,i}, \psi^{y}, \psi^{\pi}, \rho\}$. The two remaining coefficients $\alpha^{s,b}$ and $\alpha^{s,\omega}$ in equation (AS) describe the dependency of **aggregate supply** to loan growth and loan interest spread. Cúrdia and Woodford (2016) suggest $\alpha^{s,b} = 0.8$, as additional credit facilitates investment (see also Levine and Zervos; 1998). Higher spreads, on the other hand, should reduce aggregate supply, as both saving and borrowing becomes less attractive. To capture this, I set the mode of $\alpha^{s,\omega}$ to -0.6 and restrict it to be negative (Cúrdia and Woodford; 2016; Fiore and Tristani; 2013).

The **aggregate demand equation** (AD) consists of an IS-curve with added loan growth and interest rate spread. Tighter credit market conditions, measured by higher loan interest rates, should reduce aggregate demand of both borrowers and savers (Cúrdia and Woodford; 2016; Fiore and Tristani; 2013; Guerrieri and Lorenzoni; 2017). I set the prior mode of $\beta^{d,\omega}$ to -1.9 and restrict the coefficient to be negative. For the elasticity of aggregate demand to debt, $\beta^{d,b}$, I choose a mode of 1 and a scale of 1, as the theoretical value of the parameter is somewhat sensitive to the specification in Cúrdia and Woodford (2016).[14]

Our **monetary policy rule** is a Taylor-type rule with some degree of interest rate smoothing as in Baumeister and Hamilton (2018). In the standard Taylor rule, interest rate decisions only depend on the output gap and inflation. Thus, they imply a prior belief that the Fed will not systematically react to variations in the spread and debt levels. However, there is an active discussion of whether or not central banks should "lean against the wind" (Svensson; 2017; Gourio et al.; 2018; Adam and Woodford; 2021), and some empirical evidence that monetary policy takes credit developments into account

[14]Dropping the sign restriction on $\beta^{d,\omega}$, choosing large scales of 5 for $(\beta^{d,w}, \beta^{d,\omega})$ or restricting these two parameters to zero does not materially change results.

(Bachmann and Rüth; 2020). Therefore, I do not set a dogmatic prior of zero, but instead use a prior distribution with mode 0 and scale 0.4 for ψ^b and ψ^ω.[15]

3.4.3 Priors on instrument coefficients

The assumption of valid instruments implies that every instrument is only correlated with one of the structural shocks. This is captured by dogmatic zeros for most of the elements in $\mathbf{C}$, the matrix describing the relation between instruments and shocks. For the three coefficients in the instrument equations $(\chi^m, \chi^{cs}, \chi^{cd})$, I specify Student t distribution with a mode of 0, a scale of 0.4 and 3 degrees of freedom. This prior allows instruments to be potentially irrelevant, which would result in a posterior distribution also centered around zero.

3.4.4 Priors in impact effects of structural shocks

In addition to priors on individual structural contemporaneous coefficients $\mathbf{A}$, I add additional sources of information on the impact effect of structural shocks $\mathbf{H} = \mathbf{A}^{-1}$, see Table 2 for an overview. Priors on impulse response functions take the form of asymmetric Student t distributions as introduced by Baumeister and Hamilton (2018). In addition to the standard coefficients (mode μ_h, scale σ_h and $\nu_h = 3$ degrees of freedom), the distribution uses a parameter λ_h to affect the skewness of the overall distribution. Thus, asymmetric Student t distributions can shift probability mass towards a desired sign of an impulse-response, or even enforce sign restrictions by choosing $\lambda_h \to \pm\infty$.

I choose three types of priors: two informative priors on the reaction of variables to monetary policy shocks, five priors on the sign of impact effects of structural shocks, and a regularity prior on $\det(\mathbf{A})$. The prior likelihood of the matrix $\mathbf{A}$ is the simple sum of prior likelihoods based on the univariate distributions specified in Tables 1 and 2.

First, I put two priors on the reaction of output and the loan interest spread to a monetary policy contraction that increases interest rates by 1 percentage point (Baumeister and Hamilton; 2018). I denote these priors by $h_1 = \mathbf{H}_{(1,3)}/\mathbf{H}_{(3,3)}$ and $h_2 = \mathbf{H}_{(5,3)}/\mathbf{H}_{(3,3)}$.

[15]Shifting the prior mode of ψ^b to 2 to account for some of the empirical evidence does not affect the main results.

Table 2: Priors on impact effects of structural shocks

Prior variable	Prior description	μ_h	σ_h	λ_h	Sign
Asymmetric Student t priors with 3 degrees of freedom					
$h_1 = \frac{\mathbf{H}(1,3)}{\mathbf{H}(3,3)}$	Reaction of output gap to a 100bp increase of interest rates	-0.3	0.5	-2	
$h_2 = \frac{\mathbf{H}(5,3)}{\mathbf{H}(3,3)}$	Reaction of spreads to a 100bp increase of interest rates	-0.5	0.2	0	
$h_3 = \mathbf{H}(1,3)$	Output gap to MP shock	0	1	-5000	-
$h_4 = \mathbf{H}(2,3)$	Inflation to MP shock	0	1	-5000	-
$h_4 = \mathbf{H}(4,3)$	Loan growth to MP shock	0	1	-5000	-
$h_5 = \mathbf{H}(1,1)$	Output gap to AS shock	0	1	5000	+
$h_6 = \mathbf{H}(4,4)$	Loan growth to CS shock	0	1	5000	+
$h_7 = \mathbf{H}(5,4)$	Spread to CS shock	0	1	-5000	-
$h_8 = \mathbf{H}(4,5)$	Loan growth to CD shock	0	1	5000	+
$h_9 = \mathbf{H}(5,5)$	Spread to CD shock	0	1	5000	+
$h_{10} = \det\mathbf{A}$	Regularity condition	6	5	4	

With respect to output, I formulate the prior expectation that output should fall by roughly 0.3%. This prior can be achieved by an asymmetric Student t distribution with $\mu_{h_1} = -0.3$, $\sigma_{h_1} = 0.5$ and $\lambda_{h_1} = -2$, which skews the distribution moderately towards negative values. An incomplete pass-through of monetary policy shocks to loan interest rates implies a reaction of spreads between -1 and 0. As I observe interest rate spreads on existing loans, I choose a symmetric prior with mode $\mu_{h_2} = -0.5$ and scale $\sigma_{h_2} = 0.2$, allowing for a roughly 10% prior probability that the reaction of the spread falls on either side of the interval $[-1; 0]$.

Second, I acknowledge the vast literature on sign restrictions of impact effects. I choose five uncontroversial signs on (a) the output reaction to an aggregate supply shock (h_3), (b) the impact effect of a credit supply shock on credit market variables (h_4 and h_5) and (c) the impact effect of a credit demand shock on credit market variables (h_6 and h_7). I use asymmetric Student t distributions with $\mu_h = 0$, $\sigma_h = 1$, $\nu_h = 3$ and $\lambda_h = +/-5000$ as priors. They are rather uninformative about the actual size of the reaction, but restrict the prior distribution to be positive or negative, depending on the sign of λ_h.

Third, I impose as h_8 a regularity prior on $\det(\mathbf{A})$, which I calibrate based on the prior distribution of structural contemporaneous coefficients in Table 1 (Baumeister and Hamilton; 2018), again using an asymmetric student t distribution with a positive skewness without enforcing signs dogmatically.

3.5 Prior information on structural variances and lagged structural coefficients

I use a product of independent inverse-gamma distributions for the prior $p(\mathbf{D}|\mathbf{A})$ (Baumeister and Hamilton; 2015). The mean of the prior for d_{ii}^{-1} is given by $1/(\mathbf{a}_i'\mathbf{S}\mathbf{a}_i)$, where $\mathbf{S}$ is the variance-covariance matrix of residuals from univariate autoregressions with $m = 4$ lags for the elements of $\mathbf{y}_t$. The shape of the prior is $\kappa_i = 2$.

I use the same prior distributions of the lagged structural coefficients $\mathbf{B}$ as in Baumeister and Hamilton (2018). These priors are conditional Gaussian distributions, independent across equations i:

$$p(\mathbf{B}|\mathbf{A},\mathbf{D}) = \prod_{i=1}^{n} p(\mathbf{b}_i|\mathbf{A}, d_{ii}) = \prod_{i=1}^{n} \mathcal{N}(\mathbf{m}_i, d_{ii}\mathbf{M}_i).$$

That is, the vector $\mathbf{m}_i$ summarizes our best knowledge on the coefficients $\mathbf{b}_i$ prior to seeing the data, and $\mathbf{M}_i$ our confidence in this knowledge. As in Baumeister and Hamilton (2018), I combine two sources of prior knowledge. First, I use a Minnesota prior to incorporate our prior assumption that AR(1) processes with autoregressive coefficient $\phi = 0.75$ provide a good description of our time series (output gap, inflation, interest rates, loan growth rates and loan interest spreads).[16] Second, interest rate smoothing ρ implies an additional prior for the lagged elements in the monetary policy equation $\mathbf{b}^m$. In particular, lagged interest rates should enter with a coefficient of $\mathbf{b}_i^m = \rho$, and all other elements of $\mathbf{b}^m$ except the constant should be zero. I give this prior a weight of roughly 3 observations.

[16] See Baumeister and Hamilton (2018) for the exact specification of the Minnesota prior.

4 Results

In the following, I will document endogenous shifts of credit demand, and how unexpected credit demand shocks affect macroeconomic aggregates. Core to the identification of these structural forces is the information coming from the exogenous instruments. I will then use these insights to show that a strongly expansionary credit demand shock in 2020Q2 contributed to the medium-run recovery from the Corona recession, and disentangle the relative contributions of credit demand and supply to the boom and bust around the great financial crisis. I will focus the discussion in this section mainly on the parts of the model that are most relevant for the separation of credit demand and credit supply. The remaining model results are closely related to the ones of Baumeister and Hamilton (2018) and are presented in Appendix D.

4.1 Structural credit demand and supply equations

Figure 2 plots the posterior distribution of the four contemporaneous coefficients in the credit demand equation, $\delta^{cd,y}, \delta^{cd,i}, \delta^{cd,\pi}$ and $\delta^{cd,\omega}$. The data are quite informative about these parameters. The slope of the credit demand curve has a median of around -1.5 and is therefore much steeper than the prior. This finding extends to the role of risk-free interest rates. That is, in combination I find that credit demand is highly responsive to changes in nominal loan interest rates. Interestingly, I find credit demand to be inelastic with respect to inflation rates. A priori, I assumed in median a slightly negative output elasticity of credit demand. The posterior distribution shows this to be inconsistent with the data: credit demand seems to be procyclical rather than countercyclical. One reason may be the real debt burden of borrowers which depends positively on the development of output and which may constitute a possible borrowing constraint (Fisher; 1933). Better economic development is associated with rising asset prices, which induces households to borrow "out-of-wealth" (Bartscher et al.; 2020). Another way to rationalize the positive elasticity $\delta^{cd,y}$ is the role of aggregate demand shocks, as an expansion of aggregate demand may be credit-financed at first.

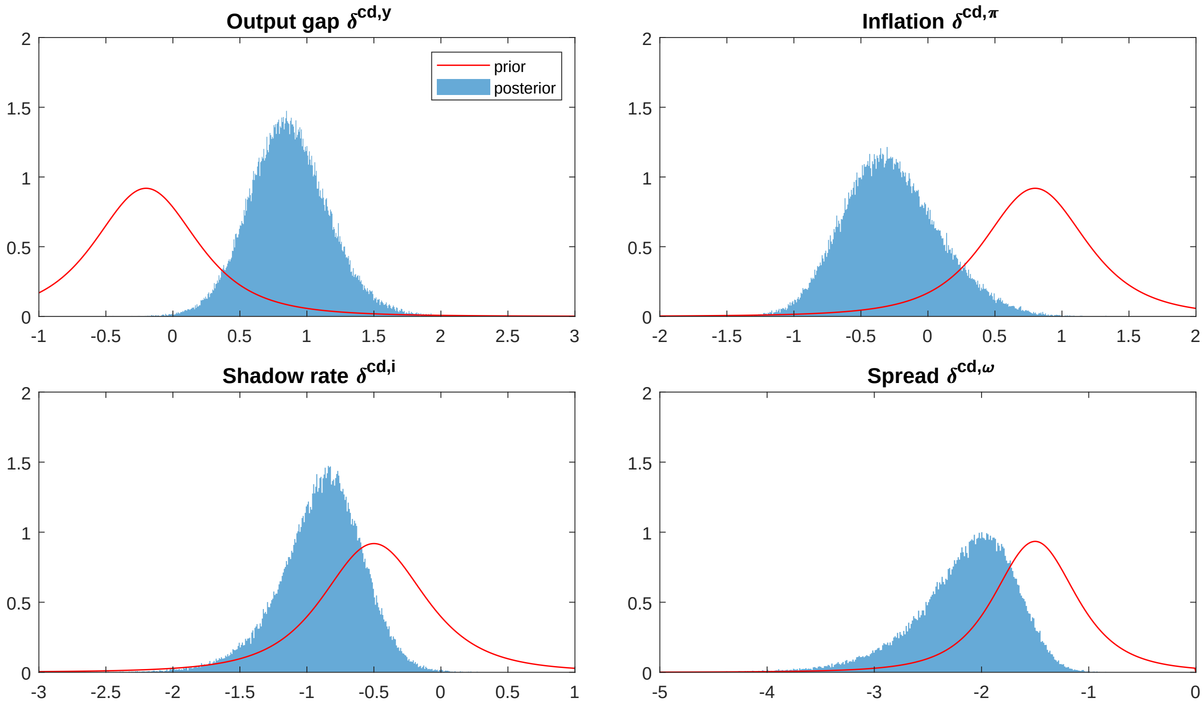

Figure 2: Contemporaneous coefficients in the credit demand equation

Note: Red dashed lines: median prior densities. Blue bars: posterior densities.

Credit supply, different to credit demand, does not seem to be very elastic, see Figure 3. This applies in particular to changes the output gap and risk-free interest rates. However, the inflation elasticity of credit supply, $\gamma^{cs,\pi}$, is strongly negative. Our results have implications for the credit market equilibrium. I find that changes in the output gap and the shadow rate shift the equilibrium along the credit supply curve, while changes in inflation imply a shift along the credit demand curve.

4.2 Credit demand shocks and their contribution to the post-2020 recovery

In 2020Q2, the US economy plunged into a deep recession, with a negative output gap of -11%, near zero inflation and a shadow rate of -5%. Given the contemporaneous elasticities, these developments should have implied a strong endogenous reduction of credit demand. Credit supply, which is fairly inelastic, should not have shifted strongly. However, opposed to that, I observe in 2020Q2 a slight uptick of loan growth by about one percentage point, and a strong increase of the loan interest spread from 3.6% to 9.3%.

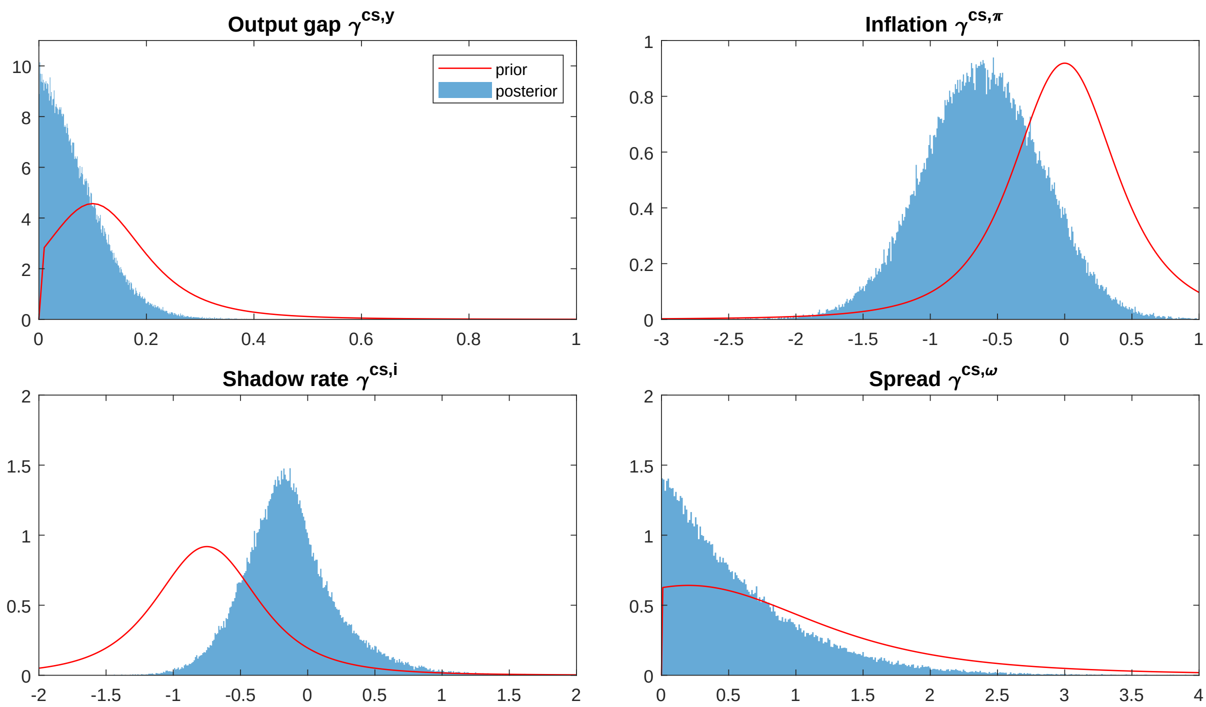

Figure 3: Contemporaneous coefficients in the credit supply equation

Note: Red dashed lines: median prior densities. Blue bars: posterior densities.

Using the baseline identification with data until 2019Q4 to predict outcomes from 2020Q1 onwards, I identify a positive credit demand shock of about 14.6% in 2020Q2 – about 13 times the usual standard deviation. Comparing standardized shocks, this shock is about 3 times as large (in absolute terms) than the second largest credit demand shock, and larger than any other structural shock in the full sample.[17] This unusually large credit demand shock did not only stabilize loan growth during a deep recession. Moreover, it contributed strongly to avoiding a stagflationary scenario in the US in 2022 and 2023. To show this, I run an experiment where I calculate the counterfactual development of endogenous variables, conditional on the credit demand shock in 2020Q2 being zero, while keeping all other structural shocks as is. I find that inflation would have been higher than observed for the whole time, with a median increase to 3.5% already in 2020 and over 7% in 2021. Cumulatively, prices would have increased by 10.9% instead of 6.7% over those two years. This would have forced monetary policy to be less accomodative than

[17] Aggregate supply and demand shocks are unusually large in 2020Q2 and 2020Q3, and I observe a large expansionary monetary policy shock in 2020Q3. Credit supply shocks, however, are not larger during the Corona recession than during previous episodes. Figure ?? in the Appendix plots time series of all structural shocks.

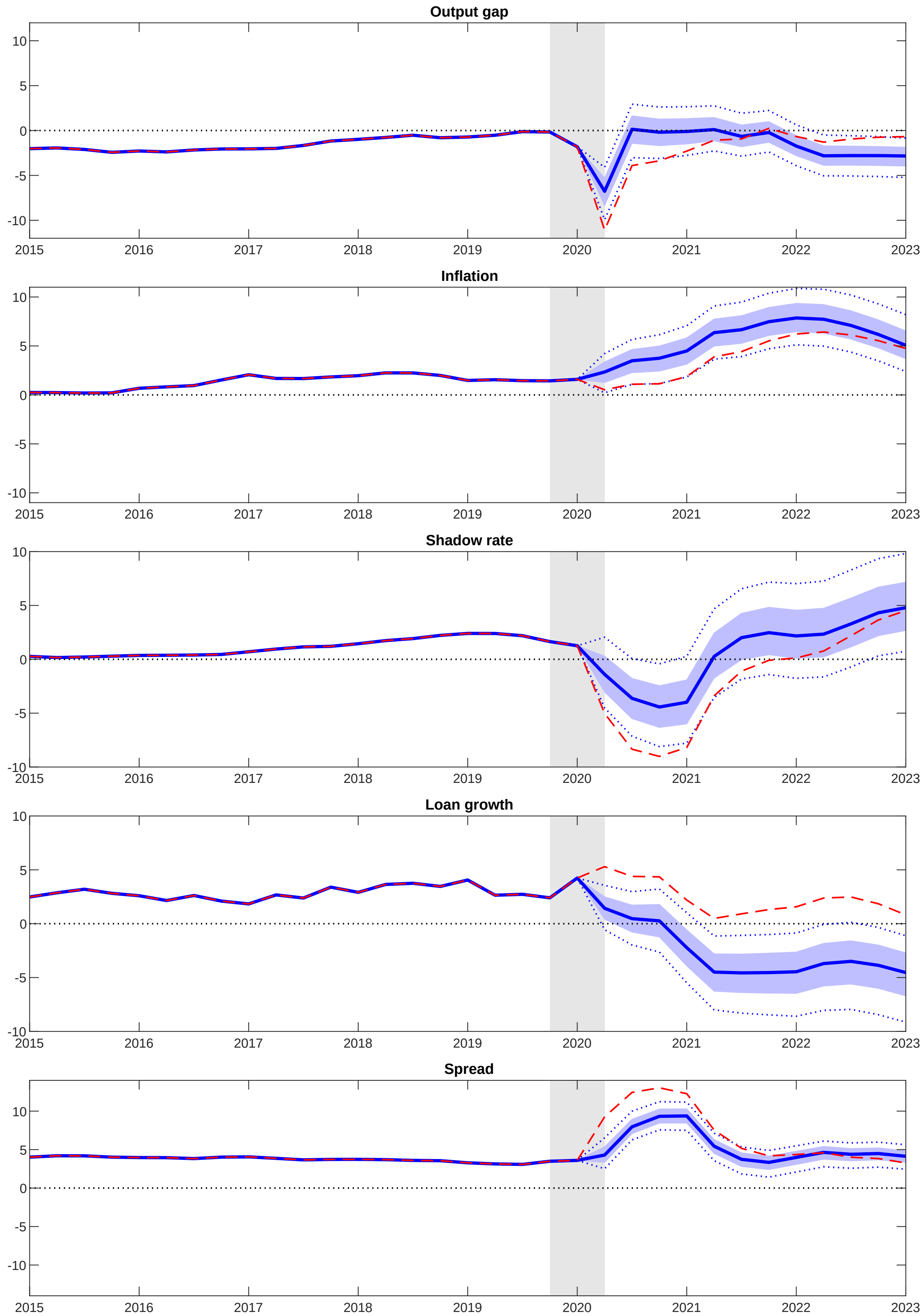

Figure 4: Counterfactual development of endogenous variables without credit demand shocks during 2020Q1-2020Q3

Note: Red dashed line: observed development of endogenous variables. Solid blue line: posterior counterfactual median. Shaded regions: 68% posterior credibility set. Dotted blue lines: 95% posterior credibility set.

observed, with a likely lift-off already in 2021Q2 or 2021Q3. Output gaps would have been very different under the counterfactual even beyond 2023. I find that the immediate Corona recession would likely have been *less* severe with a negative output gap of only -7.2%. However, the medium-run recovery would have been severely hampered, with persistently negative output gaps of -2% to -3% during all of 2022, or about -1.3% to -2% below the actual output gaps.

The positive credit demand shock, as well as the counterfactual developments, are consistent with early observations of firm behaviour during March and April 2020. Li et al. (2020) document that credit demand expanded strongly, as firms – especially those with less access to bond and equity financing (Acharya and Steffen; 2020) – drew down existing credit lines in an effort to shore up liquidity. This "dash-for-cash" was accompanied by reduced investment, which is consistent with an initial reduction of output gaps due to the 2020Q2 credit demand shock.

4.3 Impulse-response functions and shock contributions

As the 2020Q2 shock is the overwhelming driver of counterfactual developments, I can turn to impulse-response functions to get a better understanding of said developments, in particular those of counterfactual output gaps.

The model provides a very precise identification of impulse-response functions to an expansionary credit demand shock, see Figure 5. Consistent with the relatively small increase of loan growth in 2020Q1, I find that a shock of 1 percentage point only increases loan growth by 0.25% (median impact) due to general equilibrium effects. The majority of these effects stem from a short recession caused by the credit demand shock, that is followed by a boom after 1-2 years. The reason for this response lies in the endogenous negative reaction of aggregate demand to higher loan interest spreads, as shown by the posterior distribution of parameter $\beta^{d,\omega}$ in Figure D.2 in Appendix D. As output and inflation go down, the endogenous response of monetary policy implies a lower shadow rate. This somewhat mitigates the effect of credit demand on loan interest rates (rather than spreads). Yet, loan interest rates increase on average by 0.1 percentage points on

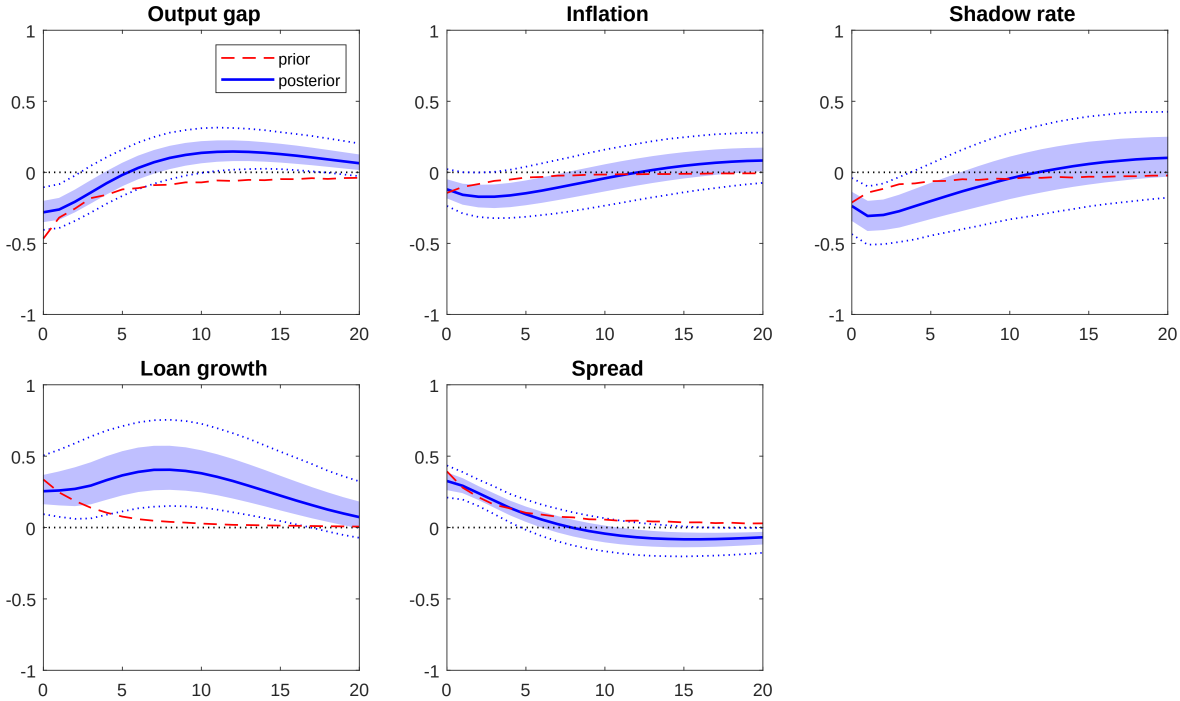

Figure 5: Impulse response function, expansionary credit demand shock

Note: Solid blue line: posterior median. Shaded regions: 68% posterior credibility set. Dotted blue lines: 95% posterior credibility set.

impact. These impulse response functions are in line with the theoretical predictions of Bernanke and Blinder (1988); Kaplan et al. (2014). However, the negative impact on output gaps contradicts the assumption of Gambetti and Musso (2017) that impulse-response functions of credit and aggregate demand shocks should be similar. However, their argument – although not specifically spelled out – seems to relate to credit-financed aggregate demand rather than to orthogonal credit demand shocks as in our case.

The impulse-response function to a credit supply shock is similarly well defined. The initial shock increases loan growth much stronger on impact than a credit demand shock. The reason for this is the relative inelasticity of the credit supply curve. The shock triggers a boom in output and a very persistent price increase, which in turn leads to higher interest rates. Although this reaction is less precisely identified, it is interesting that the reaction is substantially stronger than for credit demand shocks. The reason is that monetary policy endogenously reacts contractionary to both the economic boom and the increase in loan growth (as in Caldara and Herbst; 2019; Bachmann and Rüth; 2020, see also Figure D.3 in Appendix D). Last, I find a very persistent negative reaction

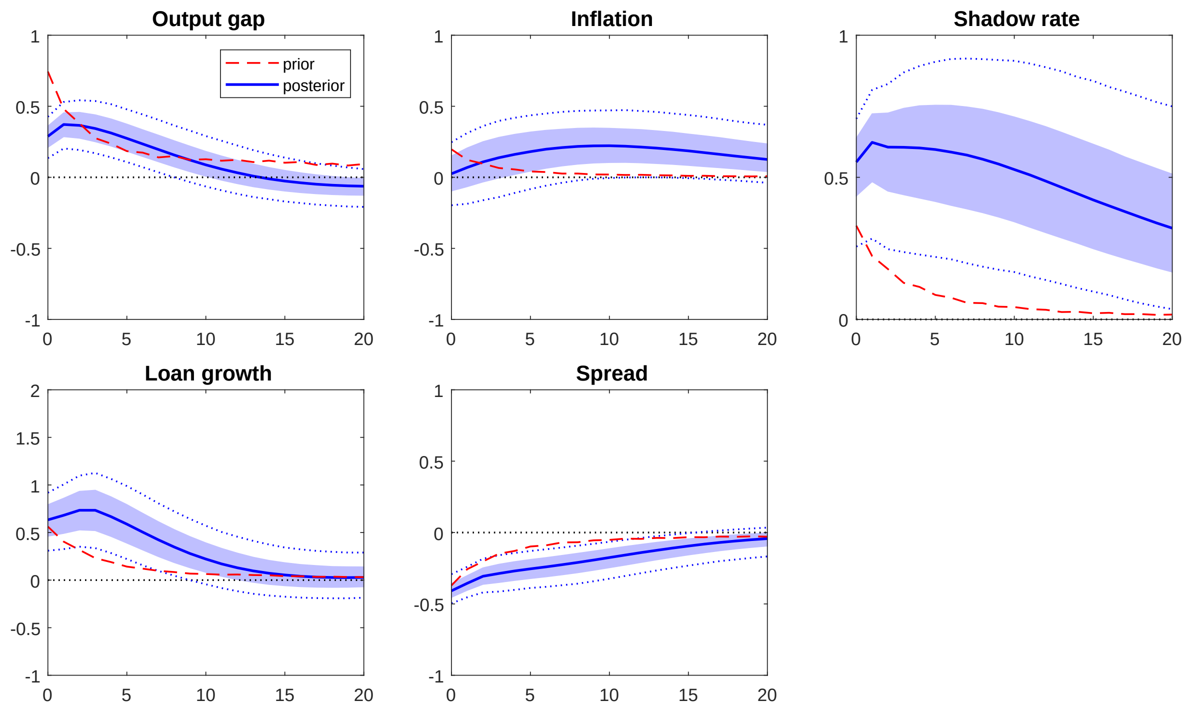

Figure 6: Impulse response function, expansionary credit supply shock

Note: Red dashed line: prior median. Solid blue line: posterior median. Shaded regions: 68% posterior credibility set. Dotted blue lines: 95% posterior credibility set.

of the loan interest spread. In total, these responses confirm findings from the previous literature (Gambetti and Musso; 2017; Mumtaz et al.; 2018).

The impulse-responses in Figures 5 and 6 show that equal-sized credit demand and supply shocks have similarly large effects on the aggregate economy. This raises the question whether these shocks are equally important for business cycle dynamics, and when this has been the case in the past. Table 3 shows that credit supply and credit demand shocks jointly account for around 40% of the variation of output two years after the initial shock, for 55% of the variation of shadow rates and for around 70% to 80% of the variation of credit market variables (the contribution to the forecast error variance is fairly constant from then on). Credit supply shocks are in general more important, however, credit demand plays a sizeable role.

Historical decompositions show if there are specific periods during which credit supply or credit demand are particularly important. Beyond the Corona recession discussed above, the time around the financial crisis is of particular interest in this regard, see Figures 7 and 8. Consistent with the forecast error variance decomposition, the contribution

Table 3: Forecast error variance decomposition to different shocks after 8 quarters

	supply	demand	mon. policy	credit supply	credit demand
Output gap	20.66%	17.46%	14.66%	30.20%	11.47%
	(9.37%, 34.42%)	(10.32%, 28.48%)	(6.52%, 25.31%)	(21.52%, 39.00%)	(6.36%, 18.66%)
Inflation	53.35%	14.26%	7.19%	8.77%	7.80%
	(38.53%, 67.21%)	(7.01%, 24.80%)	(2.09%, 15.67%)	(2.54%, 24.30%)	(1.97%, 18.08%)
Shadow rate	4.24%	23.49%	9.00%	48.38%	8.47%
	(0.77%, 12.77%)	(11.61%, 40.00%)	(5.43%, 16.42%)	(28.46%, 64.80%)	(3.16%, 17.51%)
Loan growth	22.33%	2.56%	3.30%	47.17%	16.76%
	(7.52%, 41.87%)	(0.63%, 8.10%)	(0.77%, 10.25%)	(29.07%, 65.53%)	(8.22%, 28.66%)
Spread	2.34%	4.42%	9.00%	54.31%	26.09%
	(0.62%, 7.07%)	(1.64%, 10.78%)	(5.39%, 14.01%)	(42.69%, 64.80%)	(17.24%, 35.85%)

Note: Median forecast error variance decomposition of endogenous variables to structural shocks $\mathbf{u}_t$ after 8 quarters. Numbers in brackets indicate 95% confidence sets.

of credit supply shocks tracks most endogenous well for most of the time. However, the boom years before the financial crisis, especially from 2003 onwards, are characterized by a strong positive contribution of credit demand shocks to credit growth and the output gap. That is, I find that credit demand shocks were important for the strong increase in credit volumes before the financial crisis. The crisis itself is again dominated by negative shocks to credit supply.

4.4 The importance of instruments

Figure 9 plots the posterior distribution of the instrument coefficients. All three instruments seem to be similarly relevant with more than 90% of the posterior distribution being positive. Moreover, the distribution of χ^{cd} is robust to alternative monetary policy or credit supply instruments.

In general, this is an indication that our instruments are relevant for the structural shocks (Nguyen; 2019).

Formally, I can estimate marginal data densities to gauge the relevancy of the instruments, which indicate that the model with instrument barely outperforms the model without.[18] However, instrument relevancy in our Bayesian model is likely to suffer if the instrument is missing for extended periods of time (as is the case here). To overcome this, I could for example use Romer-Romer type instruments from Coibion et al. (2017)

[18]Direct estimations as in Nguyen (2019), and a comparison via Savage-Dickey density ratios (Verdinelli and Wasserman; 1995) produces similar results.

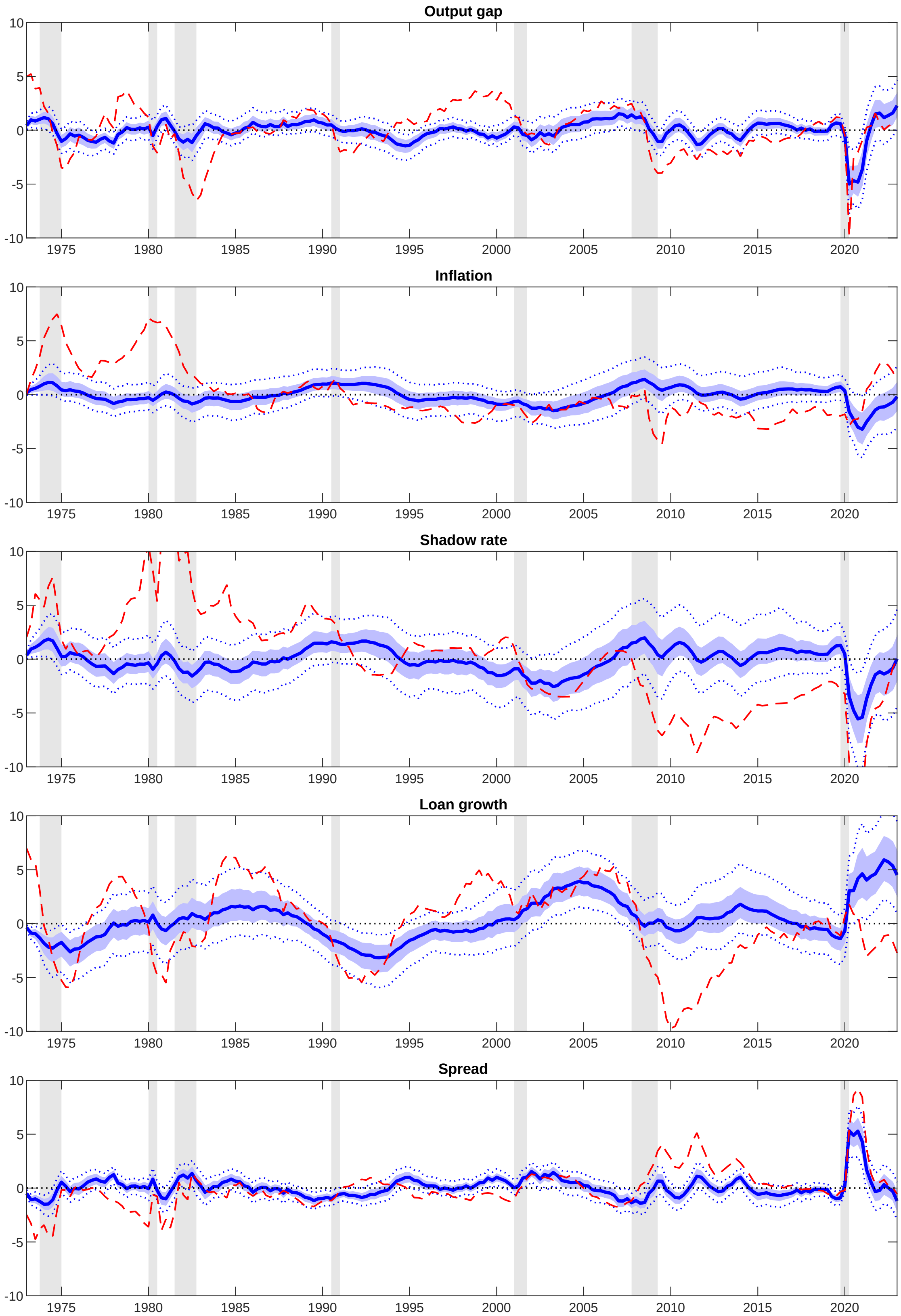

Figure 7: Historical decomposition, contribution of credit demand shocks

Note: Red dashed line: observed data (demeaned). Solid blue line: posterior median. Shaded regions: 68% posterior credibility set. Dotted blue lines: 95% posterior credibility set. Recession bars in gray.

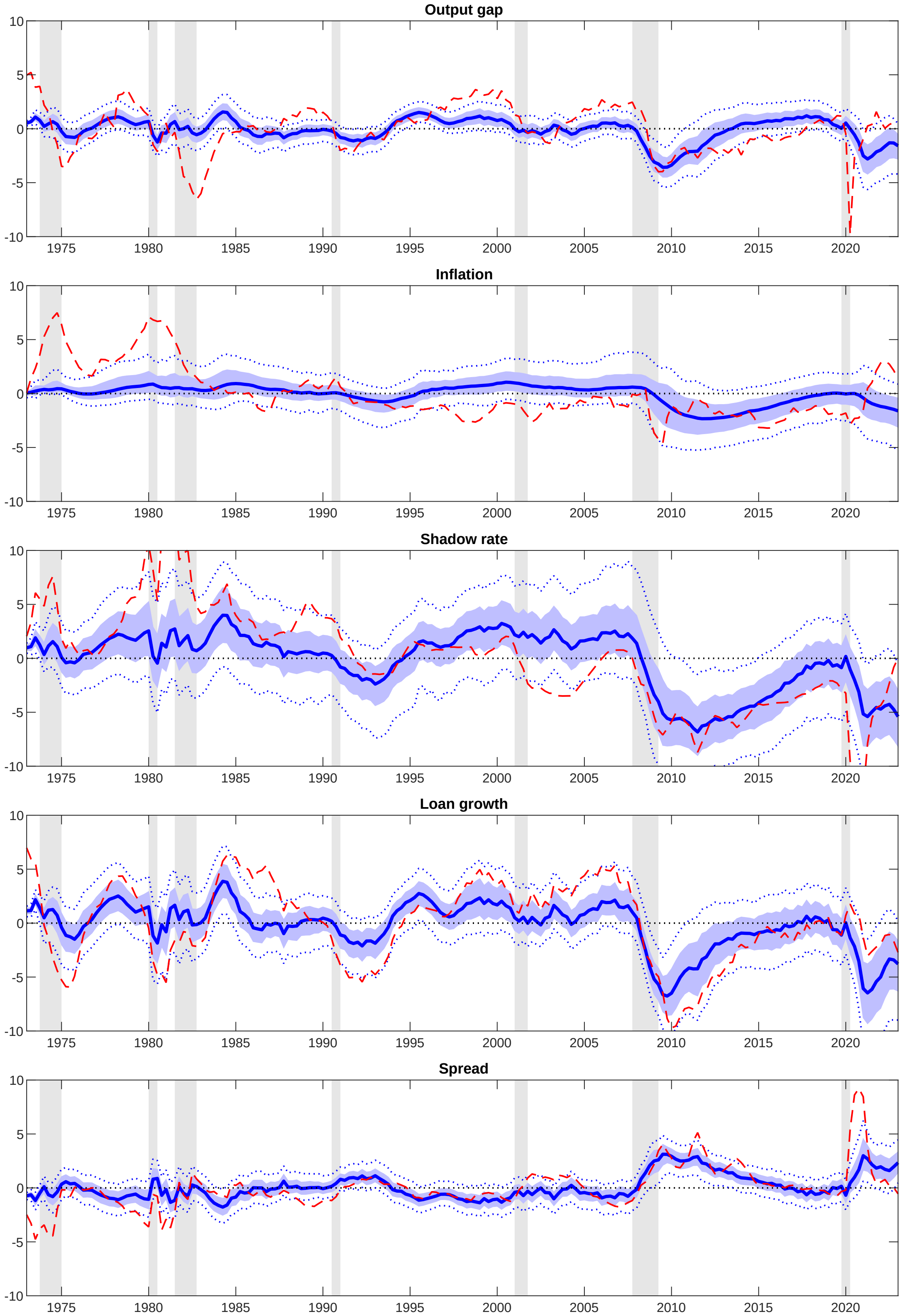

Figure 8: Historical decomposition, contribution of credit supply shocks

Note: Red dashed line: observed data (demeaned). Solid blue line: posterior median. Shaded regions: 68% posterior credibility set. Dotted blue lines: 95% posterior credibility set. Recession bars in gray.

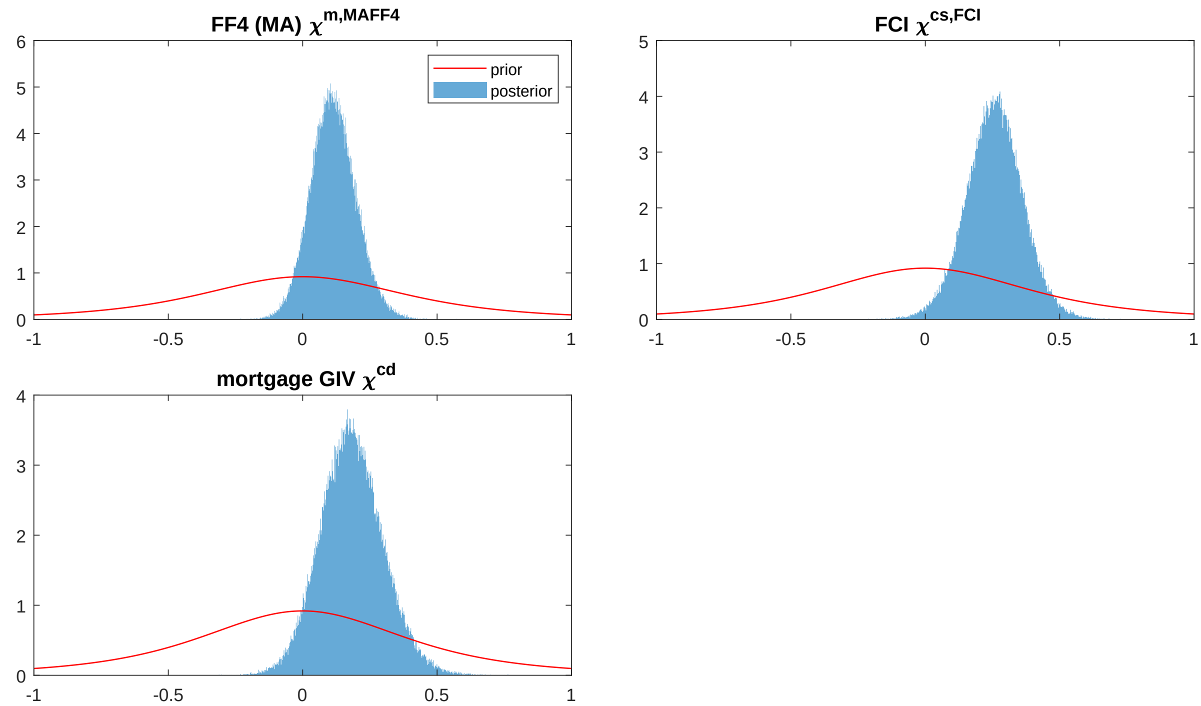

Figure 9: Instrument coefficients

Note: Red dashed lines: median prior densities. Blue bars: posterior densities.

for monetary policy shocks instead, which are available from 1972Q1 to 2008Q4. Results indicate a highly relevant monetary policy instrument, albeit at the cost of a price puzzle, see Figures D.9 and D.10 in Appendix D and discussions by Barakchian and Crowe (2013) and Ramey (2016). All results concerning credit demand and credit supply remain robust.

To illustrate this issue further, I re-estimate the model with data from 1994Q2 to 2016Q4 (the availability of the credit demand instrument). The baseline results remain qualitatively robust. The smaller data sample increases estimation uncertainty, especially for structural lag coefficients, and thereby increases the size of credibility sets of impulse response functions. Yet, instrument coefficients are more precisely estimated, see Figure D.11 in Appendix D, and Savage-Dickey density ratios indicate individual log Bayes factors of 6 and 2 for the credit supply and credit demand instrument. According to Jeffrey's criteria (Kass and Raftery; 1995, as in), this provides "strong" and "positive" evidence against the alternative model without the respective instrument.

5 Conclusion

In this paper, I shed additional light on the importance of credit market developments for macroeconomic fluctuations by explicitly differentiating between credit demand and credit supply. I find that shocks to both structural equations are important for aggregate developments. Credit demand shocks mattered in particular during the boom before the financial crisis and during the Corona recession. I find that an expansionary credit demand shock in 2020Q2 mitigated the longer-run negative impacts of the Corona recession. It strongly contributed to a balanced output gap in the end of 2021, thereby helping to stave off a stagflationary scenario in 2022. This result underscores the importance of policy tools that aim to support credit demand in times of crises, and measures that try to reduce the size of credit bubbles fueled by excessive demand.

To show this core result, I introduce two additional novelties to the literature. First, I extend Bayesian structural VARs (Baumeister and Hamilton; 2015) to the case where multiple instruments provide information for the identification of multiple structural shocks. Second, I are the first to develop a new granular instrument (Gabaix and Koijen; 2020) for credit demand shocks based on the variation of mortgages across time and US regions.

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A Granular instrument for credit demand

In this appendix, I describe in detail our approach to construct the granular instrument for mortgage demand. In the next subsections, I first describe the sources of our data explain how I transform them to the county-quarter level needed for our analysis, and then describe the estimation approach to derive the regional credit demand shocks from the panel model (see equation (1) in the main text)

$$\frac{L_{it}}{\bar{L}_i} = X_{i,t-1}\beta + \alpha_i + \gamma_t + \kappa_i \eta_t + \sum_b w_{bi\tau}\lambda_{b\tau} + \epsilon_{it}$$

A.1 Regional data

A.1.1 Regional mortgage origination

I derive our granular instrument from county-level mortgage originations. Data on these are provided through the Home Mortgage Disclosure Act (HMDA). By law, financial institutions need to report all mortgage applications and originations on a single-loan level. Publicly available information on these loans covers the year, county and bank ID of every loan. In addition, Neil Bhutta – using confidential information on the exact date of application or origination – provides total loan origination by county and month between 1994 and 2016 on his website.[19] I use only mortgages that are used for home purchases, and drop those that refinance an existing mortgage. His data cover the top 500 counties in a given year in terms of total mortgage originations. These counties are on average responsible for around 90% of US mortgage originations for home purchases. Figure A.1 shows the empirical cumulative density function of average mortgage shares, relative to the US for all counties, displaying the counties in our quarterly sample in red.

There are a few "borderline" counties which are not continuously among the 500 largest ones. I drop counties for which I only have one or two years of continuous observations. These observations account for an average of 0.3% of total mortgage originations. In

[19] The data from HMDA are available through the Consumer Financial Protection Bureau `https://ffiec.cfpb.gov/`. The aggregation of the confidential data to the county level are available at `https://sites.google.com/site/neilbhutta/data`.

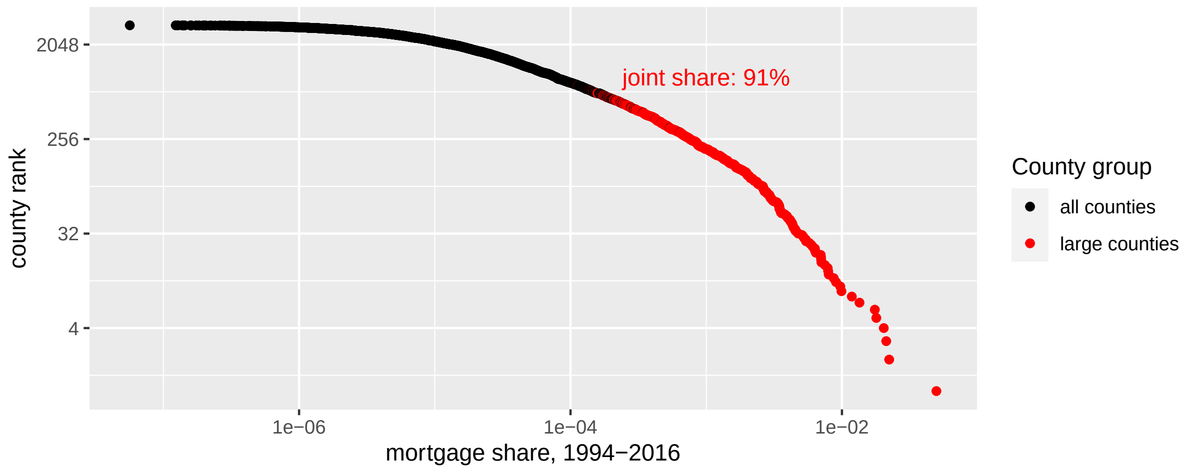


Figure A.1: Log-log plot of county mortgage share distribution

Note: The plot can be read as an inverse cumulative distribution of mortgage shares. It reports the share of county-level mortgage origination relative to the US aggregate (averaged over years) on the horizontal axis and the county rank in the overall distribution on the vertical axis. Black dots refer to all counties from the publicly available yearly HMDA-datasets. Red dots refer to large counties provided by Neil Bhutta in his quarterly county-level aggregates.

a second step, I remove seasonal variation in loan originations for every county and normalize loan originations L_i by dividing through the . The final dataset contains 40'229 county-quarter observations.

A.1.2 Control variables

Household mortgage demand is driven by two main forces. First, mortgages are used to finance the acquisition of a house (and consume housing services). Second, they allow households to extract wealth increases from rising house prices for purposes of consumption smoothing (Bartscher et al.; 2020). Thus, mortgage demand should be affected both by the budget and the borrowing constraint. The following describes the definition of all control variables combined in $X_{i,t-1}$. Table 4 reports summary statistics of all variables, while Table 5 reports on the data sources. In the panel regression, I add both the level and the year-on-year growth rates of most control variables. All controls are lagged by one quarter.

I use data derived from the population and personal income statistics by the BEA to control for income per capita and population growth, which are available yearly for counties and quarterly for states. I use the quarterly state-level information of aggregate

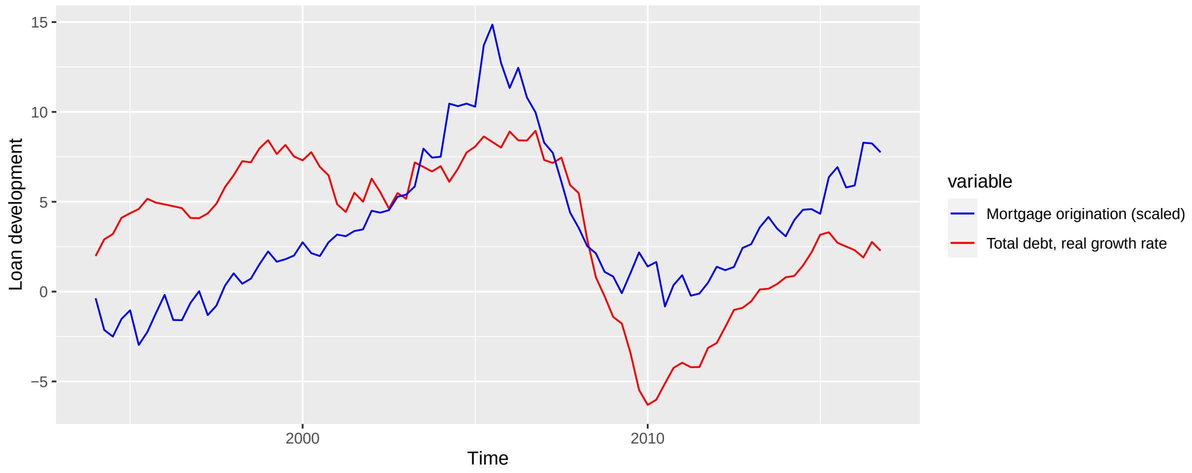


Figure A.2: US real loan volume growth and mortgage origination

Note: The figure compares the real growth rate of loans to households and nonfinancial corporations (used as endogenous variable in the structural VAR) to the aggregate of county-level mortgage originations (used in the construction of the granular instrument). County-level mortgage originations are scaled to be comparable to the real growth rate of loans.

personal income ($inc_{\iota t}$) to construct quarterly personal income per capita ($inc(p.c.)_{it}$) and population (pop_{it}) for all the counties in the state. Let t be the quarters in year τ, and i the counties in state ι:

$$inc(p.c.)_{it} = \frac{inc_{\iota t}}{\sum_{t\in\tau} inc_{\iota t}} inc(p.c.)_{i\tau}, \qquad pop_{it} = \frac{pop_{\iota t}}{\sum_{t\in\tau} inc_{\iota t}} pop_{i\tau} \tag{5}$$

I combine the above data with information from the Quarterly Census of Employment and Wages (QCEW), in particular average weekly wages, total quarterly wages, the number of employed people and the number of establishments. For these four variables, I remove seasonal variation in every county. Afterwards, I express quarterly wages, employed people and number of establishments in per capita terms. All controls based on BEA and BLS data are available for the full sample of mortgages.

As a third source of information, I make use of publicly available information on housing markets provided by the Federal Housing Finance Agency (FHFA) and Fannie Mae and Freddie Mac (FMFM). The FHFA provides a quarterly house price index at a 3-digit zip-code level, based on sales and appraisals of houses with mortgages insured by FMFM. The house-price index allows us to control for the wealth-channel described above. FMFM report the interest rate as well as different measures of credit-worthiness (fico scores, debt-service-to income ratios and loan-to-value ratios) for all loans they purchase. I aggregate their single-loan information on a 3-digit zip code level (the smallest regional aggregation) for every quarter and remove seasonality from all data for every 3-digit zip code. There are three limiting features on these data. First, data by FMFM start only in 2000Q1. Thus, I include these controls only in a robustness check, finding no differences in the resulting aggregate granular instrument. Second, only around 25% of our mortgages are purchased by FMFM. However, it is probably reasonable to assume that any systematic difference between the loan portfolio purchased by FMFM and the overall sample can be captured by fixed effects. Third, data are at a zip-code and not on the county-level. To match these data, I distribute the information from zip code j according to population shares over all counties i that it covers. Let s_{ji} denote the share of the population in zip code j living in county i.[20] Let v_{jt} denote any of the variables reported by FMFM or FHFA in zip-code j and quarter t. Then the corresponding value v_{it} in county i is the weighted mean with weights s_{ji}:

$$v_{it} = \frac{1}{\sum_{\text{zip codes } j} s_{ji}} \sum_{\text{zip codes } j} s_{ji} v_{jt} \,,\; v \in \{rate, fico, dsti, ltv, hpi\} \tag{6}$$

Here I make the implicit assumption that variable v does not vary systematically across zip code j. This should be acceptable as the large counties in our dataset usually encompass (near-)complete zip codes, and should therefore be less affected than the smaller counties which are not part of our data.

In addition to the control variables mentioned above, our data allow us to remove the influence of bank-level credit supply shocks. To do so, I calculate the market share $w_{bi\tau}$ of bank b in county i in year τ using the publicly available loan-level HMDA data (which contain information about banks). Given these market shares, model the influence of a credit supply shock to bank b in year τ on mortgage development in county i as $w_{bi\tau}\lambda_{b\tau}$. Here, $\lambda_{b\tau}$ is a bank-year fixed effects that captures the idiosyncratic credit supply shock. This model rests on the assumption that a credit supply shock at bank b changes the

[20] I use time-invariant shares from the 2010 census, as provided by the 2018 version of the Geocorr project of the Missouri Census Data Center.

Table 4: Variables, summary statistics

Statistic	N	Mean	St. Dev.	Min	Max
$mortgages.pc$	45'572	671.27	471.13	53.36	7'533.06
$wages.w$	45'572	714.97	207.10	275.08	3'719.61
$\Delta wages.w$	45'572	3.06	4.57	−80.90	484.28
$wages.q.pc$	45'572	4'137.23	2'412.61	553.19	52'185.85
$\Delta wages.q.pc$	45'572	3.36	7.38	−90.07	1'113.10
$inc.pc$	45'572	36'191.29	12'437.40	11'014.86	168'269.00
$\Delta inc.pc$	45'572	3.63	3.29	−26.46	72.48
Δpop	45'572	1.33	1.85	−54.30	18.49
$employment.pc$	45'572	0.43	0.13	0.13	1.57
$\Delta employment.pc$	45'572	0.26	2.89	−43.15	144.56
$est.count.pc$	45'572	0.03	0.01	0.01	0.08
$\Delta est.count.pc$	45'572	0.45	3.03	−27.19	103.65
hpi	43'592	161.27	45.43	85.92	435.08
Δhpi	41'612	3.52	6.46	−38.93	43.54
$irate$	35'672	5.56	1.30	3.14	8.82
$fico$	35'672	743.26	17.75	638.19	785.19
$dsti$	35'672	34.41	2.44	16.59	44.52
ltv	35'672	78.77	3.99	43.08	91.17

credit supply in all regions proportional to the engagement of bank b in that region. That is, an increase in credit supply by 10% has the same *relative* effect in all counties. Implicit in this assumption is that a shock to bank b only affects regions where b is already active (where the market share $w_{bi\tau}$ is nonzero) – that is, I assume that the choice of banks *where* to operate is independent of *how strongly* to operate. The sum $\sum_b w_{bi\tau}\lambda_{b\tau}$ thus models the joint effect of shocks to all banks which are active in county i in year τ.

A.2 Panel estimation of regional mortgage demand

Our estimation proceeds in three steps. First, I remove the fixed effects through within transformation, where I introduce a minor adaptation to estimate bank-year fixed effects, as these do not correspond directly to the county-quarter level of analysis. Second, I regress the within-transformed mortgage origination on the set of economic controls. Third, I remove the first principal component from the residual of the second-step regression. The remaining residual is then interpreted as a idiosyncratic mortgage demand shocks. The following explains all steps in more detail.

Table 5: Variables and data sources for the estimation of regional credit demand

variable	time coverage	source	level	yoy growth
		Variable of interest		
Mortgage origination, per capita	1994Q1-2016Q4			
		BEA data*		
Employment, per capita	1990Q1-2019Q4	BEA	X	X
Population	1990Q1-2019Q4	BEA		X
		BLS-QCEW data		
Total quarterly wages, per capita	1990Q1-2020Q2	BLS	X	X
Average weekly wage	1990Q1-2020Q2	BLS	X	X
Establishment count, per capita	1990Q1-2020Q2	BLS	X	X
Personal income, per capita	1990Q1-2019Q4	BLS	X	X
		FHFA/FMFM data**		
House price index	1995Q1-2020Q3	FHFA	X	X
Interest rate new mortgages	2000Q1-2019Q2	FMFM	X	
Credit score	2000Q1-2019Q2	FMFM	X	
Debt-service to income ratio	2000Q1-2019Q2	FMFM	X	
Loan-to-value ratio	2000Q1-2019Q2	FMFM	X	

Notes: * County-level data are interpolated from yearly data using state-quarter information on total personal income. ** Data are originally at the 3-digit zip code level.
Sources: Mortgage origination for the 500 largest counties comes from Neil Bhuttas website `https://sites.google.com/site/neilbhutta/data`; BEA data are from `https://www.bea.gov/data/gdp/gdp-county-metro-and-other-areas`; BLS-QCEW data are from `https://www.bls.gov/cew/downloadable-data-files.htm`; FHFA data are from `https://www.fhfa.gov/DataTools/Downloads/Pages/House-Price-Index.aspx`; FMFM data are from `https://loanperformancedata.fanniemae.com/lppub/` and `http://www.freddiemac.com/research/datasets/sf_loanlevel_dataset.page`.

Let $\hat{\nu}_{it} = \kappa_i \eta_t + \epsilon_{it}$ be the residuals from the estimation of equation (1) before accounting for the role of principal components $\kappa_i \eta_t$. To deal with the comparatively large number of fixed effects, I perform multiple within transformations. For the within transformation of any regression variable v_{it} with respect to the bank-year fixed effects $\lambda_{b\tau}$, I use the fact that market shares in a given county sum to one across banks, $\sum_i w_{bi\tau} = 1$. Let us define bank-year means $\bar{v}_{b\tau}$ of variable v over the regions $j \in N_{b\tau}$ in which bank b is active in year τ:

$$\bar{v}_{b\tau} := \frac{\sum_{j \in N_{b\tau}, t \in \tau} v_{jt}}{4|N_{b\tau}|}$$

Taking the weighted sum of bank-year means $\bar{\cdot}$ over banks b active in county i in year τ, I get

$$\begin{aligned} \sum_b w_{bi\tau} \bar{y}^b_{b\tau} &= \sum_b w_{bi\tau} \left[\bar{X}_{b\tau}\beta + \bar{\alpha}_{b\tau} + \bar{\gamma}_{b\tau} + \bar{\lambda}_{b\tau} + \bar{\epsilon}_{b\tau} \right] \\ &= \sum_b w_{bi\tau} \left[\bar{X}_{b\tau}\beta + \frac{\alpha_i}{|N_{b\tau}|} + \frac{\gamma_t}{4} + \lambda_{b\tau} \right] \end{aligned} \tag{7}$$

The difference between equation (1) and equation (7) removes bank-year fixed effects:[21]

$$\begin{aligned} y_{it} - \sum_b w_{bi\tau} \bar{y}_{b\tau} &= \left[X_{it} - \sum_b w_{bi\tau} \bar{X}_{b\tau} \right] \beta + \left[1 - \sum_b \frac{w_{bi\tau}}{|N|_{b\tau}} \right] \alpha_i + \left[1 - \sum_b \frac{w_{bi\tau}}{4} \right] \gamma_t + \epsilon_{it} \\ &= \left[X_{it} - \sum_b w_{bi\tau} \bar{X}_{b\tau} \right] \beta + \left[1 - \sum_b \frac{w_{bi\tau}}{|N|_{b\tau}} \right] \alpha_i + \frac{3}{4}\gamma_t + \nu_{it}. \end{aligned}$$

Removing time and region fixed effects through further within transformations is standard. In the second step, I estimate the within-transformed panel regression. The resulting coefficient estimates for control variables are reported in Table 6. In the third step, I remove the first principal component η_t and its loading κ_i from ν_{it}. The remaining residuals $\epsilon_{it} = \nu_{it} - \kappa_i \eta_t$ are thus free of predictable changes of credit demand (controls X_{it}), aggregate shocks (the fixed effects), bank-specific credit supply shocks (bank-year

[21] This can be thought of as a within transformation at the county-bank-quarter level, aggregated over banks.

fixed effects) and aggregate shocks with region-specific effects (the first principal component).

Table 6: Regression results for equation (1)

	Dependent variable:
	mortgage origination
mortgage origination (lag)	0.954^{***}
	(0.002)
wages.w	0.0002^{***}
	(0.00005)
Δ*wages.w*	0.0002
	(0.001)
wages.q.pc	0.00001^{*}
	(0.00000)
Δ*wages.q.pc*	-0.001^{*}
	(0.001)
inc.pc	-0.00000
	(0.00000)
Δ*inc.pc*	0.001^{***}
	(0.001)
Δ*pop*	0.001
	(0.001)
employment.pc	-0.023
	(0.073)
Δ*employment.pc*	-0.0002
	(0.001)
est.count.pc	0.464
	(1.027)
Δ*est.count.pc*	0.0001
	(0.001)
hpi	-0.001^{***}
	(0.0001)
Δ*hpi*	0.006^{***}
	(0.0003)
irate	-0.000
	(0.001)
Observations	40, 229
County fixed effects	TRUE
Quarter fixed effects	TRUE
Bank-year fixed effects	TRUE
R^2, within	0.966
R^2, overall	0.994
Note:	*p<0.1; **p<0.05; ***p<0.01

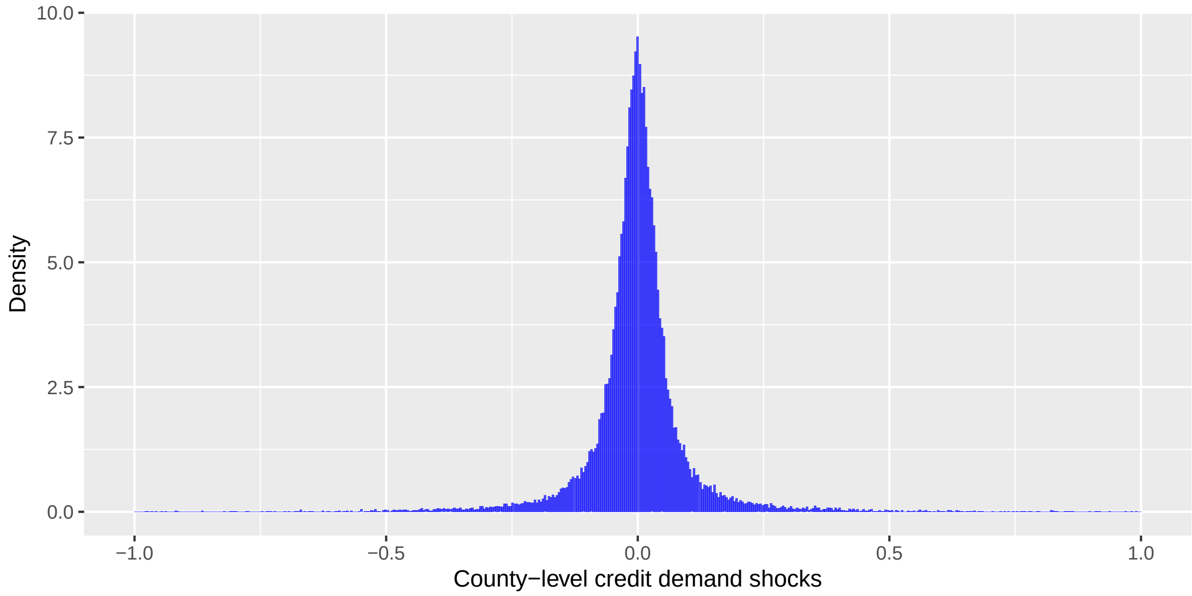


Figure A.3: Histogram of county-level mortgage demand shocks

Note: The histogram refers to residuals from regression (1).

A.3 Construction of the GIV

Figure A.3 shows the histogram of residuals of regression 1, which is our main object of interest. These residuals capture unpredictable changes in county-level mortgage demand. They feature heavy tails in general, which are slightly more pronounced for negative residuals, as indicated by a negative skewness of the empirical distribution.

The estimation residuals $\hat{\epsilon}_{it}$ are used to form a granular instrument Gabaix and Koijen (2020). Granular instruments use a granularity condition, whereby shocks from individual large regions are important enough for aggregate developments for the law of large numbers to fail. If granularity holds, and if I can use the panel dimension to identify regional credit demand shocks, the aggregation of regional impacts forms a valid instrument for an aggregate credit demand shock. The aggregation takes the form of the difference between the size-weighted and an equal-weighted mean of idiosyncratic (see equation 2 in the main text)

$$z_t = \underbrace{\sum_i s_{it}\hat{\epsilon}_{it}}_{\text{size-weighted mean}} - \underbrace{\sum e_i\hat{\epsilon}_{it}}_{\text{equal-weighted mean}} .$$

I use average mortgage origination $\bar{L}_i$ as size weights s_{it} and equal weights $e_i = 1/N$.

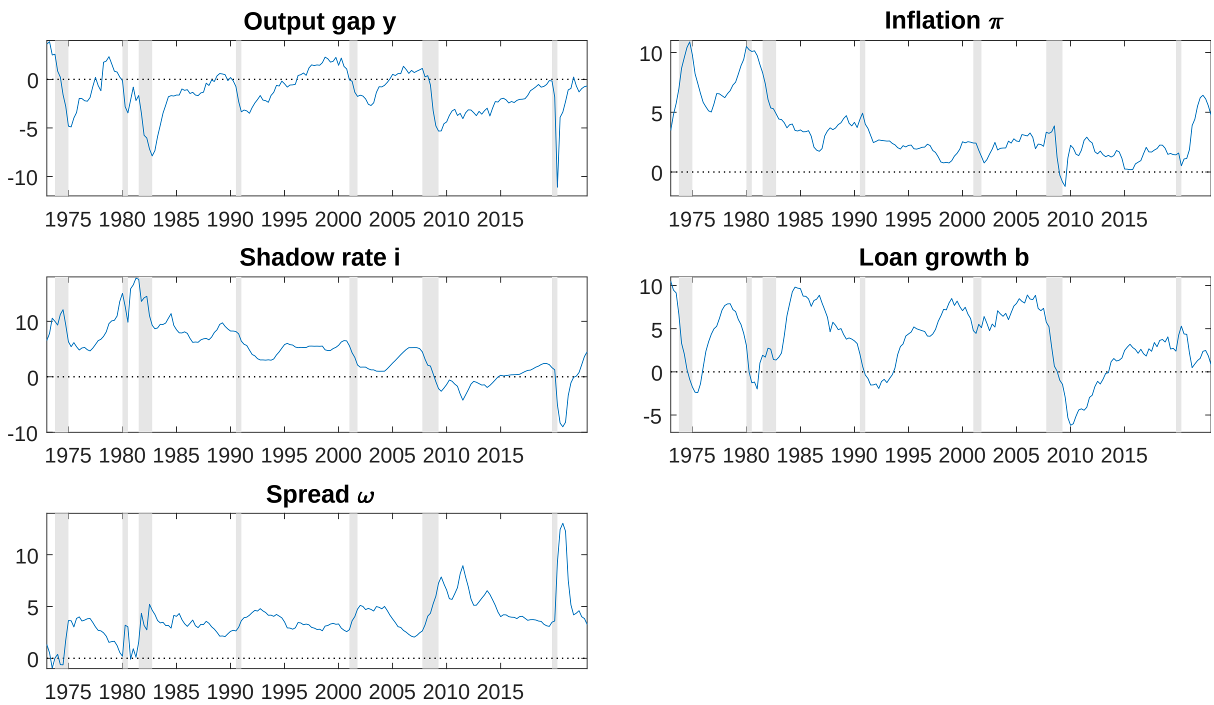


Figure B.1: Endogenous variables

Alternative size weights could be county population or time-varying weights as in Amiti and Weinstein (2018). An alternative for equal weights would be a heteroscedasticity-adjusted version proposed by Gabaix and Koijen (2020). I find that the choice of the weighting scheme has no effect on the resulting granular instrument.

B Macroeconomic data

This appendix describes the construction of endogenous variables, plotted in Figure B.1. I define the output gap y_t as 100 times the log difference between observed and potential real GDP as estimated by the congressional budget office. Inflation π_t is measured as 100 times the year-on-year log difference of the personal consumption expenditures deflator. For the nominal shadow interest rate i_t, I combine the average federal funds rate over the quarter with data on the shadow interest rate provided by (Lombardi and Zhu; 2018). I choose these data over alternative specifications because they are obtained using many different aspects of US monetary policy and because they are designed to be valid measures of monetary policy from a macroeconomic perspective. Estimations with alternative shadow rates lead to similar results.

Debt growth b_t is 100 times the year-on-year log difference of loans to the nonfinancial sector. The interest rate spread ω_t is the difference between a composite lending rate of the nonfinancial sector and the nominal shadow interest rate. For the computation of loan volumes and the composite lending rate, I follow (Gambetti and Musso; 2017) and (Mumtaz et al.; 2018). The sources of all underlying series can be found in Table 7. There are the following differences to the sample computed in (Gambetti and Musso; 2017) (1980Q1-2011Q4): For loan volumes (6) and (8), the denomination of "Municipal Securities and Loan" is reduced to "Municipal Securities". For loan volumes (5), the denomination has changed from "Credit Market Instruments" to "Debt Securities and Loans". These changes have minor effects. On the interest rate side, the Survey of Terms of Business Lending (STBL) has been stopped in 2017Q2. In 2018Q1 it has been replaced by the Small Business Lending Survey (SBLS). However, the two surveys are not well comparable: the STBL captures the average commercial and industrial lending rates by domestic banks on existing loans, while the SBLS only covers loan rates on newly originated loans extended to small businesses. Therefore, I use the (first difference of the) bank prime loan rate MPRIME to extend STBL-rates both backward and forward.

I employ a monetary policy and a credit supply instrument in addition to our own mortgage granular instrument, see Figure B.2. The instrument for monetary policy shocks stems from (Miranda-Agrippino; 2016) (denoted *MA FF4*), who remove information from Greenbook forecasts (the central bank information effect) from high-frequency changes of the fourth federal funds futures around FOMC meeting days. Innovations to the financial conditions index by Jermann and Quadrini (2012) (denoted as JQ) are a standard instrument for credit supply shocks (Mumtaz et al.; 2018). The index captures the tightness of financing constraints for firms in an estimated RBC model with financial frictions and financial shocks.

Table 7: Computation of loan volumes and composite lending rate

#	Description	Sample	Code (Original)	Code (FRED)	Source (Original)	Source (Download)	Formula
(1)	Loan volumes						$= (3) + (4)$
(2)	Composite lending rate						$= \frac{SA(3)\times(13)+SA(4)\times(14)}{SA(3)+SA(4)}$
(3)	Nominal outstanding loan amounts to households						$= (5) - (6)$
(4)	Nominal outstanding loan amounts to nonfinancial corporations						$= (7) - (8) - (9) - (10)$
(5)	Households and Nonprofit Organizations; Debt Securities and Loans; Liability	1951Q4-2020Q1	FL154104005.q	TCMILBSHNO	Flow of Funds	FRED	
(6)	Nonprofit Organizations; Municipal Securities; Liability	1951Q4-2023Q1	FL163162003.q	MSLBSHNO	Flow of Funds	FRED	
(7)	Nonfinancial Business; Debt Securities and Loans; Liability	1951Q4-2023Q1	FL144104005.q	BOGZ1FL144104005Q	Flow of Funds	FRED	
(8)	Nonfinancial Corporate Business; Municipal Securities; Liability	1951Q4-2023Q1	FL103169100.q	CPLBSNNCB	Flow of Funds	FRED	
(9)	Nonfinancial Corporate Business; Corporate Bonds; Liability	1951Q4-2023Q1	FL103163003.q	MSLBSNNCB	Flow of Funds	FRED	
(10)	Nonfinancial Corporate Business; Commercial Paper; Liability	1951Q4-2023Q1	FL103169100.q	CBLBSNNCB	Flow of Funds	FRED	
(11)	Households and Nonprofit Organizations; Total Mortgages; Liability	1951Q4-2023Q1	FL153165005.q	HNOTMLQ027S	Flow of Funds	FRED	
(12)	Households and Nonprofit Organizations; Consumer Credit; Liability	1951Q4-2023Q1	FL153166000.q	CCLBSHNO	Flow of Funds	FRED	
(13)	Interest rates, loans to households						$= \frac{SA(11)\times(15)+SA(12)\times(16)}{SA(11)+SA(12)}$
(14)	Interest rates, loans to nonfinancial corporations						$= \frac{1}{2}\left((21) + (21)\right)$
(15)	30-Year Conventional Mortgage Rate	1972Q1-2023Q1	U.S. 30yr FRM		Freddie Mac		Quarterly average
(16)	Personal loan rate						$= \frac{1}{3}\left((17) + (18) + (19)\right)$
(17)	Interest rate on 48-months new car loans	1972Q1-2023Q1	G19/TERMS/RIFLPBCIANM48_N.M		FRB: Consumer Credit - G.19		
(18)	Interest rate on 24-months personal loans	1972Q1-2023Q1	G19/TERMS/RIFLPBCIPLM24_N.M		FRB: Consumer Credit - G.19		
(19)	Interest rate on credit card plans	1994Q4-2023Q1	G19/TERMS/RIFSPBCICC_N.M		FRB: Consumer Credit - G.19		Extended to full sample using first difference of $\frac{(17)+(18)}{2}$
(20)	Bank prime loan rate	1949Q1-2023Q1	MPRIME		FRED		Quarterly average
(21)	Commercial and industrial loan rate	1986Q3-2017Q2	Actual Spread (All loans) + Intended Fed Funds		FRB: STBL, C&I Loan Rates Spreads		Extended to full sample using first difference of (20)

STBL: Survey of Terms of Business Lending
SA(·): seasonal adjustment, see also Mumtaz et al. (2018)
URL codes: #(15) `http://www.freddiemac.com/pmms/`; #(17)-#(19):`https://www.federalreserve.gov/datadownload/Download.aspx?rel=G19`; #(21): `https://www.federalreserve.gov/releases/e2/e2chart.htm`

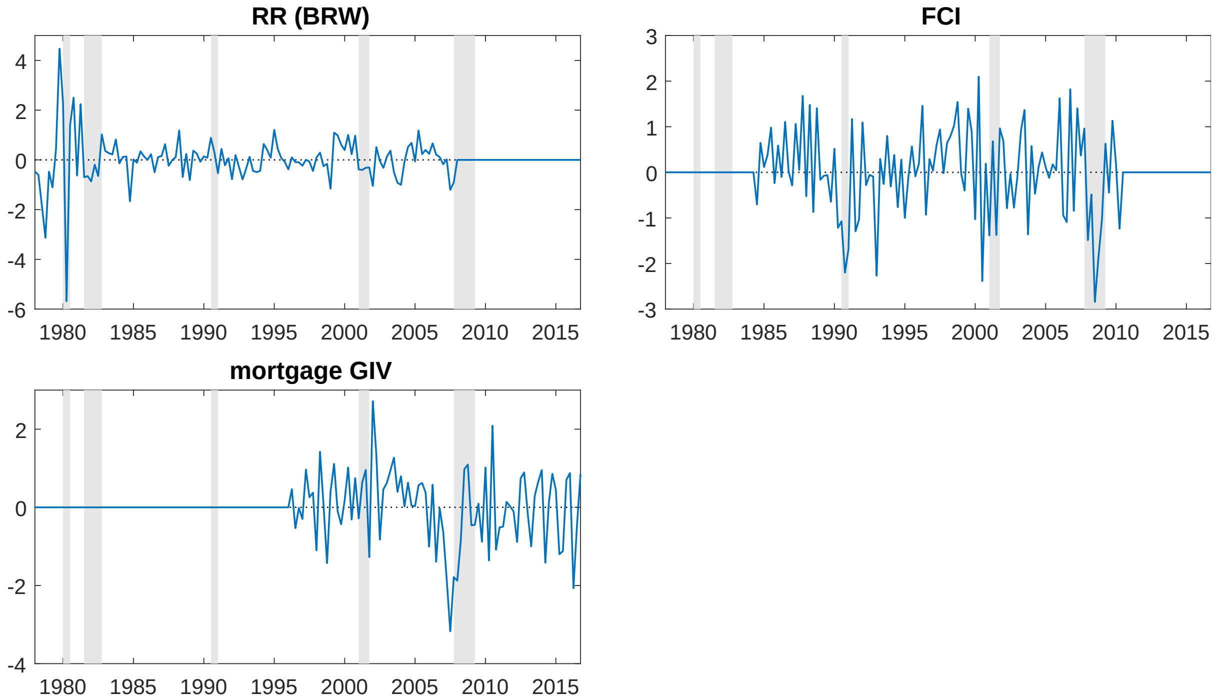


Figure B.2: Instruments, baseline model

C Econometric model

C.1 Derivation of the posterior distribution

In proposition 1, I formulate a posterior distribution for the structural VAR

$$\mathbf{A}\mathbf{y}_t = \mathbf{B}\mathbf{x}_{t-1} + \mathbf{C}\mathbf{z}_t + \mathbf{v}_t$$

$$\mathbf{v}_t \overset{\text{i.i.d.}}{\sim} \mathcal{N}(0, \mathbf{D}).$$

using arbitrary prior distributions for $\mathbf{A}$ and $\mathbf{C}$. Conditional on these, the model is uses independent normal-inverse gamma priors $\mathbf{B}$ and $\mathbf{D}$. Note that the individual equations (rows) in $\mathbf{B}$ and $\mathbf{D}$ are mutually independent conditional on $\mathbf{A}$ and $\mathbf{C}$ as the variance-covariance matrix $\mathbf{D}$ is diagonal. The overall prior distribution of the model is thus

$$p(\mathbf{A}, \mathbf{B}, \mathbf{C}, \mathbf{D}) = p(\mathbf{A}, \mathbf{C}) \prod_{i=1}^{n} \left[\gamma\left(d_{ii}^{-1}; \kappa_i, \tau_i\right) \phi\left(\mathbf{b}_i; \mathbf{m}_i, d_{ii}\mathbf{M}_i\right) \right].$$

For a characterizations of posterior parameter distributions, I make use of augmented data (Baumeister and Hamilton; 2015; Nguyen; 2019). Let the full data be denoted by $\mathbf{Y}_T, \mathbf{X}_T$ and $\mathbf{Z}_T$, and set $\mathbf{P}_i$ as the Cholesky decomposition of the prior variance of $\mathbf{B}$,

$\mathbf{M}_i^{-1} = \mathbf{P}_i\mathbf{P}_i'$:

$$\tilde{\mathbf{Y}}_i = [\mathbf{a}_i\mathbf{Y}_T - \mathbf{c}_i\mathbf{Z}_T \quad \mathbf{m}_i'\mathbf{P}_i]'$$
$$\tilde{\mathbf{X}}_i = [\mathbf{X}_T \quad \mathbf{P}_i]'.$$

The following proposition expands on 1 in specifying explicitly the posterior distributions.

Proposition 2. *If the prior distributions of* $\mathbf{B}$ *and* $\mathbf{D}$ *are defined as above, and if residuals are normally distributed, the posterior distribution of the model can be written as*

$$p(\mathbf{A}, \mathbf{B}, \mathbf{C}, \mathbf{D}|\mathbf{Y}_T, \mathbf{Z}_T) = p(\mathbf{A}, \mathbf{C}|\mathbf{Y}_T, \mathbf{Z}_T) \prod_{i=1}^{n} \left[\gamma\left(d_{ii}^{-1}; \kappa_i^*, \tau_i^*\right) \phi\left(\mathbf{b}_i; \mathbf{m}_i^*, d_{ii}\mathbf{M}_i^*\right)\right].$$

Using the estimate of the reduced-form variance-covariance matrix $\hat{\mathbf{\Omega}}_T = \frac{1}{T}\sum_{t=1}^{T} \hat{\varepsilon}_t\hat{\varepsilon}_t'$ *and augmented data, the different terms in the posterior distribution are defined as*

$$\mathbf{m}_i^* = \left(\tilde{\mathbf{X}}_i'\tilde{\mathbf{X}}_i\right)^{-1}\left(\tilde{\mathbf{X}}_i'\tilde{\mathbf{Y}}_i\right) \tag{8}$$
$$\mathbf{M}_i^* = \left(\tilde{\mathbf{X}}_i'\tilde{\mathbf{X}}_i\right)^{-1} \tag{9}$$
$$\zeta_i^* = \left(\tilde{\mathbf{Y}}_i'\tilde{\mathbf{Y}}_i\right) - \left(\tilde{\mathbf{Y}}_i'\tilde{\mathbf{X}}_i\right)\left(\tilde{\mathbf{X}}_i'\tilde{\mathbf{X}}_i\right)^{-1}\left(\tilde{\mathbf{X}}_i'\tilde{\mathbf{Y}}_i\right) \tag{10}$$
$$\kappa_i^* = \kappa_i + (T/2) \tag{11}$$
$$\tau_i^* = \tau_i + (\zeta_i^*/2) \tag{12}$$
$$p(\mathbf{A}, \mathbf{C}|\mathbf{Y}_T, \mathbf{Z}_T) = \frac{k_T p(\mathbf{A}, \mathbf{C})\left[\det\left(\mathbf{A}\hat{\Omega}\mathbf{A}'\right)\right]^{T/2}}{\prod_{i=1}^{n}\left[2\tau_i^*/T\right]^{\kappa_i^*}} \prod_{i=1}^{n} \frac{|M_i^*|^{1/2}}{|M_i|^{1/2}} \frac{\Gamma(\kappa_i^*)}{\Gamma(\kappa_i)} \tau_i^{\kappa_i}, \tag{13}$$

where k_T *is a constant that integrates* $p(\mathbf{A}, \mathbf{C}|\mathbf{Y}_T, \mathbf{Z}_T)$ *to unity.*

Baumeister and Hamilton (2015) provide a detailed proof for the model without instruments. It rests on showing the following relationship, where the posterior distributions on the right-hand side are defined as in the proposition:

$$p(\mathbf{A})\,p(\mathbf{D}|\mathbf{A})\,p(\mathbf{B}|\mathbf{A}, \mathbf{D})\,p(\mathbf{Y}_T|\mathbf{A}, \mathbf{B}, \mathbf{D}) = p(\mathbf{Y}_T)\,p(\mathbf{A}|\mathbf{Y}_T)\,p(\mathbf{D}|\mathbf{A}, \mathbf{Y}_T)\,p(\mathbf{B}|\mathbf{A}, \mathbf{D}, \mathbf{Y}_T)$$

To show a similar result in our case, it suffices to show that the likelihood of the instrument is independent of the model parameters. That is, I show that the likelihood of the data fulfills

$$p\left(\mathbf{Y}_T, \mathbf{Z}_T | \mathbf{A}, \mathbf{B}, \mathbf{C}, \mathbf{D}\right) = p\left(\mathbf{Y}_T | \mathbf{Z}_T, \mathbf{A}, \mathbf{B}, \mathbf{C}, \mathbf{D}\right) p(\mathbf{Z}_T). \tag{14}$$

If this is the case, the proof of Proposition 1 follows Baumeister and Hamilton (2015), with the posterior distributions on the right-hand side conditional on instruments $\mathbf{Z}_T$:

$$\begin{aligned} &p\left(\mathbf{Z}_T\right) p\left(\mathbf{A}, \mathbf{C}\right) p\left(\mathbf{D} | \mathbf{A}, \mathbf{C}\right) p\left(\mathbf{B} | \mathbf{A}, \mathbf{C}, \mathbf{D}\right) p\left(\mathbf{Y}_T | \mathbf{Z}_T, \mathbf{A}, \mathbf{B}, \mathbf{C}, \mathbf{D}\right) \\ &\quad = p\left(\mathbf{Z}_T\right) p\left(\mathbf{Y}_T\right) p\left(\mathbf{A}, \mathbf{C} | \mathbf{Y}_T, \mathbf{Z}_T\right) p\left(\mathbf{D} | \mathbf{A}, \mathbf{C}, \mathbf{Y}_T, \mathbf{Z}_T\right) p\left(\mathbf{B} | \mathbf{A}, \mathbf{C}, \mathbf{D}, \mathbf{Y}_T, \mathbf{Z}_T\right). \end{aligned}$$

To show the equality in equation (14), I follow Nguyen (2019). Consider that instruments $\mathbf{Z}_T$ are normally distributed with arbitrary variance-covariance matrix $\mathbf{W}$. That is, the model in equation (4) can be described by the two equations

$$\begin{aligned} \mathbf{A}\mathbf{y}_t &= \mathbf{C}\mathbf{z}_t + \mathbf{B}\mathbf{x}_{t-1} + \mathbf{v}_t, & \mathbf{v}_t &\sim \mathcal{N}(0, \mathbf{D}) \\ \mathbf{z}_t &= \mathbf{w}_t, & \mathbf{w}_t &\sim \mathcal{N}(0, \mathbf{W}). \end{aligned}$$

Alternatively, I may write this in compact form

$$\breve{\mathbf{A}}\breve{\mathbf{y}}_t = \begin{bmatrix} \mathbf{A} & -\mathbf{C} \\ \mathbf{0} & \mathbf{I}_q \end{bmatrix} \begin{bmatrix} \mathbf{y}_t \\ \mathbf{z}_t \end{bmatrix} = \begin{bmatrix} \mathbf{B} \\ \mathbf{0} \end{bmatrix} \mathbf{x}_{t-1} + \begin{bmatrix} \mathbf{v}_t \\ \mathbf{w}_t \end{bmatrix} = \breve{\mathbf{B}}\mathbf{x}_{t-1} + \breve{\mathbf{u}}_t$$

$$\breve{\mathbf{u}}_t \sim \mathcal{N}\left(0, \breve{\mathbf{D}}\right), \qquad \breve{\mathbf{D}} = \begin{bmatrix} \mathbf{D} & \mathbf{0} \\ \mathbf{0} & \mathbf{W} \end{bmatrix}$$

The likelihood of the data is

$$
\begin{aligned}
p\left(\mathbf{Y}_T, \mathbf{Z}_T | \mathbf{A}, \mathbf{B}, \mathbf{C}, \mathbf{D}, \mathbf{W}\right) =& p\left(\breve{\mathbf{Y}}_T | \breve{\mathbf{A}}, \breve{\mathbf{B}}, \breve{\mathbf{D}}\right) \\
&= (2\pi)^{-T(n+q)/2} \left|\det(\breve{\mathbf{A}})\right|^T \left|\breve{\mathbf{D}}\right|^{-T/2} \\
&\times \exp\left[-\frac{1}{2}\sum_{t=1}^{T}\left(\breve{\mathbf{A}}\breve{\mathbf{y}}_t - \breve{\mathbf{B}}\mathbf{x}_{t-1}\right)' \breve{\mathbf{D}}^{-1}\left(\breve{\mathbf{A}}\breve{\mathbf{y}}_t - \breve{\mathbf{B}}\mathbf{x}_{t-1}\right)\right].
\end{aligned}
$$

Using the three relationships

$$
\left|\det\left(\breve{\mathbf{A}}\right)\right| = \left|\det\left(\mathbf{A}\right)\right|; \qquad |\breve{\mathbf{D}}| = |\mathbf{D}||\mathbf{W}|; \qquad \left(\breve{\mathbf{D}}\right)^{-1} = \begin{bmatrix} \mathbf{D}^{-1} & \mathbf{0} \\ \mathbf{0} & \mathbf{W}^{-1} \end{bmatrix},
$$

I can split the likelihood into parts associated with Y_T and Z_T and rewrite it as

$$
\begin{aligned}
p\left(\mathbf{Y}_T, \mathbf{Z}_T | \mathbf{A}, \mathbf{B}, \mathbf{C}, \mathbf{D}\right) =& (2\pi)^{-Tn/2} \left|\det(\mathbf{A})\right|^T \left|\mathbf{D}\right|^{-T/2} \\
&\times \exp\left[-\frac{1}{2}\sum_{t=1}^{T}\left(\mathbf{A}\mathbf{y}_t - \mathbf{C}\mathbf{z}_t - \mathbf{B}\mathbf{x}_{t-1}\right)' \mathbf{D}^{-1}\left(\mathbf{A}\mathbf{y}_t - \mathbf{C}\mathbf{z}_t - \mathbf{B}\mathbf{x}_{t-1}\right)\right] \\
&\times (2\pi)^{-Tq/2} \left|\mathbf{W}\right|^{-T/2} \exp\left[-\frac{1}{2}\sum_{t=1}^{T}\mathbf{z}_t'\mathbf{W}^{-1}\mathbf{z}_t\right] \\
&= p\left(\mathbf{Y}_T | \mathbf{Z}_T, \mathbf{A}, \mathbf{B}, \mathbf{C}, \mathbf{D}\right) p\left(\mathbf{Y}_T | \mathbf{W}\right).
\end{aligned}
$$

Bayesian inference on the structural parameters can be based on the conditional likelihood $p\left(\mathbf{Y}_T | \mathbf{Z}_T, \mathbf{A}, \mathbf{B}, \mathbf{C}, \mathbf{D}\right)$, if the priors $p\left(\mathbf{A}, \mathbf{B}, \mathbf{C}, \mathbf{D}\right)$ are independent from the prior $p\left(\mathbf{W}\right)$. Among other things, this implies that priors on structural coefficients should not be based on information from the instruments. If this is the case, I can also abstract from $\mathbf{W}$.

C.2 Convergence statistics

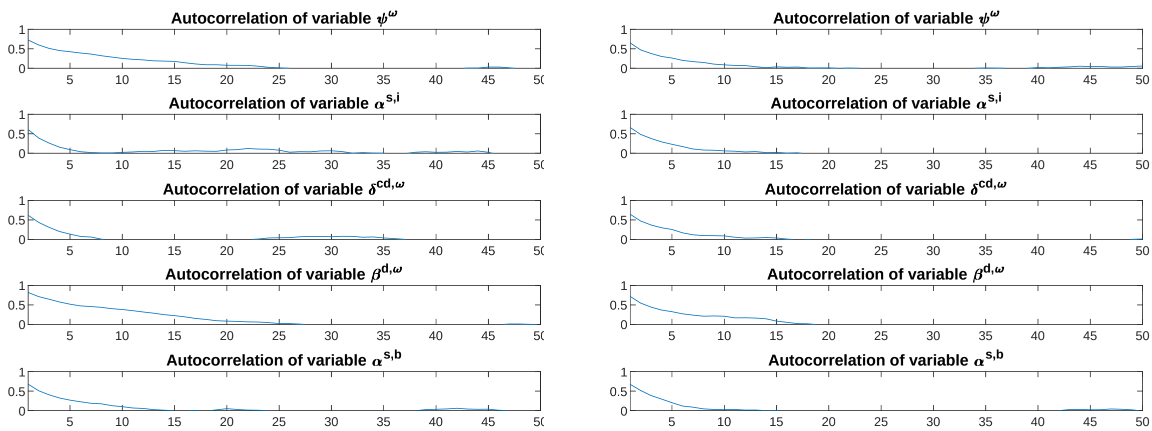
As in Baumeister and Hamilton (2015), a new candidate draw for the elements of $\mathbf{A}$ in step $l+1$ is generated as $\theta^{(l+1)} = \theta^{(l)} + \xi(\mathbf{V}^{-1})'\mathbf{v}_{l+1}$, where $\mathbf{v}_{l+1}$ is a 23×1-vector of independent standard Student t variables with 2 degrees of freedom. For efficient sampling, the matrix

V should ideally be similar to the scale of the posterior distribution, while ξ is a scalar tuning parameter that ensures a 30% acceptance probability of retained draws. Other than in Baumeister and Hamilton (2015, 2018), I cannot analytically calculate the mode of the posterior likelihood and the Hessian at that point, leaving me without a good candidate for the scaling matrix **V**. To overcome this, I run a RWMH-V algorithm with adaptive tuning parameter (Herbst and Schorfheide; 2016). This alternative algorithm proceeds in two steps: a pre-sampling with identity scaling matrix returns 100 final draws (keeping every 1'000th draw after a burn-in of 200'000). The variance-covariance matrix of these draws serves as the scaling matrix of the actual sampling, while the draws themselves are used as starting values for 100 parallel chains. In every chain, I keep every 100th draw after a burn-in of 100'000 draws. In both sampling steps, I adapt the tuning parameter ξ during the burn-in period such that the acceptance probability is 30% for retained draws.

Figure C.1 and C.2 plots the autocorrelation and retained draws (after burn-in) from the first two chains (exemplary for all) for the coefficients which have the weakest convergence statistics. We see that the autocorrelation drops quickly, and that the retained draws seem to cover the full posterior distribution fairly well in all cases. This indicates that the sampler has indeed converged to the posterior distribution.

Figure C.1: Autocorrelations of draws

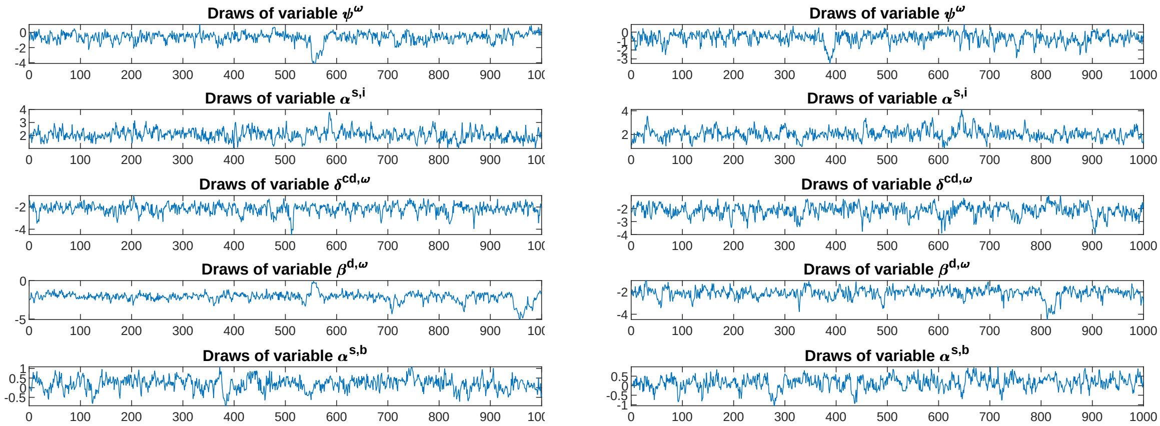
(a) chain 1 (b) chain 2



Note: The plots show the autocorrelation across draws (after burn-in) of the structural parameters with the weakest convergence statistics (per plot), exemplary for the first two chains.

Figure C.2: Trace plot of draws

(a) chain 1 (b) chain 2



Note: Trace plots of the structural parameters with the weakest convergence statistics (per plot), exemplary for the first two chains.

D Further results

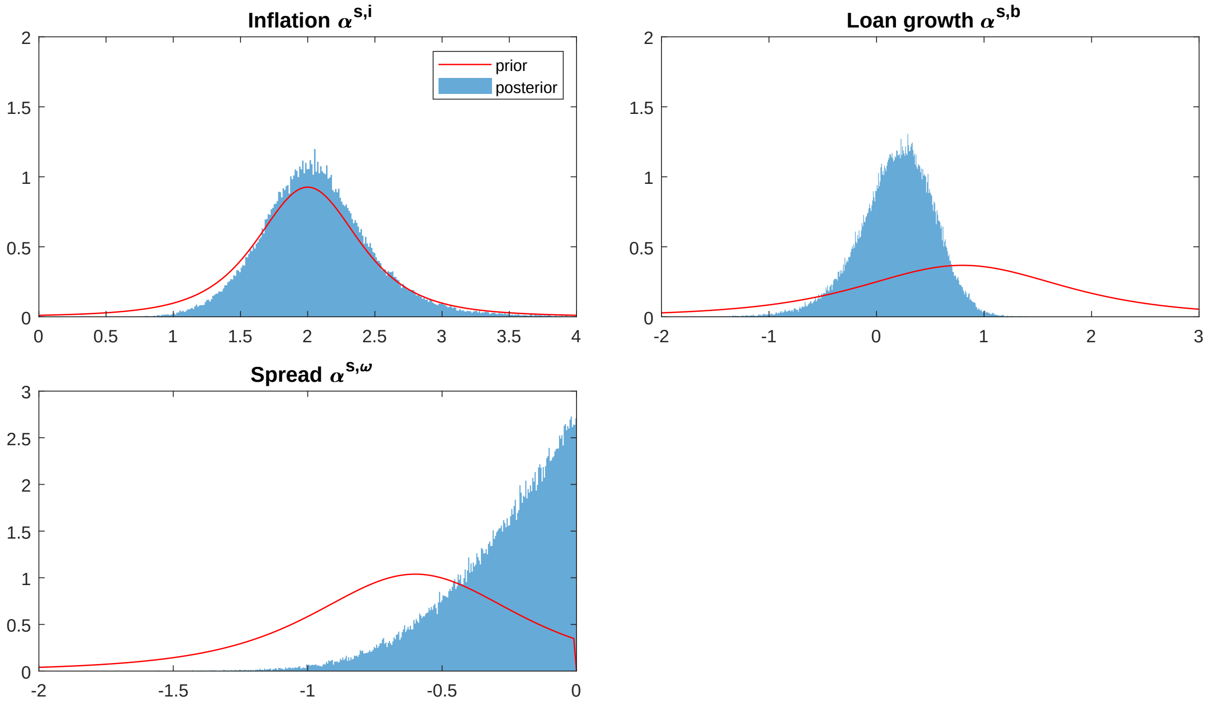


Figure D.1: Contemporaneous coefficients in the aggregate supply equation

Note: Red dashed lines: median prior densities. Blue bars: posterior densities.

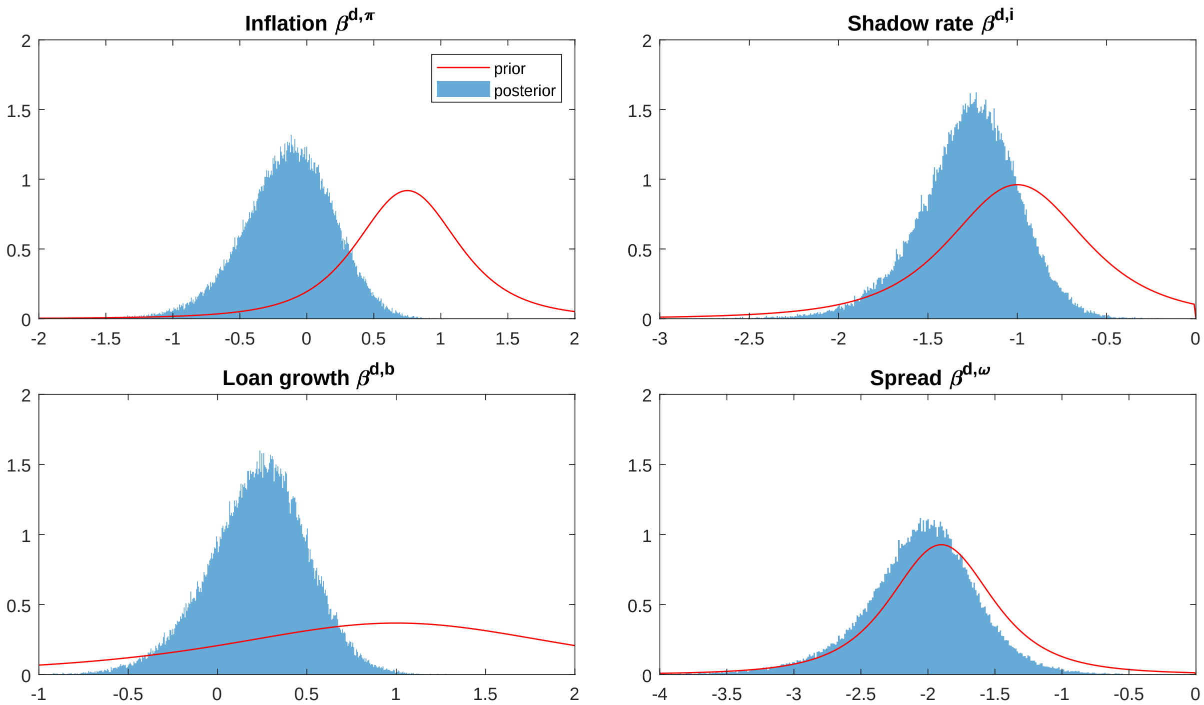


Figure D.2: Contemporaneous coefficients in the aggregate demand equation

Note: Red dashed lines: median prior densities. Blue bars: posterior densities.

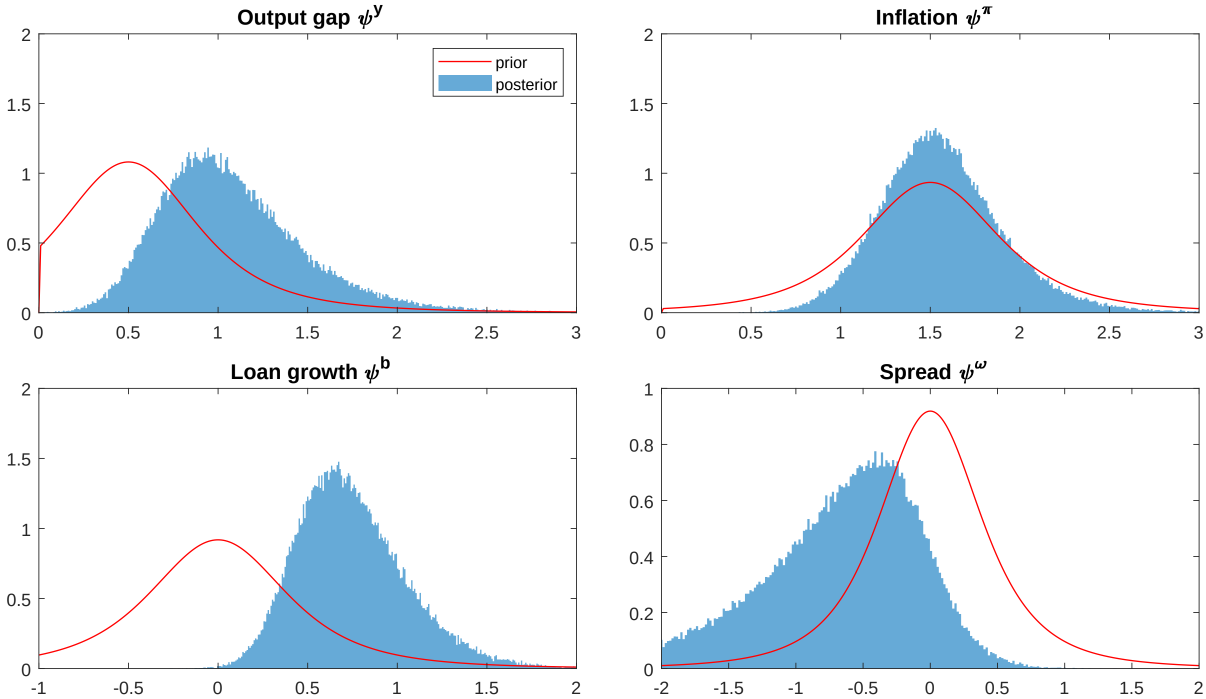


Figure D.3: Contemporaneous coefficients in the monetary policy equation

Note: Red dashed lines: median prior densities. Blue bars: posterior densities.

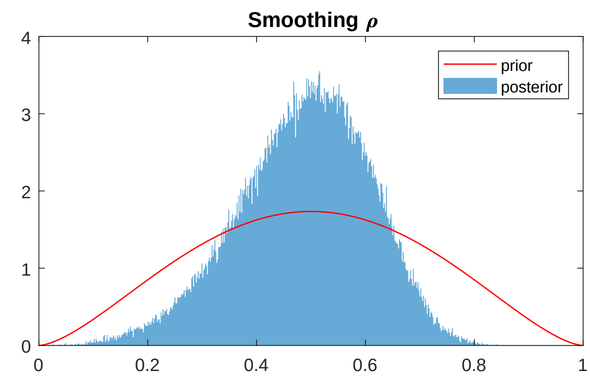


Figure D.4: Monetary policy equation, interest rate smoothing

Note: Red dashed lines: median prior densities. Blue bars: posterior densities.

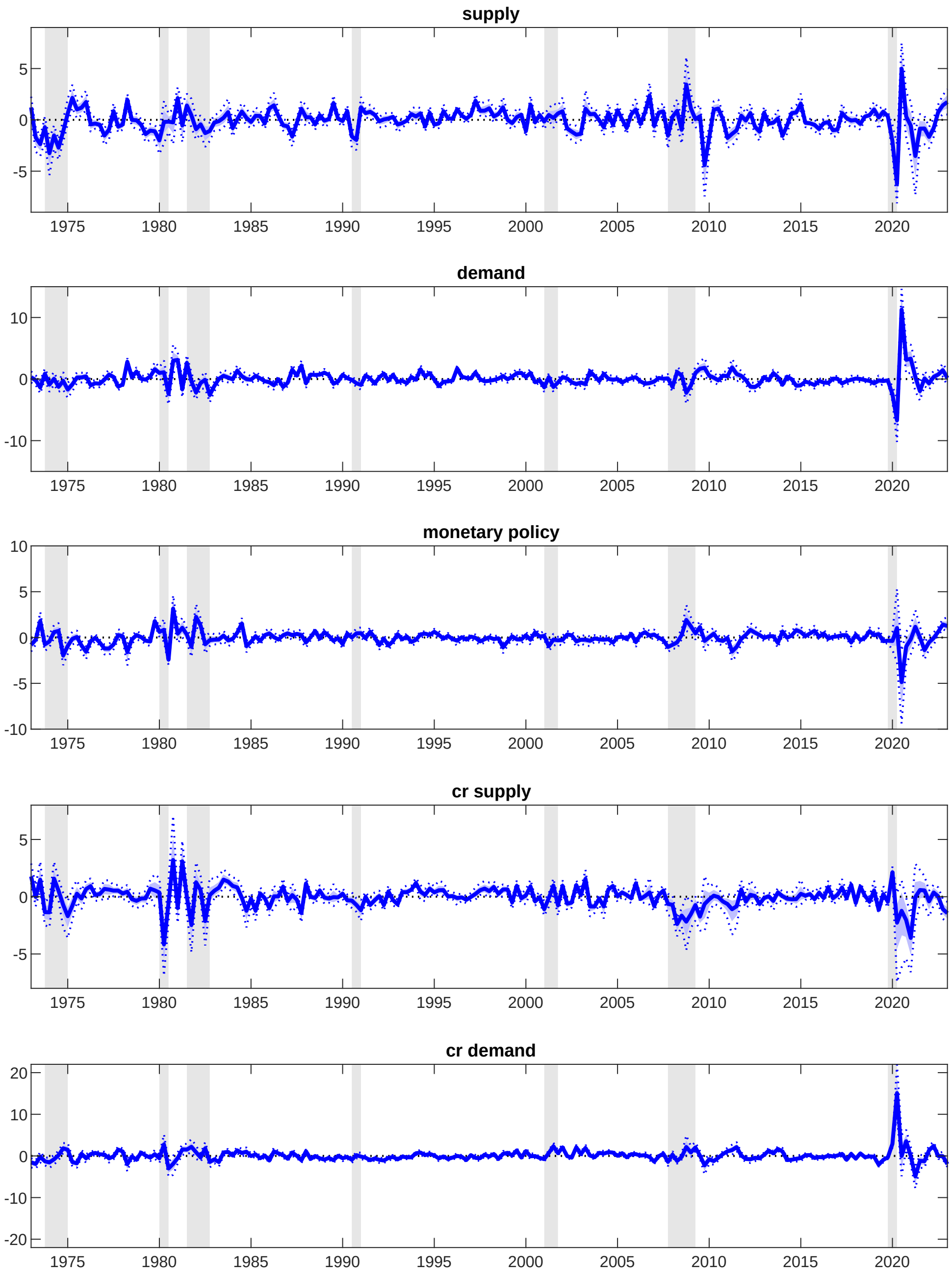


Figure D.5: Structural shocks

Note: Solid blue line: posterior median. Shaded regions: 68% posterior credibility set. Dotted blue lines: 95% posterior credibility set. Recession bars in gray. Data from 2020Q1 onwards are not used to identify the model.

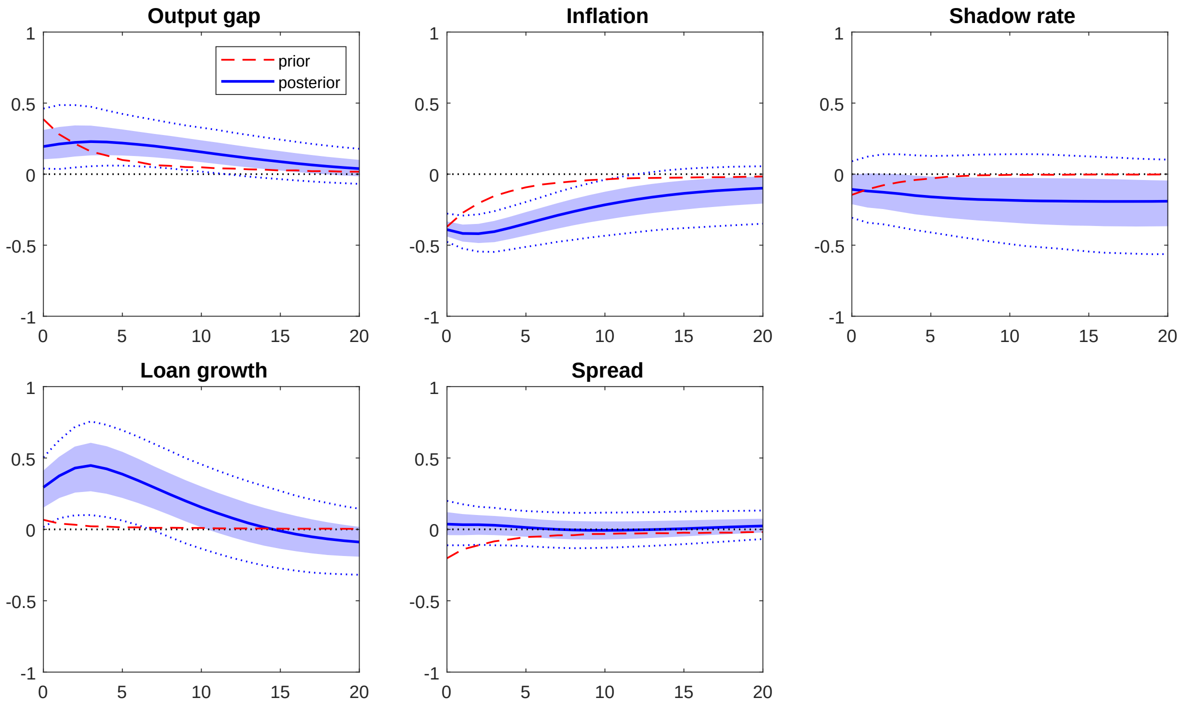


Figure D.6: Impulse response function, aggregate supply shock

Note: Solid blue line: posterior median. Shaded regions: 68% posterior credibility set. Dotted blue lines: 95% posterior credibility set.

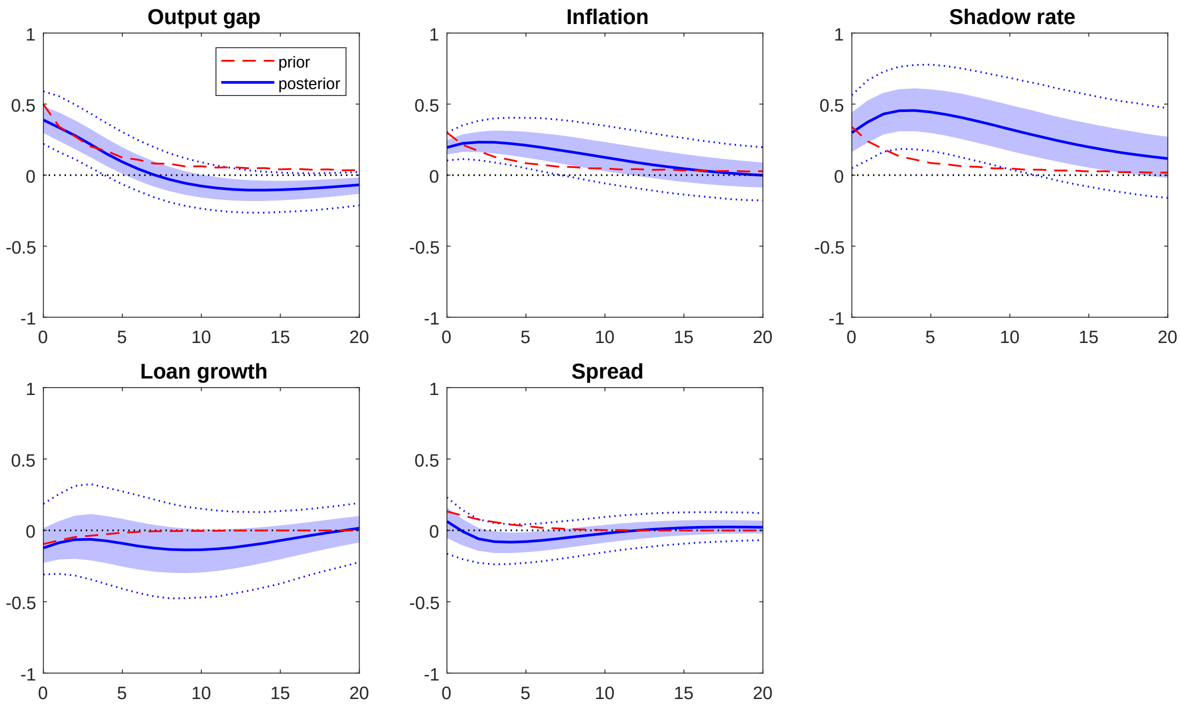


Figure D.7: Impulse response function, aggregate demand shock

Note: Solid blue line: posterior median. Shaded regions: 68% posterior credibility set. Dotted blue lines: 95% posterior credibility set.

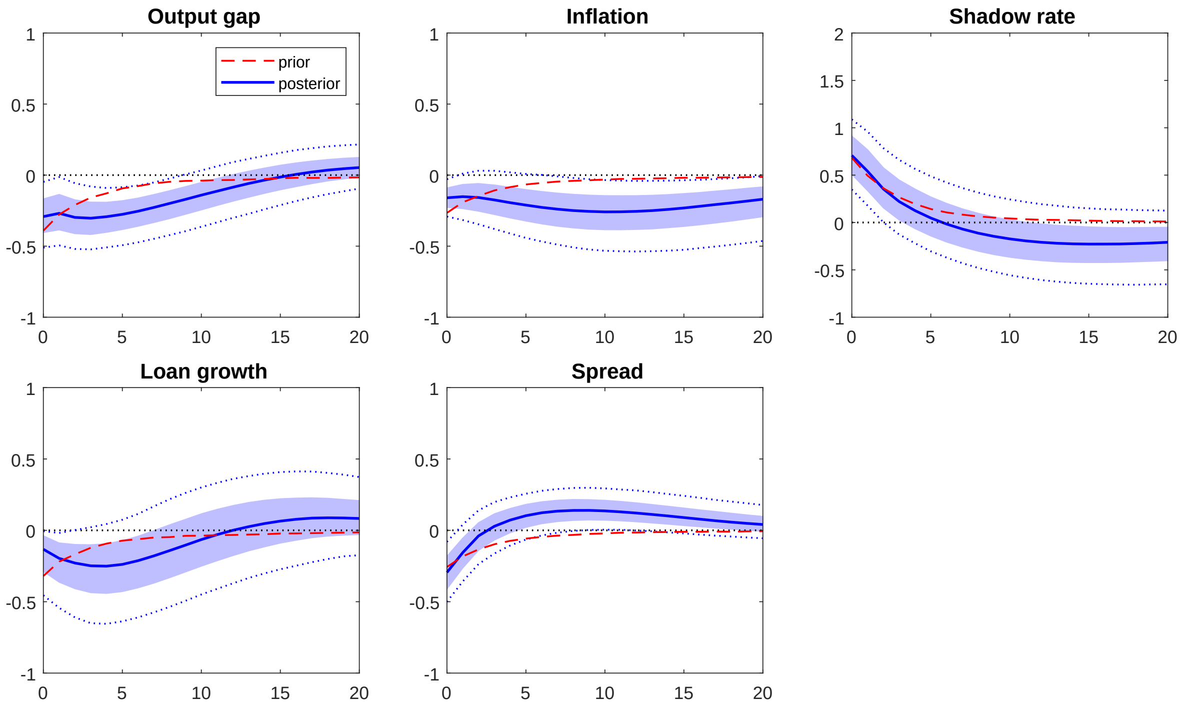


Figure D.8: Impulse response function, monetary policy shock

Note: Solid blue line: posterior median. Shaded regions: 68% posterior credibility set. Dotted blue lines: 95% posterior credibility set.

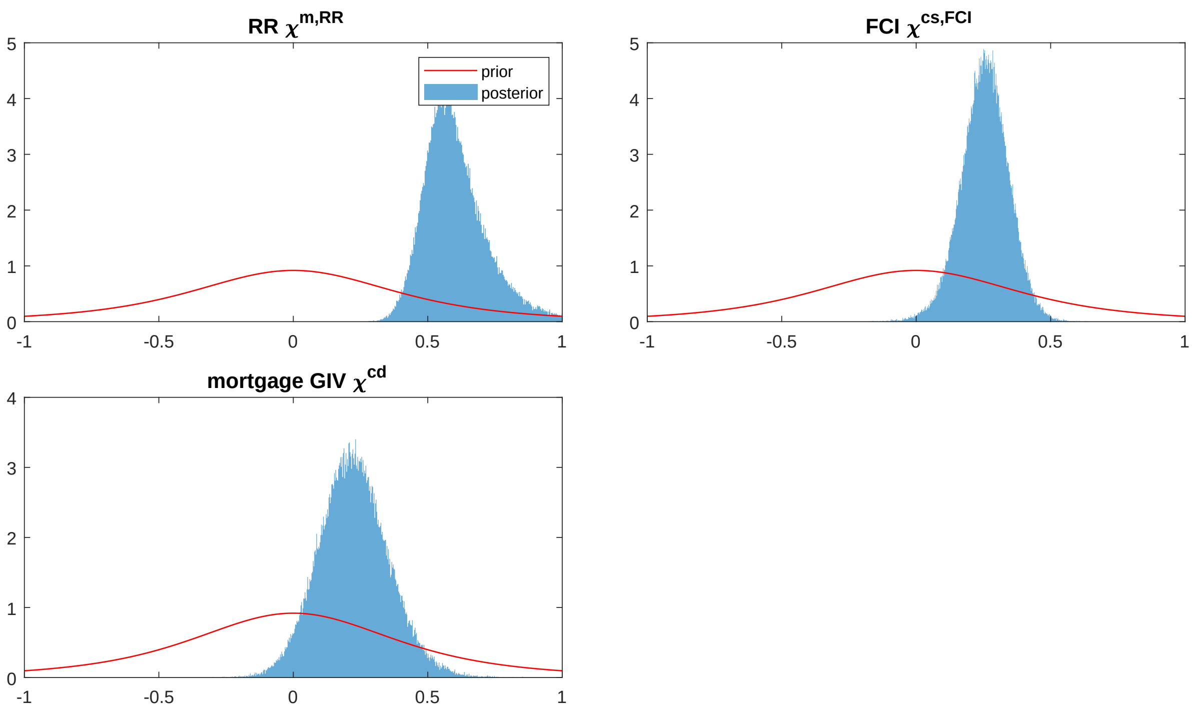


Figure D.9: Instrument coefficients, model with Romer-Romer instrument

Note: Red dashed lines: median prior densities. Blue bars: posterior densities.

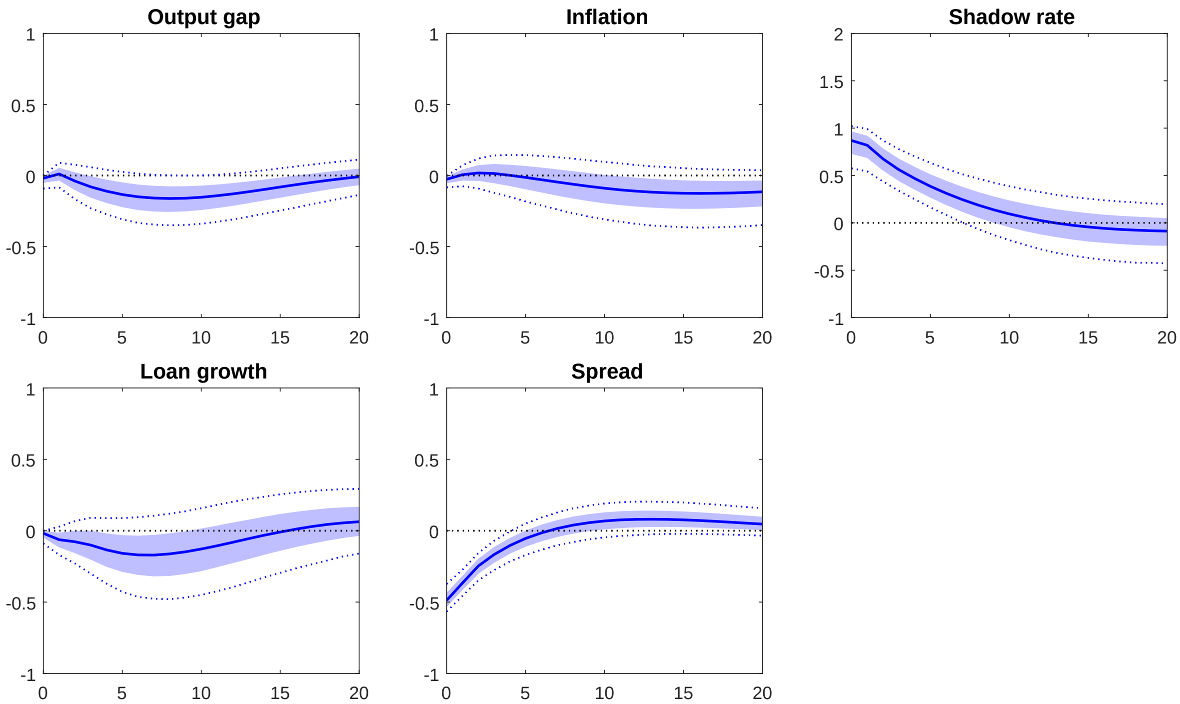


Figure D.10: Impulse response function, monetary policy shock identified using Romer-Romer instrument

Note: Solid blue line: posterior median. Shaded regions: 68% posterior credibility set. Dotted blue lines: 95% posterior credibility set.

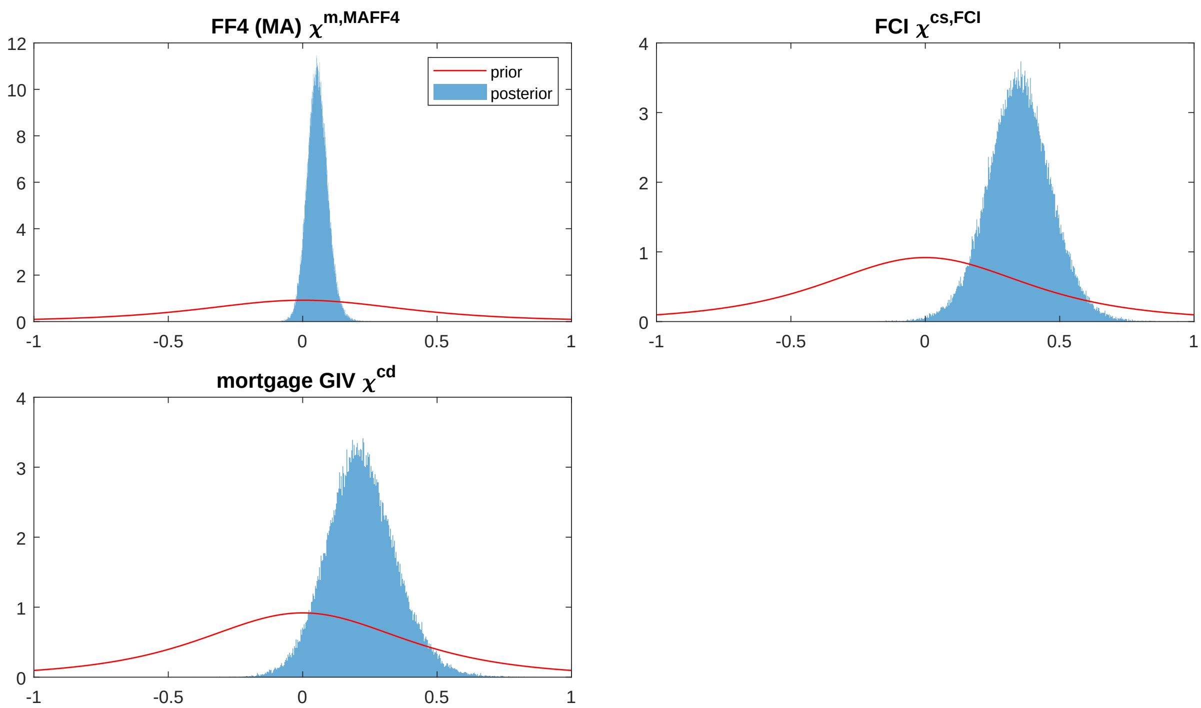


Figure D.11: Instrument coefficients, estimation sample 1994Q1 to 2016Q4

Note: Red dashed lines: median prior densities. Blue bars: posterior densities.