The importance of credit demand for business cycle dynamics

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Abstract

This paper contributes to a better understanding of the important role that credit demand plays for credit markets and aggregate macroeconomic developments as both a source and transmitter of economic shocks. I an the first to 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. In order to improve identification of the credit demand shocks, I construct a new granular instrument 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 show that credit supply and demand shocks matter for aggregate fluctuations, albeit at different times: credit demand shocks mostly drove the boom prior to the financial crisis, while credit supply shocks were responsible during and after the crisis itself. In an out-of-sample exercise, I find that the Covid pandemic induced a large expansion of credit demand in 2020Q2, which pushed the US economy towards a sustained recovery and helped to avoid a stagflationary scenario in 2022.

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1 Introduction

Credit markets are closely related to aggregate macroeconomic developments, both as a source and transmitter of economics shocks. However, it is a priori unclear whether these links are structurally driven by the supply or demand side of credit markets. Mostly after the financial crisis, this has spurred a very active research agenda with new theoretical macroeconomic models and new causal results in the finance literature. However, the empirical macroeconomic literature mostly looks at the interaction between credit markets and aggregate macroeconomic developments through the lens of either unspecified credit market fluctuations or credit supply alone, ignoring the potentially important role of credit demand.[1] This paper fills this gap.

I use a fully-identified Bayesian structural VAR to differentiate between credit demand and credit supply, covering US developments between 1972Q1 and 2023Q1. My model provides three main results. First, credit demand is much more elastic than credit supply with respect to all macroeconomic 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 (i.e., movements along the multidimensional credit curve) explain a large share of the development on credit markets (Mian and Sufi; 2011). It also implies that policy shocks that target aggregate developments will most likely transmit to credit markets via credit demand, while policy shocks that aim directly at credit market developments should focus on shifting credit supply. Second and beyond the endogenous shifts of credit demand, I find a substantial role of credit demand shocks. These shocks are orthogonal to aggregate demand shocks, which I identify separately in my model. Thus, they are not related to changes in credit demand for consumption purposes (to name just

[1] Important theoretical models are, among others, Bernanke and Blinder (1988); Iacoviello and Neri (2010); Jermann and Quadrini (2012); Christiano et al. (2014); Cúrdia and Woodford (2016); Justiniano et al. (2019). Selected contributions by the finance literature are Mian and Sufi (2011); DeFusco and Paciorek (2017); Loutskina and Strahan (2015); Acharya and Steffen (2020); Li et al. (2020). The literature using structural VARs includes Meeks (2012); Gambetti and Musso (2017); Mumtaz et al. (2018); Stock and Watson (2018); Furlanetto et al. (2019); Boivin et al. (2020). To my knowledge, Balke et al. (2021) is the only paper that explicitly aims at distinguishing credit demand and credit supply using sign restrictions in a structural VAR.

one example). Instead, they might stem from unexpected changes in the liquidity needs of firms (Bernanke and Blinder; 1988; Li et al.; 2020) or unpredicted changes in collateral restrictions and corresponding changes in the mortgage demand of households (Justiniano et al.; 2019). I find that credit demand shocks trigger a short recession on impact, but result in a more sustained boom period starting one to two years after the shock. Credit supply shocks, however, create an immediate boom for around three years. The potential of credit demand shocks to trigger a longer-run boom leads to the third main result. 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). Moreover, credit supply and demand shocks matter at different times. In the boom-bust cycle around the financial crisis, credit demand shocks mostly contributed to the boom before financial crisis, while credit supply shocks were the dominant force during the crisis. An out-of-sample exercise further shows that the Covid pandemic induced a large exogenous shift in credit demand in 2020Q2 (Acharya and Steffen; 2020; Li et al.; 2020), which helped the US economy to avoid a stagflation in 2022 and 2023 by dampening inflation in 2020 and by facilitating a faster recovery (credit supply shocks were small and comparably unimportant).

The Bayesian structural VAR contains two credit market equations that 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 liter-

[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 Brüggemann; 2023).

ature: high frequency monetary policy surprises controlling for central bank information 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 between 1996Q1 and 2016Q4. 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.

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 non-financial corporations). On average they account for 68% (43%) of household (total) loans. They also feature very similar dynamics to aggregate credit growth, see Appendix Figure A.2. Last, a complete dataset of all US mortgages is freely available at very disaggregated levels due to the Home Mortgage Disclosure Act.

Granular instruments aggregate residuals from a panel regression to the national level. This aggregate is a valid instrument if individual units (in my case, US counties) have

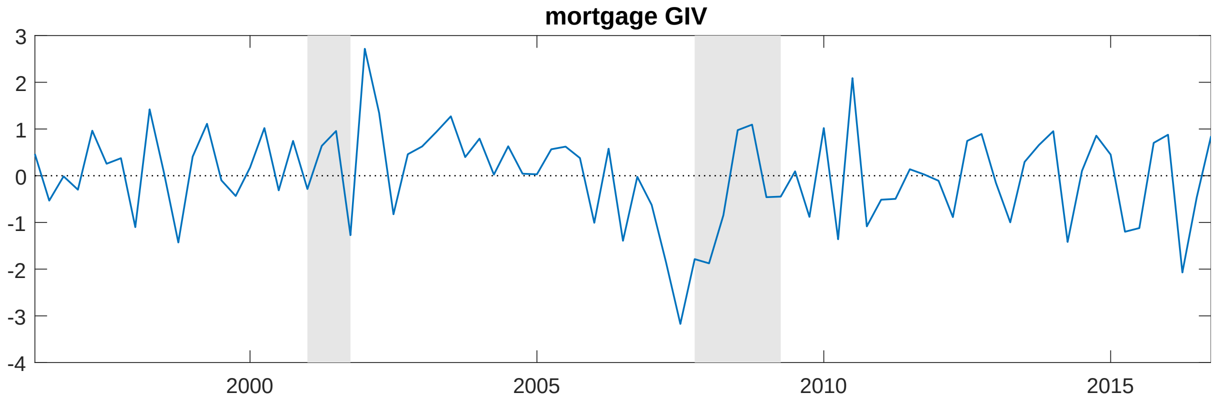

Figure 1: Granular instrument for credit demand

highly unequal sizes, which is indeed the case. Then, shifts to local mortgage demand curves in large counties have aggregate effects. The residuals are also relevant if the regression controls for all other determinants of local mortgage market outcomes, i.e. if residuals can be interpreted as unexpected local shifts of mortgage demand.[3] Shocks resulting in such unexpected shifts may encompass, among others, *local* labor market shocks, changes to local zoning regulations or changing collateral constraints due to unexpected house price developments.

Figure 1 plots the time series of the granular mortgage demand instrument for the US. The instrument suggests that the credit demand curve experienced substantial exogenous 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.

[3]Thus, my residuals are not "measures of ignorance", because I explicitly do not control for contemporaneous changes in credit demand.

2.1 Regional shifts of mortgage demand

In a first step, I obtain regional mortgage demand shifts from a panel regression of county-level mortgage origination. Residuals from this regression are interpreted as regional mortgage demand shifts after I control for all alternative sources of variation of local mortgage origination (Gabaix and Koijen; 2020). Thus, I control for predictable shifts of local mortgage demand and the local effects of contemporaneous shocks other than credit demand 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 after removing seasonal variation at the county level. I 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]

The set of lagged explanatory variables $X_{i,t-1}$ captures all predictable changes of credit demand.[5] The selection of variables follows theoretical arguments: Mortgages are an important component of a household budget constraint. Moreover, they are limited by a borrowing constraint, which is a function of household credit worthiness and collateral value (see, for example, Iacoviello and Neri; 2010; Justiniano et al.; 2019). In the baseline regression, I therefore combine data from three different sources. First, I cover labor market outcomes through average weekly wages, total quarterly wages, the

[4]The original data and their description are available on `https://sites.google.com/site/neilbhutta/data`. The data also contain information on loan applications. However, it is unclear whether these offer a better way to measure mortgage demand because applicants can apply for a mortgage at multiple banks. Note that the county composition changes from year to year. The original data contain a total of 615 different counties, of which I exclude 45 counties due to low data availability. Appendix A contains additional descriptions and robustness checks.

[5]Lagged variables may additionally capture predictable changes of credit supply or other structural relationships. This only strengthens identification.

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.[6]

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. Moreover, 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, 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).

Last, I control for bank-level mortgage supply shocks. This is necessary because the above-mentioned controls alone would yield residuals that are simultaneously affected by mortgage supply and demand shocks, whereas I am only interested in the latter. With data at a bank-county-year level, I could separate these two shocks using bank-year fixed effects $\lambda_{b\tau}$ as in Khwaja and Mian (2008); Amiti and Weinstein (2018).[7] I use the publicly available HMDA data to add the missing disaggregation by banks to my original data in three steps, see also Appendix A. First, I calculate the mortgage market share $w_{bi\tau}$ of each bank b in each county i and year τ. Second, I aggregate all variables in my original county-quarter data to the county-year level by taking the simple sum. Third, I disaggregate the intermediate county-year data to the bank-county-year level using the market shares $w_{bi\tau}$. I then proceed to remove bank-year fixed effects in these counterfactual data and

[6] In a robustness check, I also control for different measures of creditworthiness provided by Fannie Mae and Freddie Mac (FMFM) from 2000 onward. 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.

[7] This approach assumes that bank-level mortgage supply shocks are homogeneous across counties. Implicit in this assumption is that shocks to bank b only affect counties where b has a nonzero market share. That is, the choice of banks *where* to operate is independent of *how strongly* to operate.

transform the demeaned variables back to the county-quarter level. The key assumption for this transformation to work is that market shares are independent of other explanatory variables. That is, I assume that the mortgage portfolios of different banks in the same county differ only in size, but not, for example, in the income of borrowers.

2.2 Exploiting granularity to construct the credit demand instrument

In a second step, estimates of idiosyncratic regional mortgage demand shifts $\hat{\epsilon}_{it}$ from equation (1) are aggregated to the national level. In this aggregation, idiosyncratic variation would cancel largely out if the US counties in my 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 origination in every single year, and the 10 largest counties combined are responsible for around 20% of US mortgages, see also Appendix Figure A.1. Indeed, the estimate for the Pareto rate is around 0.5 for the counties in my quarterly sample. This implies a particularly heavy-tailed distribution of county sizes, and thus an important role of idiosyncratic shocks in large counties for aggregate fluctuations.

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 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 $\hat{\epsilon}_{it}$. I use average mortgage origination as weights s_i as my baseline. The granular instrument is robust to the use of different weighting schemes in equation (2):

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

3 Bayesian inference in a model of credit supply and demand

I model credit supply and demand as two equations of a medium-sized 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

The structural VAR combines credit market variables with a standard 3-variable macro model. It is a quarterly model with data from 1972Q1 to 2019Q4 on 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, thereby properly capturing unconventional policy decisions by the Fed during the financial crisis.[8]

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 feature contemporaneous dependencies (i.e., elasticities and semi-elasticities) and use $m = 4$ 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

[8] I am grateful to Marco Lombardi for providing me with an update of his shadow rates. During the Covid recession, the shadow rate drops to -5.0% (2020Q2) and -8.3% (2020Q3). This is consistent with the unprecedented pace of bond-buying programs by the Fed, and matches the usual policy response to the severe recession. Results are robust to using the Wu-Xia shadow rate (Wu and Xia; 2016). They are also robust to alternative identification periods: data prior to the financial crisis (1972-2008Q3); using all data from 1972Q1 to 2023Q1; excluding or down-weighting only the immediate Covid recession (2020Q1-2020Q2) (Baumeister and Hamilton; 2019; Lenza and Primiceri; 2022).

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, my 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 replace missing instrument values by zero.[9] 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.;

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

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).[10] The following instrument equations link the structural shocks directly to the instrument:

$$u_t^m = \chi^m z_t^m + v_t^m; \qquad u_t^{cs} = \chi^{cs} z_t^{cs} + v_t^{cs}; \qquad u_t^{cd} = \chi^{cd} z_t^{cd} + v_t^{cd} \tag{3}$$

Equation (3) can be written in matrix notation, $\mathbf{u}_t = \mathbf{C}\mathbf{z}_t + \mathbf{v}_t$. Replacing the vector of structural shocks, the full structural VAR including instrument becomes

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

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

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

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

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 joint posterior distribution of all structural parameters extend to this case. Namely, we have

$$p\left(\mathbf{A},\mathbf{B},\mathbf{C},\mathbf{D}|\mathbf{Y}_T,\mathbf{Z}_T\right) = p\left(\mathbf{A},\mathbf{C}|\mathbf{Y}_T,\mathbf{Z}_T\right)\prod_{i=1}^{n}\left[\gamma\left(d_{ii}^{-1};\kappa_i^*,\tau_i^*\right)\phi\left(\mathbf{b}_i;\mathbf{m}_i^*,d_{ii}\mathbf{M}_i^*\right)\right]. \quad (5)$$

Appendix C contains a derivation of the posterior distribution in equation (5), including a complete specification of the distribution parameters. 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. Importantly, 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 $p\left(\mathbf{A},\mathbf{C}\right)$, which I specify in the following.

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). In the next parts, I describe first the prior choices for the elasticities and semi-elasticities of structural equations, $\mathbf{A}$, focusing in particular on the new credit supply and credit demand equation. Second, I discuss my priors on instrument coefficients $\mathbf{C}$ and third, the prior choice on the impact effects of structural shocks, $\mathbf{A}^{-1}$.

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	$0 \leq \rho \leq 1$

3.4.1 Priors on elasticities and semi-elasticities

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 semi-elasticity to be -1.5 and -1.3, respectively.[11] Microeconomic data lead to similar values: DeFusco and Paciorek (2017) estimate a value between -1.5 and -2, using 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 a values of -1.1. An outlier is a DSGE-model fitted to European data by Gerali et al. (2010), which sets the semi-elasticity to around -3. I restrict $\delta^{cd,\omega}$ to be negative and set the prior mode to -1.5. This assigns a prior probability of 15% for values of $\delta^{cd,\omega}$ below -2. Because loan interest rates (and not only spreads) should be relevant for credit demand, we might assume that the interest rate semi-elasticity $\delta^{cd,i}$ should equal $\delta^{cd,\omega}$. However, the theoretical literature (Christiano et al.; 2010; Fiore and Tristani; 2013) uses smaller or even positive values, and empirical estimates provide inconclusive evidence. Therefore, I set the prior mode to -0.5 and keep the parameter unrestricted. 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 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 wider scale of 1, restricted to be positive. For the semi-elasticity of credit supply to risk-free interest rates, $\gamma^{cs,i}$, the empirical literature provides strong evidence for negative values in the range $[-1.5, 0]$, as lower interest rates

[11] The semi-elasticity from Cúrdia and Woodford (2016) is a function of deep structural parameters and variables such as expected future spreads. In my calibration, I use an intertemporal elasticity of substitution of 0.5. To replace expectations, I proceed as Baumeister and Hamilton (2018), who assume an AR(1)-process to rewrite expectations as $x_{t+1|t} = 0.75x_t$ (see also Doan et al.; 1984).

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. I restrict the output elasticity of credit supply, $\gamma^{cs,y}$, to be positive, as credit supply should shift outwards with expectations of a future boom (Christiano et al.; 2010). Very precise estimates of Jiménez et al. (2012) inform a prior mode of 0.1 and a smaller 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 literature. Therefore, I center the prior distribution around 0.

Abstracting from the possible role of loan growth and loan interest spreads, the remaining three equations are standard. The parameters $\left\{\alpha^{s,\pi}, \beta^{d,\pi}, \beta^{d,i}, \psi^{y}, \psi^{\pi}, \rho\right\}$ have the same prior distributions as Baumeister and Hamilton (2018). 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) is an empirical 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 wider scale of 1, as the theoretical value of the parameter is somewhat sensitive to the specification choice in Cúrdia and Woodford (2016).[12]

The **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

[12]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.

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 (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.[13]

3.4.2 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 equally centered around zero.

3.4.3 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, eight 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

[13] 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	-
$h_5 = \mathbf{H}(4,3)$	Loan growth to MP shock	0	1	-5000	-
$h_6 = \mathbf{H}(1,1)$	Output gap to AS shock	0	1	5000	+
$h_7 = \mathbf{H}(4,4)$	Loan growth to CS shock	0	1	5000	+
$h_8 = \mathbf{H}(5,4)$	Spread to CS shock	0	1	-5000	-
$h_9 = \mathbf{H}(4,5)$	Loan growth to CD shock	0	1	5000	+
$h_{10} = \mathbf{H}(5,5)$	Spread to CD shock	0	1	5000	+
$h_{11} = \det\mathbf{A}$	Regularity condition	6	5	4	

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 $h_2 = \mathbf{H}_{(5,3)}/\mathbf{H}_{(3,3)}$. 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. Restrictions on the impact effect of a monetary policy shock on output gaps, inflation and loan growth (h_3 to h_5) guard against a prize puzzle. Five additional uncontroversial signs serve to sharpen identification: (a) the output reaction to an aggregate supply shock (h_6), (b) the impact effect of a credit supply shock on credit market variables (h_7 and h_8) and

(c) the impact effect of a credit demand shock on credit market variables (h_9 and h_{10}). 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_{11} 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 remaining 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:

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

The vector $\mathbf{m}_i$ summarizes my best knowledge on the coefficients $\mathbf{b}_i$ prior to seeing the data, and $\mathbf{M}_i$ my confidence in this knowledge. As in Baumeister and Hamilton (2018), I combine two sources of prior knowledge. First, I use a Minnesota prior with an autoregressive coefficient of 0.75, assuming a priori that this AR(1) process provides a good description of my time series (output gap, inflation, interest rates, loan growth rates and loan interest spreads).[14] Second, interest rate smoothing ρ leads to an additional prior for the lagged elements in the monetary policy equation $\mathbf{b}^m$. In particular, the coefficient of the first lag of interest rates should be $\mathbf{b}_i^m = \rho$, while all other elements of $\mathbf{b}^m$ should be zero. The prior confidence $\mathbf{M}_i$ is specified as in Baumeister and Hamilton (2018).

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

4 Results

In the following, I document the elasticities of credit demand with respect to the other endogenous variables, and how unexpected credit demand shocks affect macroeconomic aggregates. The identification of these structural forces is driven by informative priors and the information coming from the exogenous instruments. I then use these insights disentangle the relative contributions of credit demand and supply to the boom and bust-cycle around the great financial crisis. Last, I run an out-of-sample experiment to show that the Covid shock induced a strong exogenous expansion of credit demand in 2020Q2, which contributed strongly to the medium-run recovery until today. 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 $\delta^{cd,\omega}$. In general, I find that the credit demand curve is much more elastic than I expected a priori, speaking to the informativeness of the data, while credit supply is quite inelastic.

The posterior slope of the credit demand curve has a median of around -2. Because the semi-elasticity with respect to risk-free interest rates has a median of -0.75 and is almost certainly negative, I find that credit demand is highly responsive to changes in nominal loan interest rates. The coefficients on output gap and inflation show that the data are not only informative with respect to the degree of elasticity, but also in the sign of the coefficient. Credit demand increases endogenously most likely with *lower* inflation rates and during an economic boom (opposed to the positive/negative prior on $\delta^{cd,\pi}/\delta^{cd,y}$). One reason for the procyclicality of credit demand may be the real debt burden of borrowers, which depends positively on the development of output and which

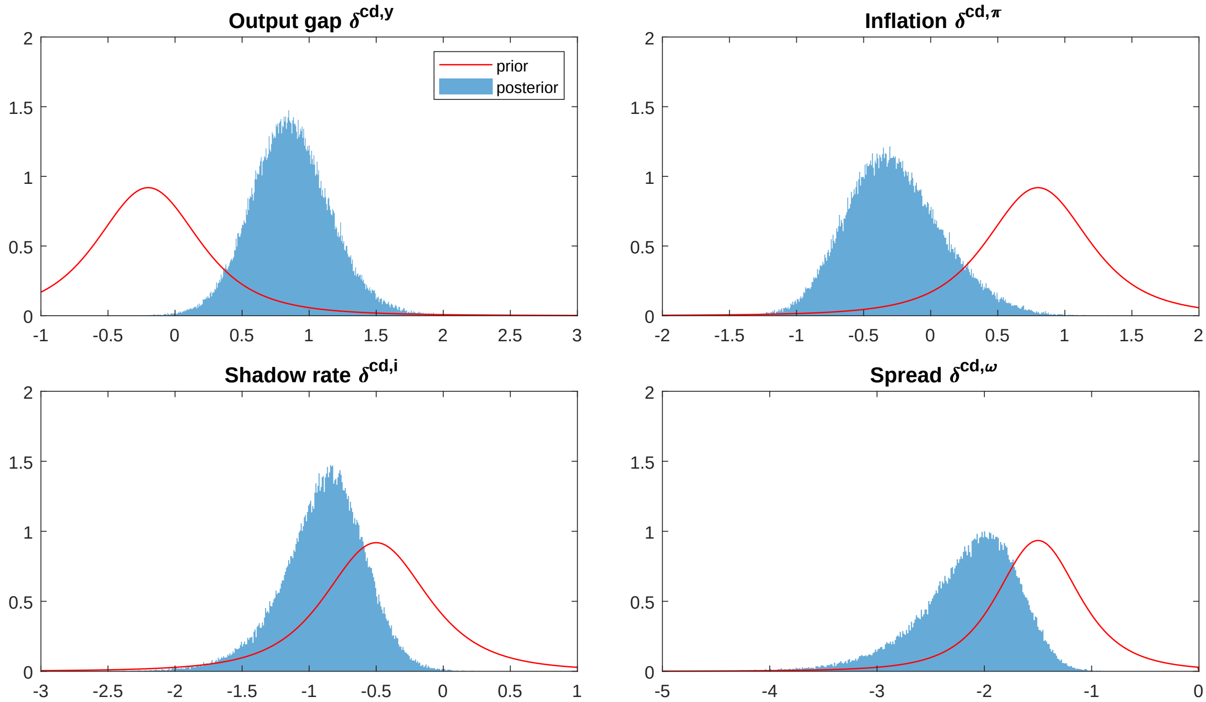

Figure 2: Contemporaneous coefficients in the credit demand equation

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

may constitute a possible borrowing constraint (Fisher; 1933). Moreover, 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 inverted coefficients on the output and inflation elasticity is the role of aggregate supply shocks, as an expansion of aggregate supply may necessitate credit-financed investment (see also Appendix Figure D.6). Credit supply is not 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.

My 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. These implications are relevant for economic policy. On the one hand, policy shocks targeting macroeconomic developments (like monetary or fiscal policy shocks) will affect credit markets mostly via shifts in credit demand. Indeed, Appendix Figure D.8 shows that – at least on impact – monetary policy shocks affect credit markets mostly via credit demand. On the other

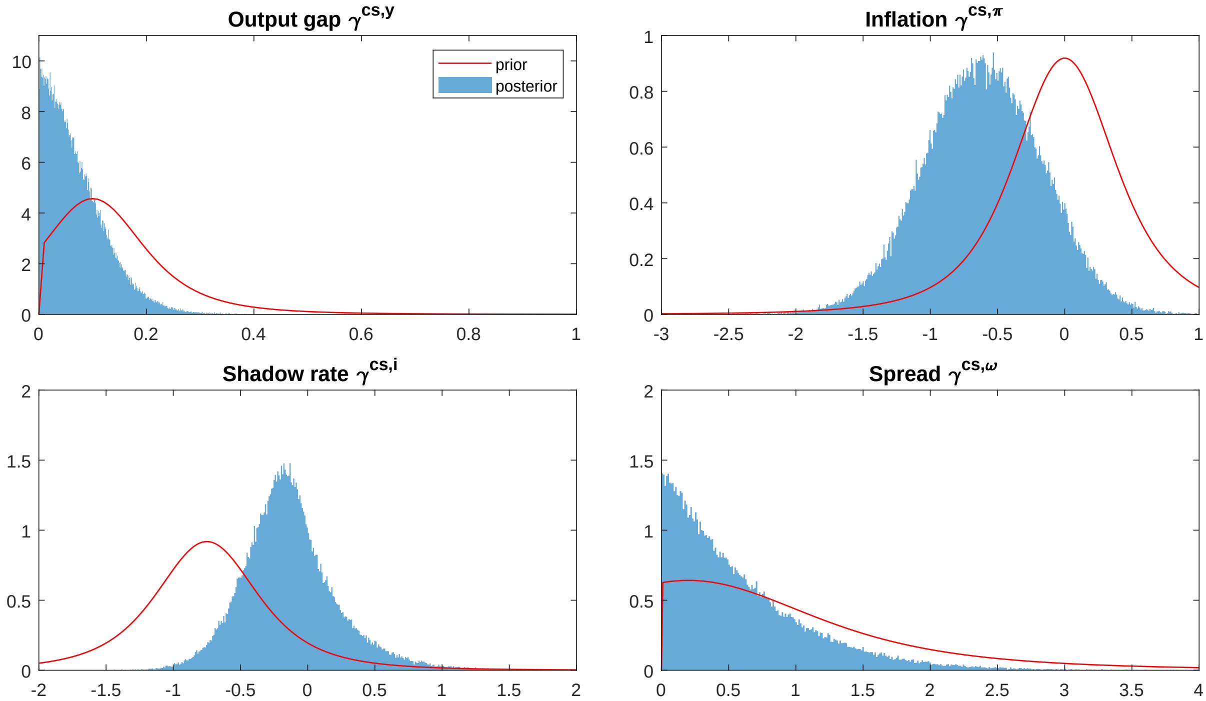

Figure 3: Contemporaneous coefficients in the credit supply equation

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

hand, policy shocks which focus on credit market developments (such as macroprudential policy) should be more effective if they target credit supply.

4.2 The importance of instruments

Figure 4 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 the credit demand coefficient, χ^{cd}, is robust to alternative monetary policy or credit supply instruments.

Formally, I can calculate Bayes factors to gauge the relevancy of the instruments, which indicate that the model with instrument barely outperforms the model without.[15] However, instrument relevancy in my Bayesian model likely suffers because the instruments are unobserved for extended periods of time. To illustrate this issue, 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

[15] Direct calculations of marginal data densities as in Nguyen (2019) and a comparison via Savage-Dickey density ratios (Verdinelli and Wasserman; 1995) produce similar results.

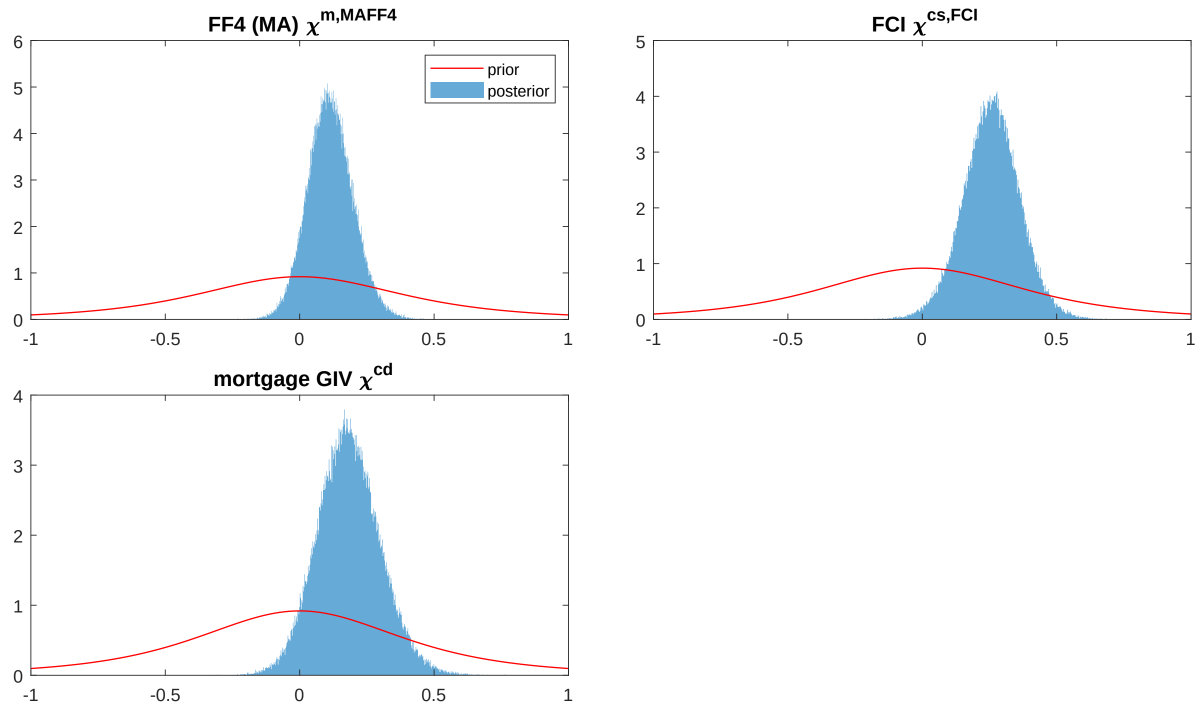

Figure 4: Instrument coefficients

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

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 Appendix Figure D.11. Moreover, according Jeffrey's criteria (Kass and Raftery; 1995, as in), Bayes factors provide "very strong" evidence against the alternative model without any instrument, and "positive" evidence against the model without credit demand instrument, see Appendix Table 8.[16]

4.3 The contribution of credit demand and supply to macroeconomic fluctuations

The shape of the structural equations, in particular the elasticities of credit demand and supply, affect impulse-response functions (IRFs) to credit market shocks. The IRFs to expansionary credit demand shock are very precisely identified, see Figure 5. The steep

[16] To overcome this issue for the monetary policy equation, I can use Romer-Romer type instruments from Coibion et al. (2017) instead, which are available from 1972Q1 to 2008Q4. This instrument would be highly relevant, albeit at the cost of a price puzzle, see Appendix Figures D.9 and D.10 and discussions by Barakchian and Crowe (2013) and Ramey (2016). All results concerning credit demand and credit supply remain robust.

slope of the credit demand curve implies that a shock of 1 percentage point increases loan growth by only 0.25% (median impact), while loan interest spreads increase by 0.33%. The effect of the shock on credit market variables is strongly muted in general because it causes a short recession on impact, that is followed by a boom only after 1-2 years. The reason for this response lies in the endogenous negative effect that higher spreads have on aggregate demand, see the posterior distribution of $\beta^{d,\omega}$ in Appendix Figure D.2. As output and inflation go down, the endogenous response of monetary policy implies a lower shadow rate. That is, loan interest rates (the sum of shadow rates and the spread) increase on average by 0.1 percentage points on impact. These impulse response functions are in line with theoretical predictions (Bernanke and Blinder; 1988; Kaplan et al.; 2014), but contradict the assumption of Gambetti and Musso (2017) that impulse-response functions of credit and aggregate demand shocks should be similar. However, this assumption – although not specifically spelled out – seems to relate to credit-financed consumption. Instead of this, my credit demand shocks are orthogonal to aggregate demand shocks. Indeed, the recent empirical literature documents that shocks to the liquidity demand of firms simultaneously reduce investment (Li et al.; 2020), and that shocks to debt-to-income ratios of households negatively affect consumption (Teulings et al.; 2023).

A credit supply shock increases loan growth much stronger on impact than a credit demand shock, and causes a persistent negative response of loan interest spreads. The first reason for this is the relative inelasticity of the credit supply curve. Second, the shock seems to affect the aggregate economy via an increase of aggregate demand, as it increases both output, inflation and shadow rates (Mian et al.; 2020). Although the reaction of shadow rates is less precisely identified, it is interesting that it 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 Appendix Figure D.3). 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

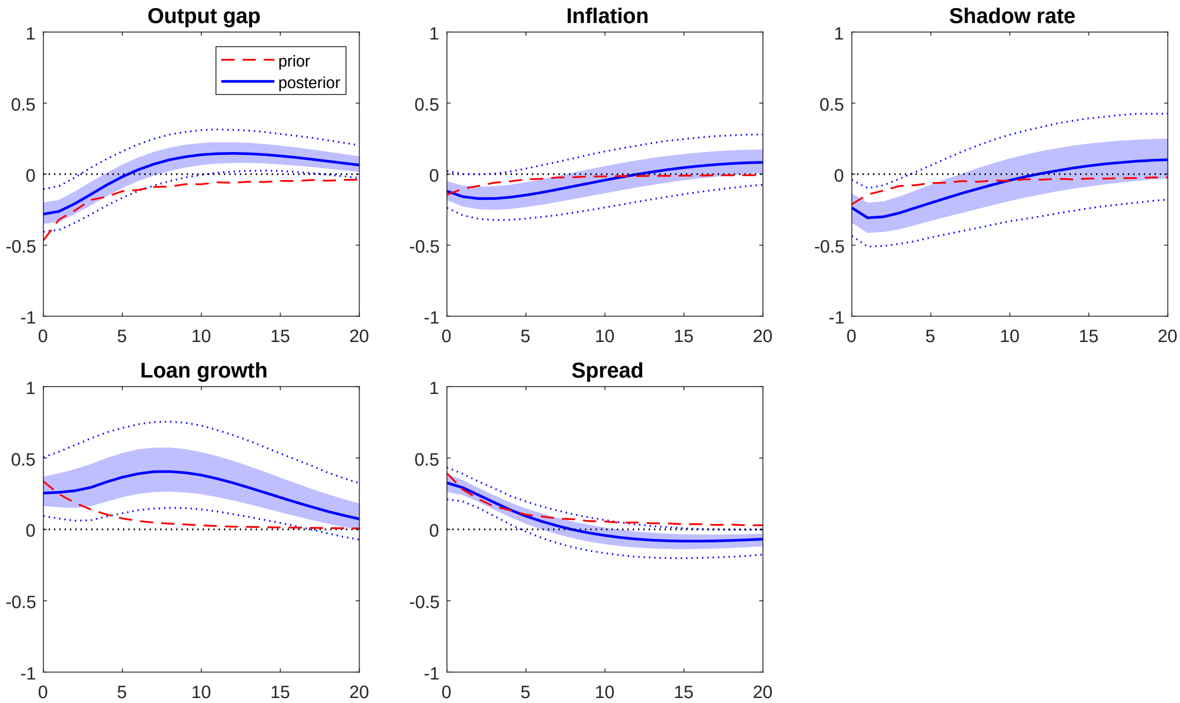

Figure 5: Impulse response function, expansionary credit demand shock

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

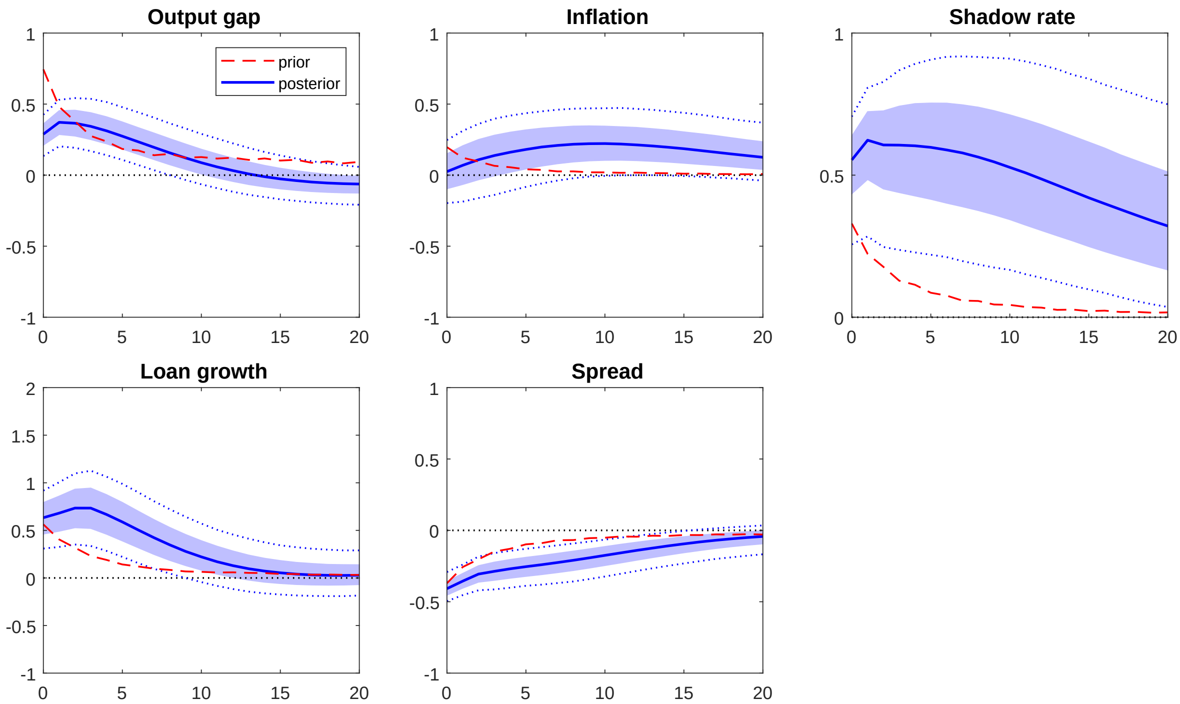

Figure 6: Impulse response function, expansionary credit supply shock

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

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.

supply shocks have comparably 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 60% 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.

Using the impulse response functions, the endogenous variables can be decomposed into the contributions of past and current structural shocks. These historical decompositions show if there are specific periods during which credit supply or credit demand are particularly important for the development of endogenous variables. Figures 7 and 8 show the identified structural credit supply and demand shocks (in the first subplot) together with their contributions (remaining subplots). Credit supply contributes particularly strongly during two subperiods. First, a series of positive credit demand shocks from 1982Q4 to 1984Q2 (Jayaratne and Strahan; 1996; Mian et al.; 2020, matching a wave of banking deregulation) contributed to the developments in the 80's. Second, contractionary credit supply shocks during the financial crisis were among the most impactful shocks in that time. The contribution of credit demand, however, drives the long run credit cycle from the 90's until the financial crisis, especially during the boom from 2003 and 2008. The latter part is explained by a series of expansionary credit demand shocks in

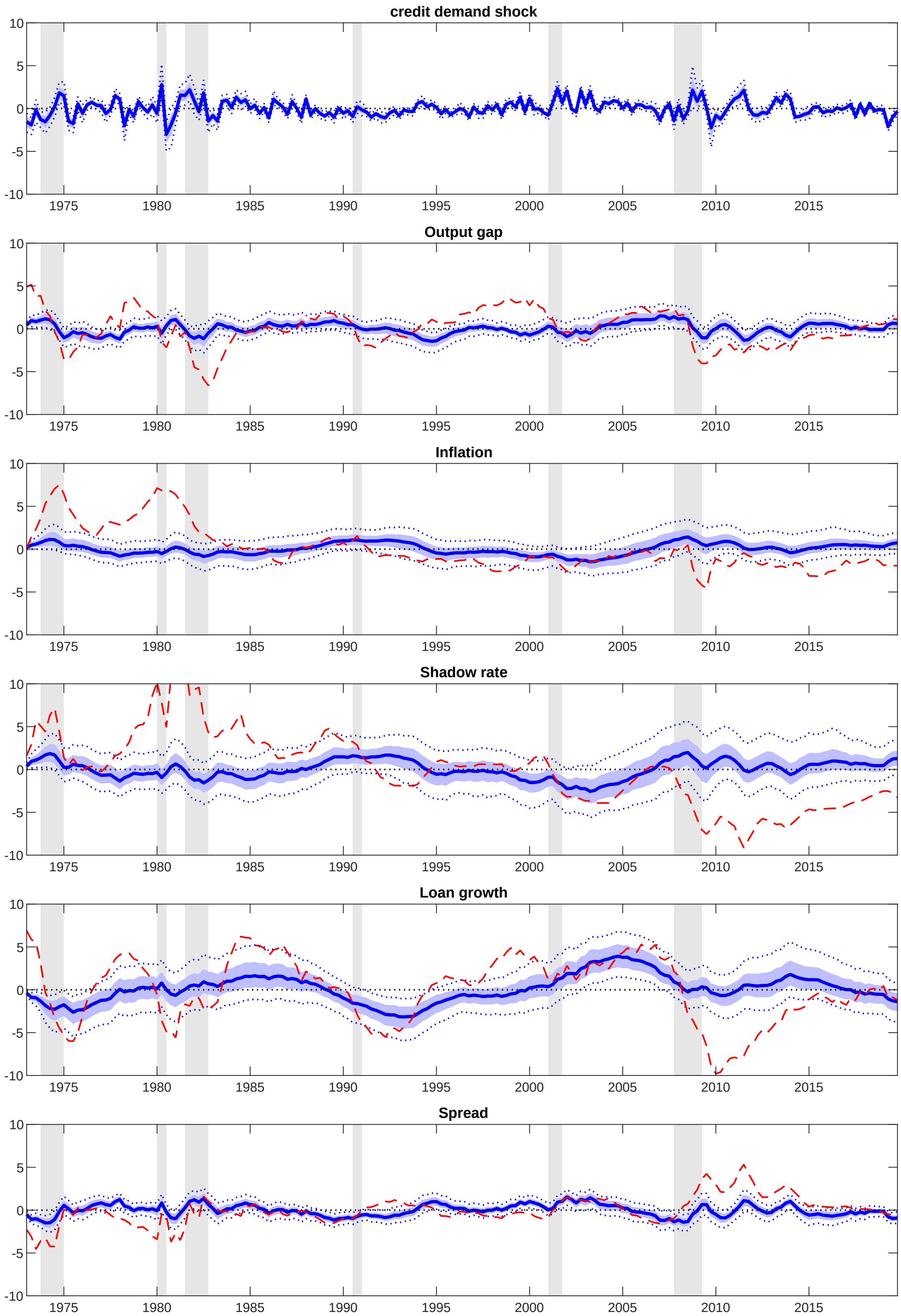

Figure 7: Credit demand shocks and their historical contributions

Note: The first subplot contains the time series of identified credit demand shocks, the remaining subplots their contribution to endogenous variables. 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.

the first half of the 2000's, which can be linked to looser collateral constraints (Favilukis et al.; 2017).

4.4 A counterfactual analysis of the post-2020 recovery

In 2020Q2, the US economy plunged into a deep recession. The output gap dropped to -11%, inflation was near zero and renewed quantitative easing reduced the shadow rate to -5%. These developments were caused by Covid, a "primitive" shock (Ramey; 2016) that shifts all structural relations simultaneously. For example, we know that aggregate demand and aggregate supply both dropped strongly due to lockdowns, workplace closures and changes in consumption behavior (Baqaee and Farhi; 2022). That is, the Covid shock can be interpreted as the underlying reason for most, if not all, of the structural shocks in 2020Q2.

With this mapping of the primitive Covid shock onto structural shocks in mind, I use my identified structural model to investigate the Covid recession in an out-of-sample exercise for the time period 2020Q1 to 2023Q1. Because these data are not included in the baseline estimation of the model, the size of shocks and their potential correlation across structural equations is unproblematic. In addition, I do several robustness checks with different estimation sample periods to make sure that there is no time-variation in the structural model parameters.

The macroeconomic developments in 2020Q2 should have implied a strong endogenous reduction of highly elastic credit demand, and no strong shifts of credit supply. However, opposed to the predicted endogenous response, there was an uptick of loan growth by about one percentage point, and a strong increase of the loan interest spread from 3.6% to 9.3%. This hints at the strong possibility that Covid also induced a large exogenous increase in credit demand. Indeed, the out-of-sample model predictions imply a positive credit demand "shock" of about 15% in 2020Q2 – about 13 times the usual standard deviation.[17] This unusually large credit demand shock did not only stabilize loan growth

[17] Not surprisingly, aggregate supply and demand shocks are also 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 Covid recession than during previous episodes. Figure **??** in the Appendix plots time series of all structural shocks.

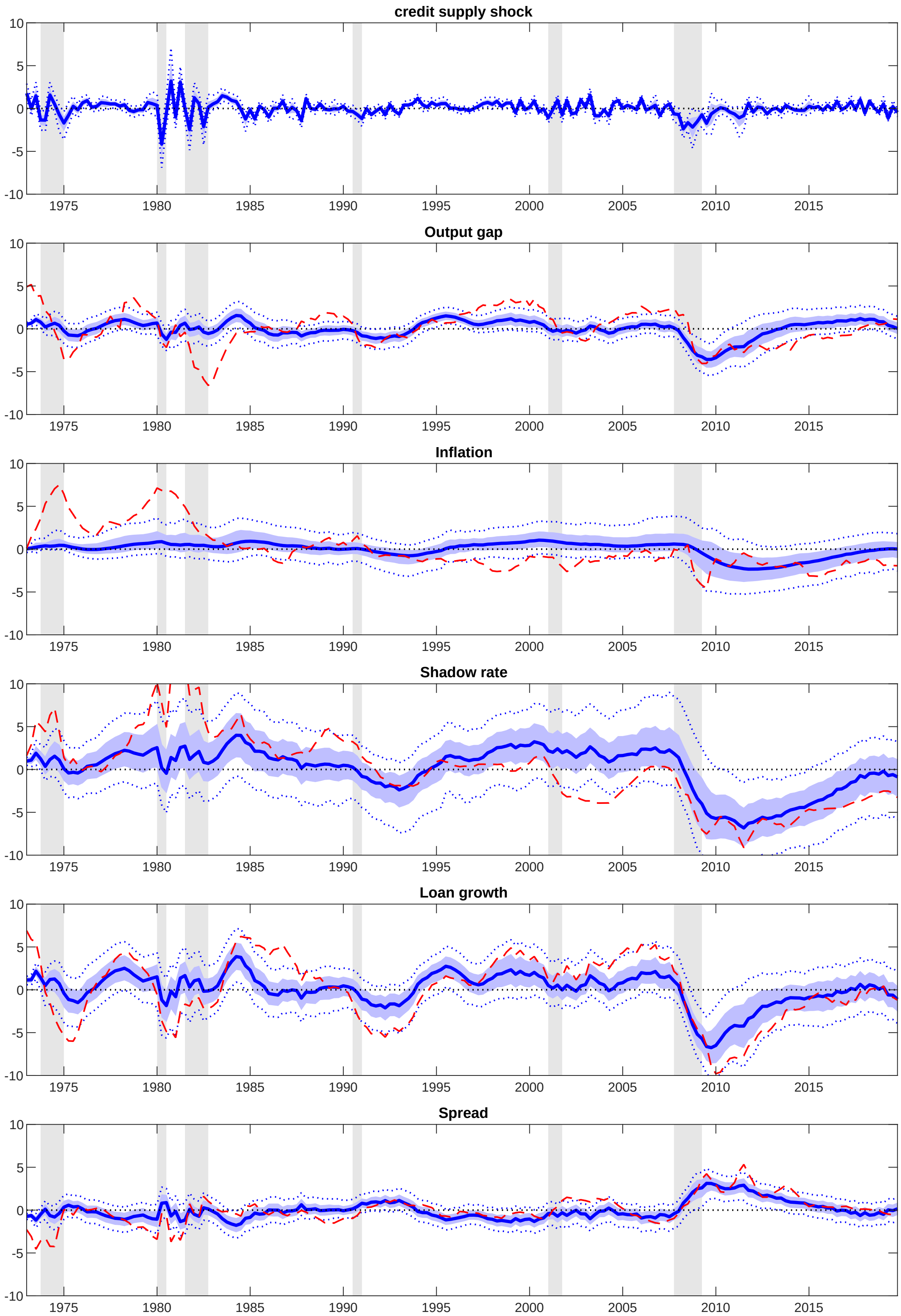

Figure 8: Credit supply shocks and their historical contributions

Note: The first subplot contains the time series of identified credit demand shocks, the remaining subplots their contribution to endogenous variables. 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.

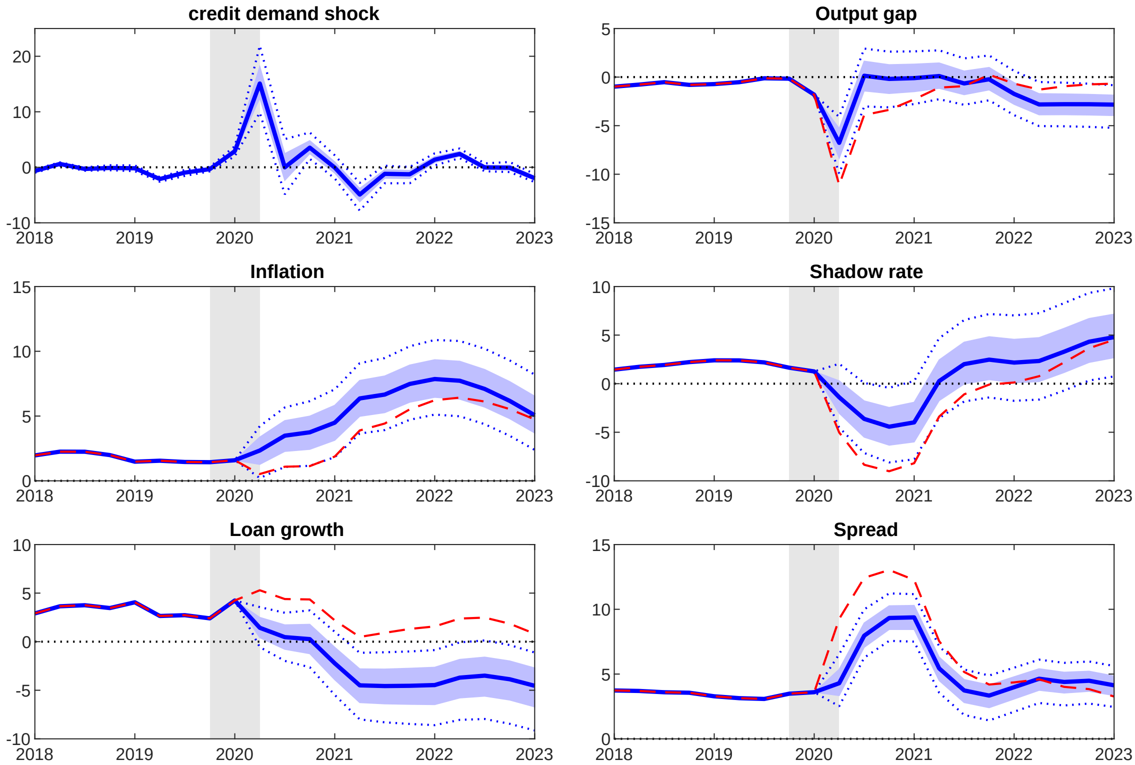

Figure 9: Counterfactual development of endogenous variables, assuming no credit demand shift in 2020Q2.

Note: The first subplot contains the time series of identified credit demand shocks. To calculate the counterfactual developments (the remaining subplots), I set the credit demand shock in period 2020Q2 to zero. Red dashed line: observed development of endogenous variables. Solid blue line: counterfactual, posterior median. Shaded regions: 68% posterior credibility set. Dotted blue lines: 95% posterior credibility set.

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 under the assumption that Covid did not shift credit demand in 2020Q2, while keeping all other structural shocks between 2020Q1 and 2023Q1 as is. Without the shift in credit demand, 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 observed, with a likely lift-off already in 2021Q2 or 2021Q3. Output gaps would have been very different under the counterfactual even beyond 2023. Consistent with the recessionary impact effect of credit demand shocks, I find that the immediate Covid 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 exogenous increase of credit demand, as well as the counterfactual developments, are consistent with early observations of firm behavior 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 and reduced investment.

5 Conclusion

In this paper, I shed additional light on the importance of credit markets for macroeconomic fluctuations by explicitly differentiating between credit demand and credit supply. I investigate both the structural economic equations as well as the resulting structural shocks. Because my data cover all loans to households and nonfinancial firms, credit demand shocks describe, among other things, unexpected changes in the liquidity demand of firms (Li et al.; 2020), or unexpected shifts of collateral constraints (Justiniano et al.; 2019).

I document three key results. First, credit demand is much more elastic than credit supply with respect to all variables except inflation. Thus, when macroeconomic shocks transmit via credit markets to aggregate macroeconomic developments, they do so mostly via credit demand, rather than credit supply. This is important because it improves the prediction of the likely effects of economic policy shocks. Furthermore, the differences between the structural equations confirms the focus of macroprudential policy, which targets credit market outcomes mostly via regulation of credit supply. Second, expansionary credit demand shocks first induce a short recession. The reason for this may be that increased liquidity demand by firms reduces investment incentives, or because larges mortgages increase the debt-to-income ratio of households and reduce consumption (Teulings et al.; 2023). However, after the initial recession, the response to credit demand shocks is a long and sustained boom. This is the reason for the third main result. I show that credit demand shocks mattered in particular during the boom before the financial crisis, while credit supply shocks contributed strongly to the recession itself and the following recovery. Moreover, I document that the Covid pandemic induced a strong expansionary shift of credit demand in 2020Q2, which mitigated the longer-run negative impacts of the Covid recession. It strongly contributed to a balanced output gap in the end of 2021, thereby helping to stave off a stagflationary scenario in 2022.

To show these core results, I introduce two methodological 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 am 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 my approach to construct the granular instrument for mortgage demand as in Gabaix and Koijen (2020). Granular instruments use a granularity condition, whereby shifts ϵ_{it} in individual large regions are so important for aggregate developments that the law of large numbers to fail. In the next subsections, I show first that granularity holds (i.e., region sizes are unequal enough). Second, I present all the relevant data for and regression residuals from the panel regression (see equation (1) in the main text)

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

By controlling for alternative structural explanations, residuals ϵ_{it} can be interpreted as "regional mortgage demand shifts". I use this in the third subsection, where I present the aggregation of ϵ_{it} to a granular instrument for US credit demand shocks.

A.1 Regional data

A.1.1 Regional mortgage origination

I derive my 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.[18] 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,

[18] 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`.

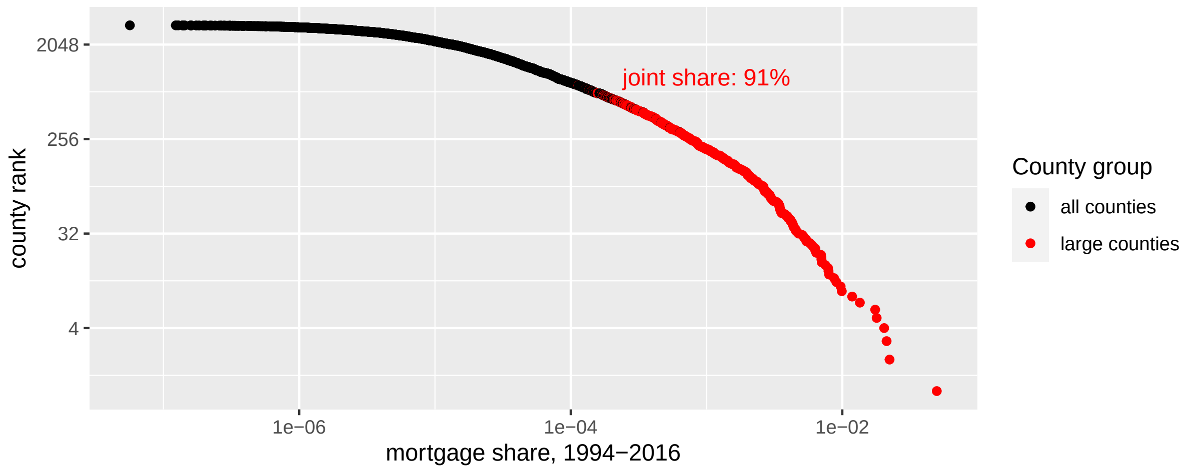


Figure A.1: Log-log plot of county mortgage share distribution

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.

relative to the US for all counties, displaying the counties in my 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 a second step, I remove seasonal variation in loan originations for every county and normalize loan originations L_{it} by the average loan amount $\bar{L}_i$ in the same county. 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

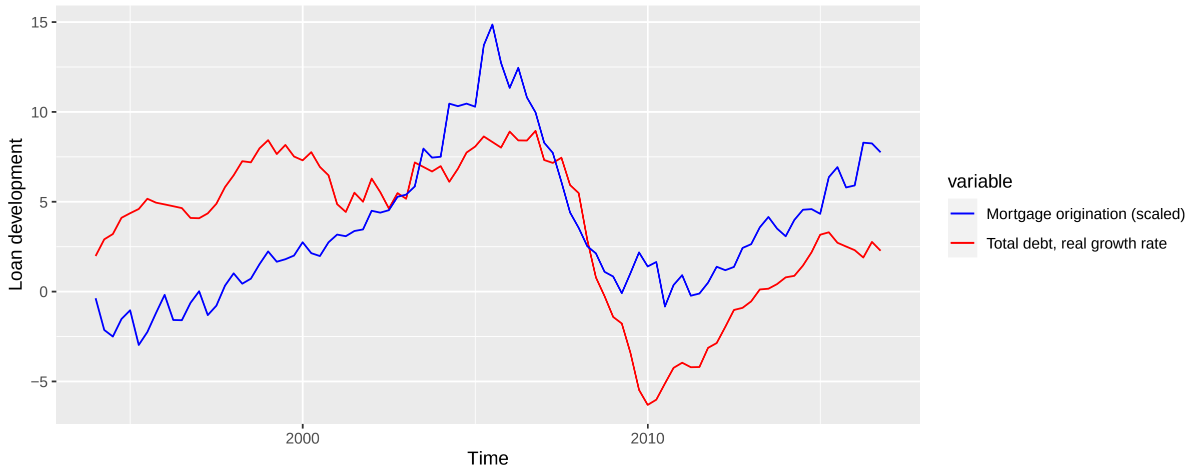


Figure A.2: US real loan volume growth and mortgage origination

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.

are lagged by one quarter.

I derive income per capita and population growth from the population and personal income statistics by the BEA. The BEA reports yearly information of income per capita and population for counties, and quarterly aggregate income for states. I use the quarterly state-level information ($inc_{\iota t}$) to distribute county-level personal income per capita ($inc(p.c.)_{it}$) and population (pop_{it}) over the 4 quarters of the year. Let t be the quarters in year τ, and i the counties in state ι:

$$inc(p.c.)_{it} = \frac{inc_{\iota t}}{\sum_{t \in \tau} inc_{\iota t}} inc(p.c.)_{i\tau}, \qquad pop_{it} = \frac{inc_{\iota t}}{\sum_{t \in \tau} inc_{\iota t}} pop_{i\tau} \tag{6}$$

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 reports 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 me 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. For this reason, I include the FMFM-based controls only in a robustness check, finding no differences in the resulting aggregate granular instrument. Second, only around 25% of my mortgages are purchased by FMFM. However, it is 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.[19] 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}:

$$v_{it} = \frac{1}{\sum_{\text{zip codes } j} s_{ji}} \sum_{\text{zip codes } j} s_{ji} v_{jt} \, , \; v \in \{rate, fico, dsti, ltv, hpi\} \tag{7}$$

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 my dataset usually encompass (near-)complete zip codes, and should therefore be less affected than the smaller counties which are not part of my data.

In addition to the control variables mentioned above, the publicly available loan-level HMDA data (which contain information about banks) allow me to remove the influence of bank-level credit supply shocks. To do so, I calculate the market share $w_{bi\tau}$ of bank b

[19] 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
Δ*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
Δ*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
Δ*inc.pc*	45'572	3.63	3.29	−26.46	72.48
Δ*pop*	45'572	1.33	1.85	−54.30	18.49
employment.pc	45'572	0.43	0.13	0.13	1.57
Δ*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
Δ*est.count.pc*	45'572	0.45	3.03	−27.19	103.65
hpi	43'592	161.27	45.43	85.92	435.08
Δ*hpi*	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

in county i in year τ. Given these market shares, I 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 credit supply in all regions proportional to the engagement of bank b in that region, see also (Khwaja and Mian; 2008; Amiti and Weinstein; 2018). 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

The estimation proceeds in three steps. First, I remove the fixed effects through within transformation, where I introduce a minor adaptation to remove bank-year fixed effects, as

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`.

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.

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 transformation steps. 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, $\sum_b w_{bi\tau} = 1$. Let me 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

$$\begin{aligned} \sum_b w_{bi\tau} \bar{y}^b_{b\tau} &= \sum_b w_{bi\tau} \left[\bar{X}_{b\tau}\beta + \bar{\alpha}_{b\tau} + \bar{\gamma}_{b\tau} + \bar{\lambda}_{b\tau} + \bar{\epsilon}_{b\tau} \right] \\ &= \sum_b w_{bi\tau} \left[\bar{X}_{b\tau}\beta + \frac{\alpha_i}{|N_{b\tau}|} + \frac{\gamma_t}{4} + \lambda_{b\tau} \right] \end{aligned} \tag{8}$$

The difference between equation (1) and equation (8) removes bank-year fixed effects:[20]

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

Removing time and region fixed effects through further within transformations is

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

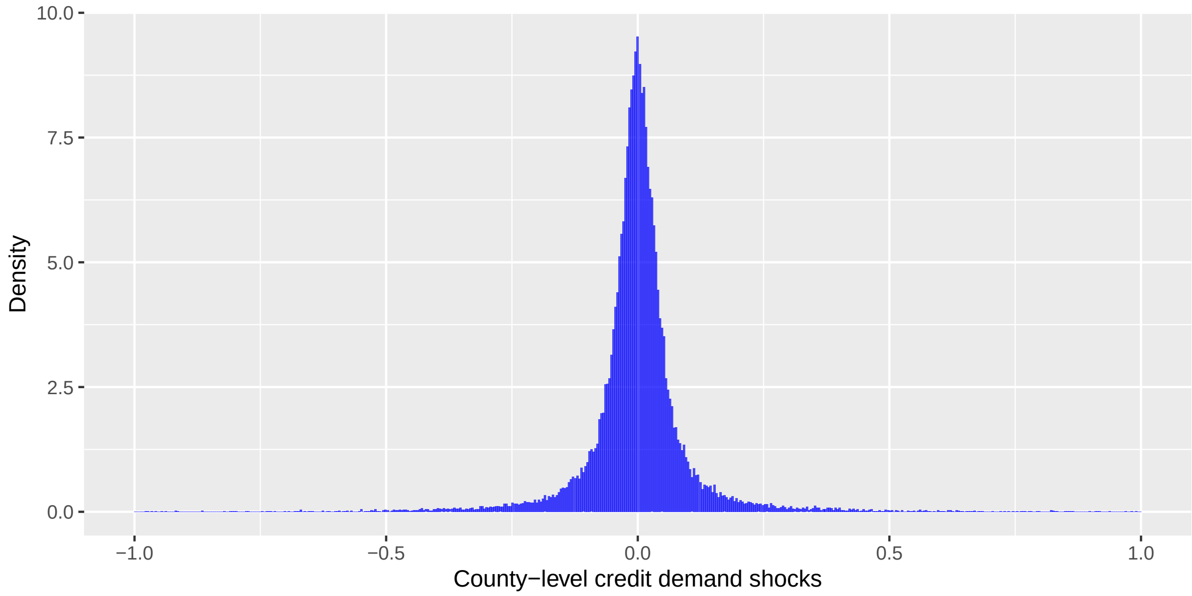


Figure A.3: Histogram of county-level mortgage demand shocks

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

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

A.3 Construction of the GIV

Figure A.3 shows the histogram of residuals of regression 1, which is my 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.

The estimation residuals $\hat{\epsilon}_{it}$ are used to form a granular instrument (Gabaix and Koijen; 2020). The aggregation takes the form of the difference between the size-weighted

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)
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

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 $e_i = 1/N$. 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.

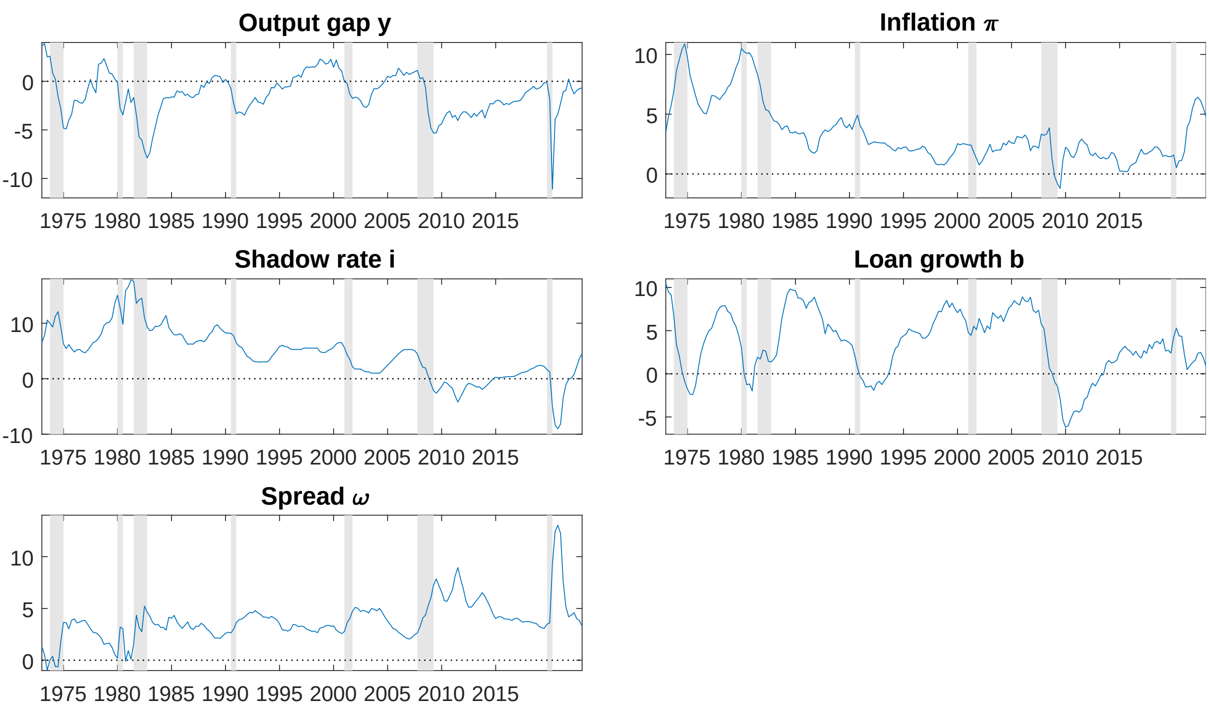


Figure B.1: Endogenous variables

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.

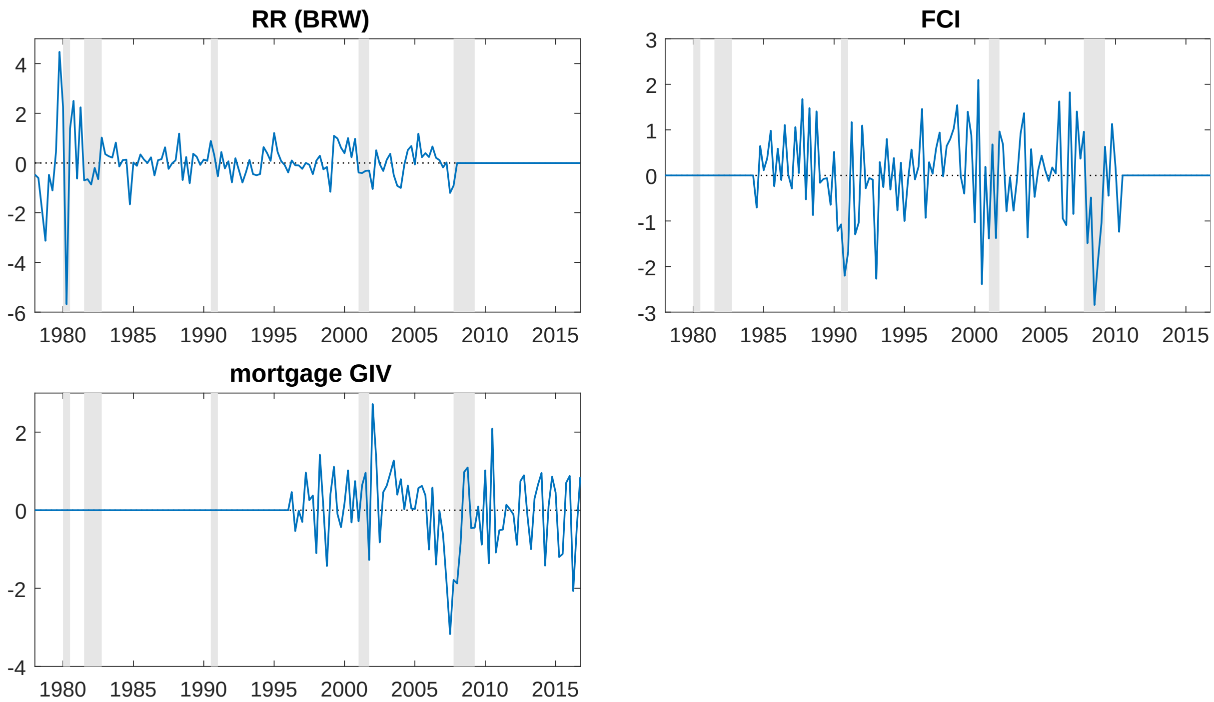


Figure B.2: Instruments, baseline model

I employ a monetary policy and a credit supply instrument in addition to the 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
$SA(\cdot)$: 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`

C Econometric model

C.1 Derivation of the posterior distribution

This section derives the posterior distribution for the structural VAR

$$\mathbf{A}\mathbf{y}_t = \mathbf{B}\mathbf{x}_{t-1} + \mathbf{C}\mathbf{z}_t + \mathbf{v}_t$$
$$\mathbf{v}_t \overset{\text{i.i.d.}}{\sim} \mathcal{N}\left(0, \mathbf{D}\right).$$

using arbitrary prior distributions for $\mathbf{A}$ and $\mathbf{C}$. Conditional on these, I use 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

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

For a characterizations of posterior parameter distributions, I make use of augmented data for each equation i (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 $\mathbf{B}$, $\mathbf{M}_i^{-1} = \mathbf{P}_i\mathbf{P}_i'$:

$$\tilde{\mathbf{Y}}_i = \begin{bmatrix}\mathbf{a}_i\mathbf{Y}_T - \mathbf{c}_i\mathbf{Z}_T & \mathbf{m}_i'\mathbf{P}_i\end{bmatrix}'$$
$$\tilde{\mathbf{X}}_i = \begin{bmatrix}\mathbf{X}_T & \mathbf{P}_i\end{bmatrix}'.$$

Because the instrument coefficients $\mathbf{C}$ can be treated similarly to the structural contemporaneous coefficients $\mathbf{A}$, the following proposition follows directly from Baumeister and Hamilton (2015):

Proposition 1. *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*

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

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*

$$\mathbf{m}_i^* = \left(\tilde{\mathbf{X}}_i'\tilde{\mathbf{X}}_i\right)^{-1}\left(\tilde{\mathbf{X}}_i'\tilde{\mathbf{Y}}_i\right) \tag{9}$$

$$\mathbf{M}_i^* = \left(\tilde{\mathbf{X}}_i'\tilde{\mathbf{X}}_i\right)^{-1} \tag{10}$$

$$\zeta_i^* = \left(\tilde{\mathbf{Y}}_i'\tilde{\mathbf{Y}}_i\right) - \left(\tilde{\mathbf{Y}}_i'\tilde{\mathbf{X}}_i\right)\left(\tilde{\mathbf{X}}_i'\tilde{\mathbf{X}}_i\right)^{-1}\left(\tilde{\mathbf{X}}_i'\tilde{\mathbf{Y}}_i\right) \tag{11}$$

$$\kappa_i^* = \kappa_i + (T/2) \tag{12}$$

$$\tau_i^* = \tau_i + (\zeta_i^*/2) \tag{13}$$

$$p\left(\mathbf{A}, \mathbf{C} | \mathbf{Y}_T, \mathbf{Z}_T\right) = \frac{k_T p\left(\mathbf{A}, \mathbf{C}\right)\left[\det\left(\mathbf{A}\hat{\Omega}\mathbf{A}'\right)\right]^{T/2}}{\prod_{i=1}^{n}\left[2\tau_i^*/T\right]^{\kappa_i^*}} \prod_{i=1}^{n} \frac{|M_i^*|^{1/2}}{|M_i|^{1/2}} \frac{\Gamma\left(\kappa_i^*\right)}{\Gamma\left(\kappa_i\right)} \tau_i^{\kappa_i}, \tag{14}$$

where k_T *is a constant that integrates* $p\left(\mathbf{A}, \mathbf{C} | \mathbf{Y}_T, \mathbf{Z}_T\right)$ *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:

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

To show a similar result in my 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

$$p\left(\mathbf{Y}_T, \mathbf{Z}_T | \mathbf{A}, \mathbf{B}, \mathbf{C}, \mathbf{D}\right) = p\left(\mathbf{Y}_T | \mathbf{Z}_T, \mathbf{A}, \mathbf{B}, \mathbf{C}, \mathbf{D}\right) p(\mathbf{Z}_T). \tag{15}$$

If this is the case, the proof of Proposition **??** 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 (15), 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

$$\mathbf{A}\mathbf{y}_t = \mathbf{C}\mathbf{z}_t + \mathbf{B}\mathbf{x}_{t-1} + \mathbf{v}_t, \qquad \mathbf{v}_t \sim \mathcal{N}(0, \mathbf{D})$$

$$\mathbf{z}_t = \mathbf{w}_t, \qquad \mathbf{w}_t \sim \mathcal{N}(0, \mathbf{W}).$$

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 $\mathbf{W}$.

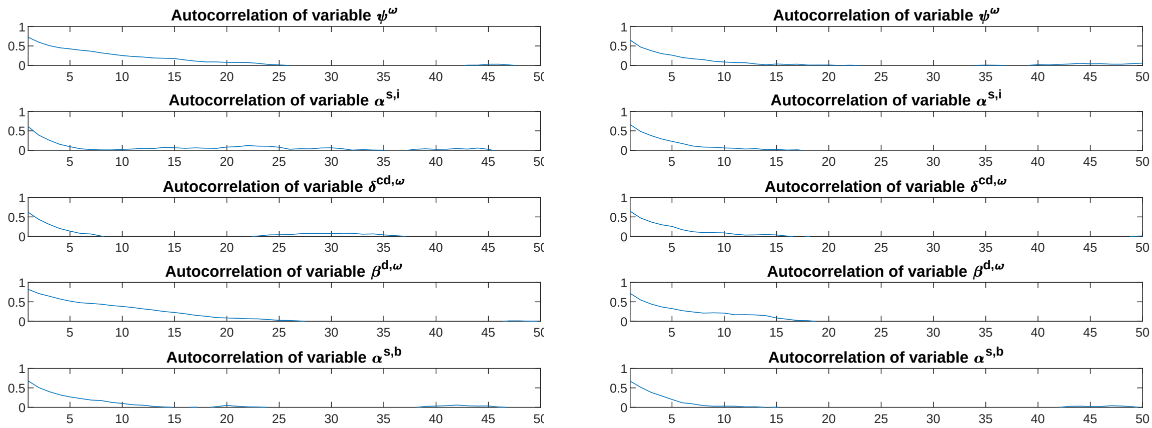
C.2 Convergence statistics

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 $\mathbf{V}$ 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 $\mathbf{V}$. 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

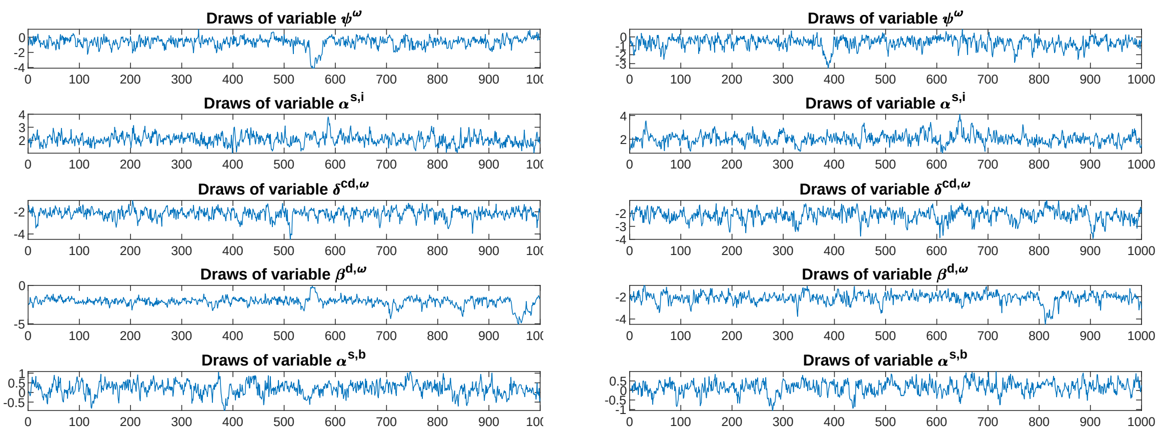
(a) chain 1 (b) chain 2



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

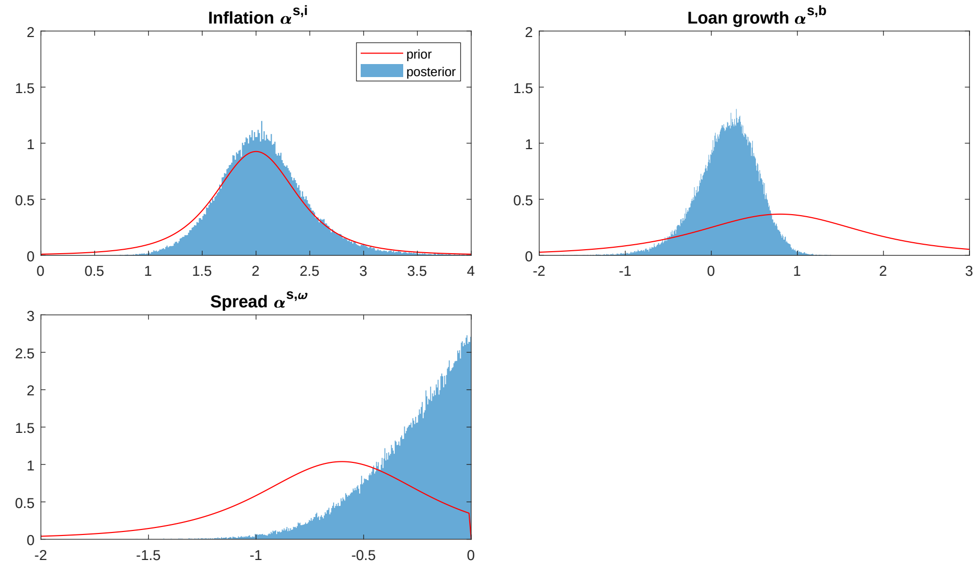


Figure D.1: Contemporaneous coefficients in the aggregate supply equation

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

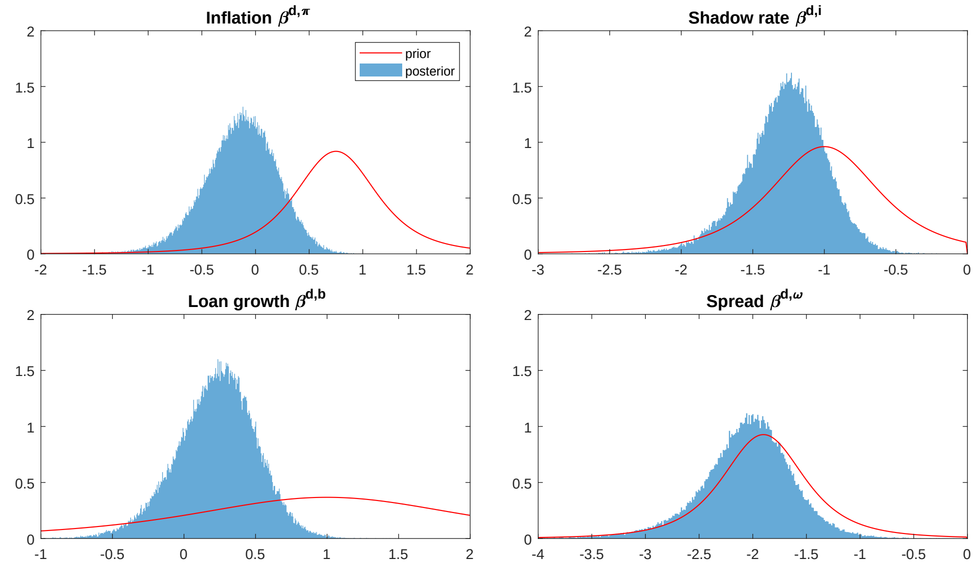


Figure D.2: Contemporaneous coefficients in the aggregate demand equation

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

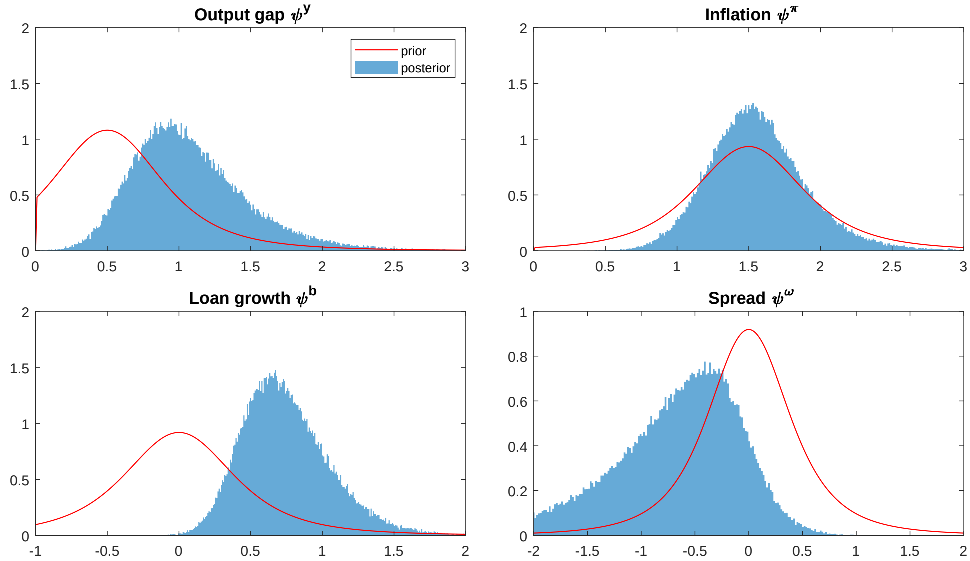


Figure D.3: Contemporaneous coefficients in the monetary policy equation

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

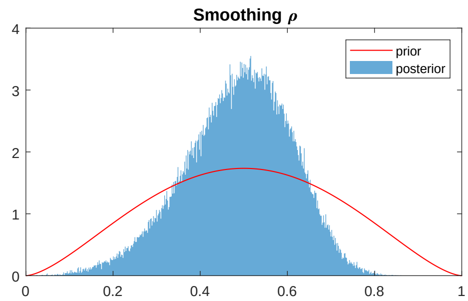


Figure D.4: Monetary policy equation, interest rate smoothing

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

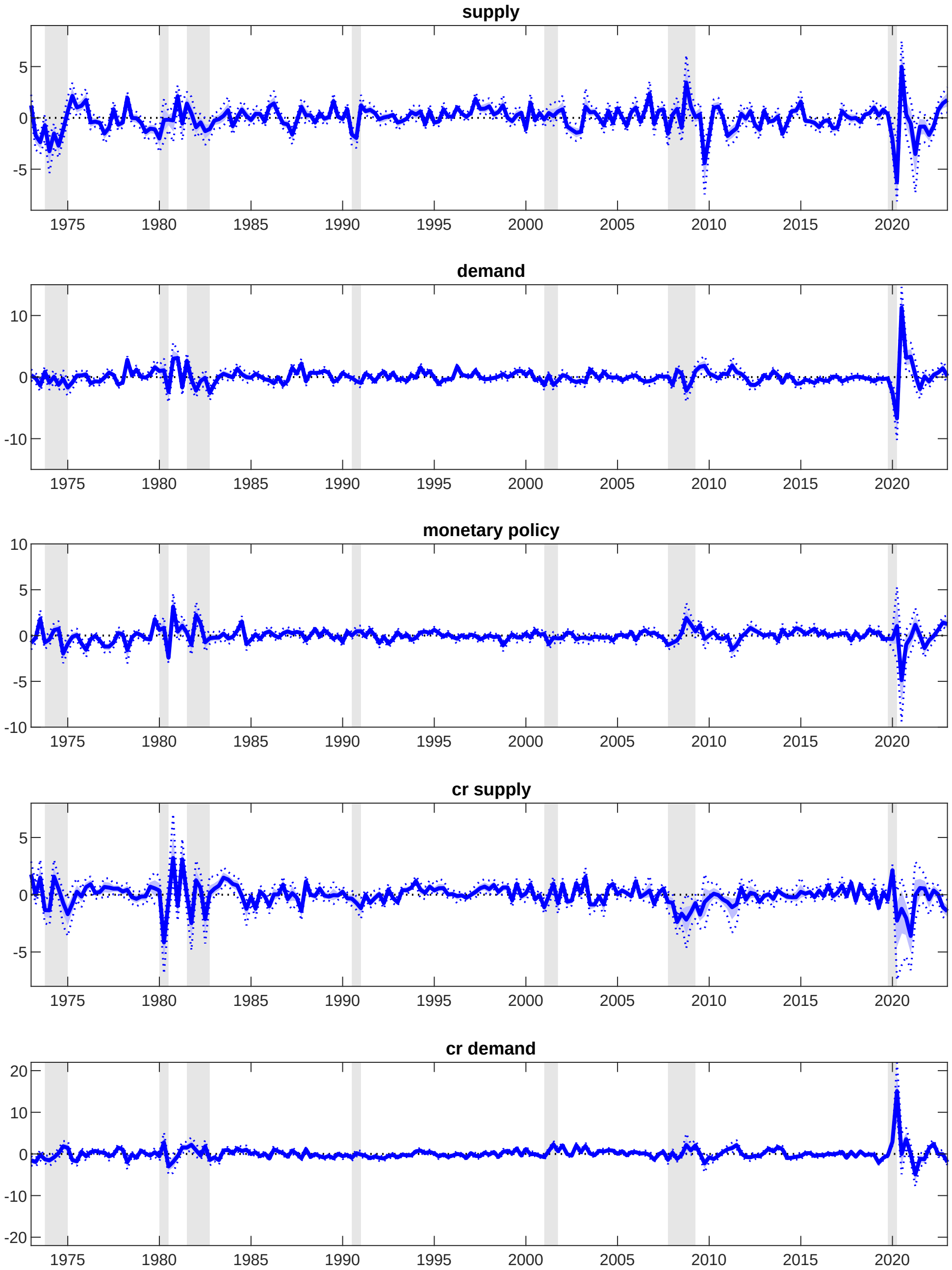


Figure D.5: Structural shocks

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.

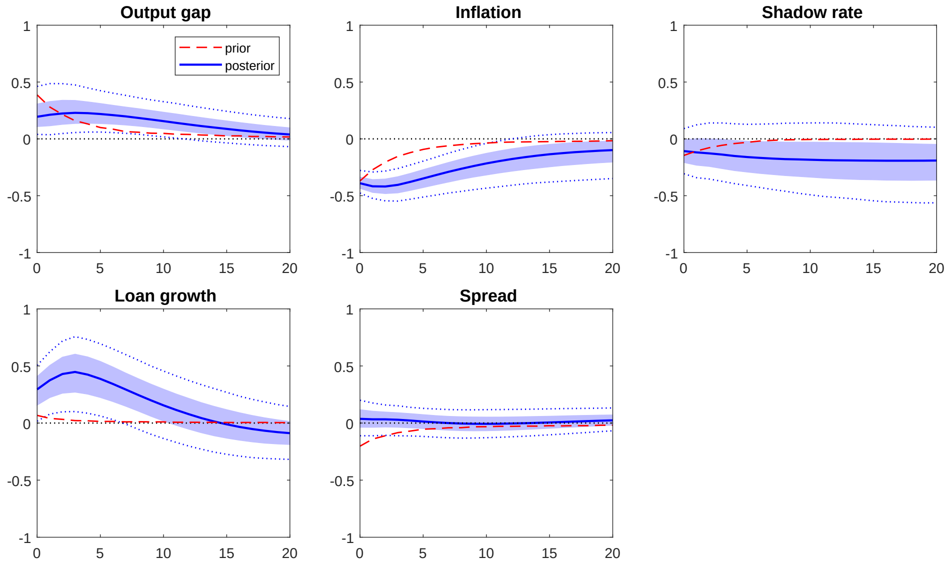


Figure D.6: Impulse response function, aggregate supply shock

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

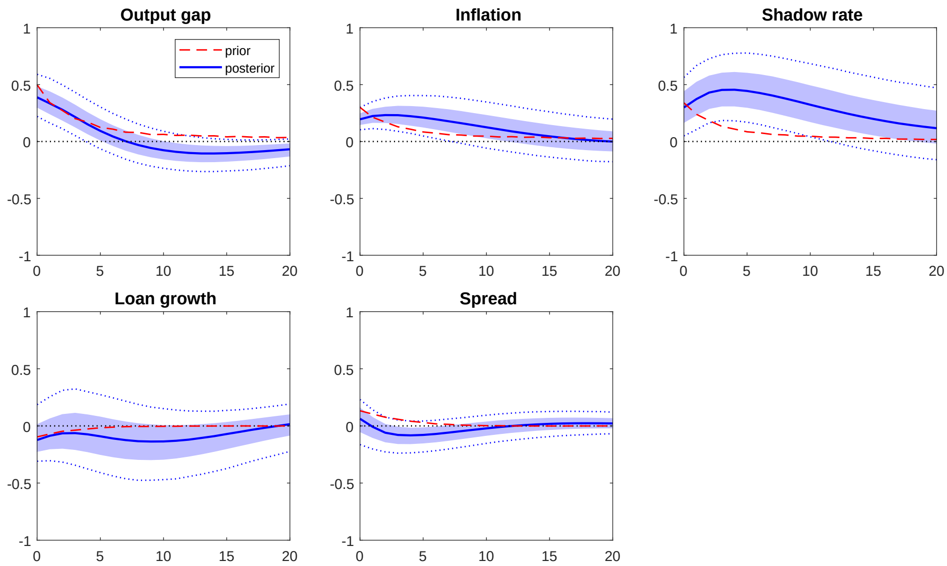


Figure D.7: Impulse response function, aggregate demand shock

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

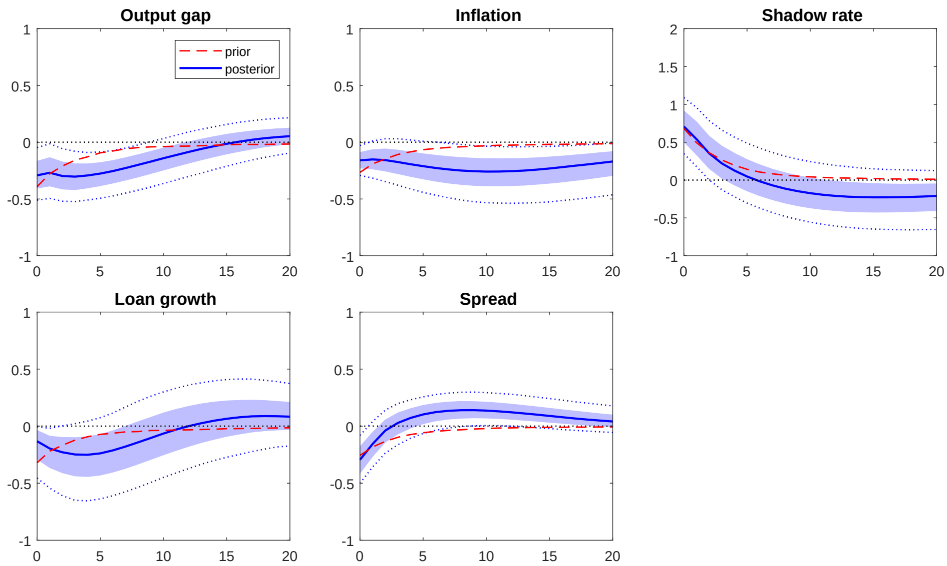


Figure D.8: Impulse response function, monetary policy shock

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

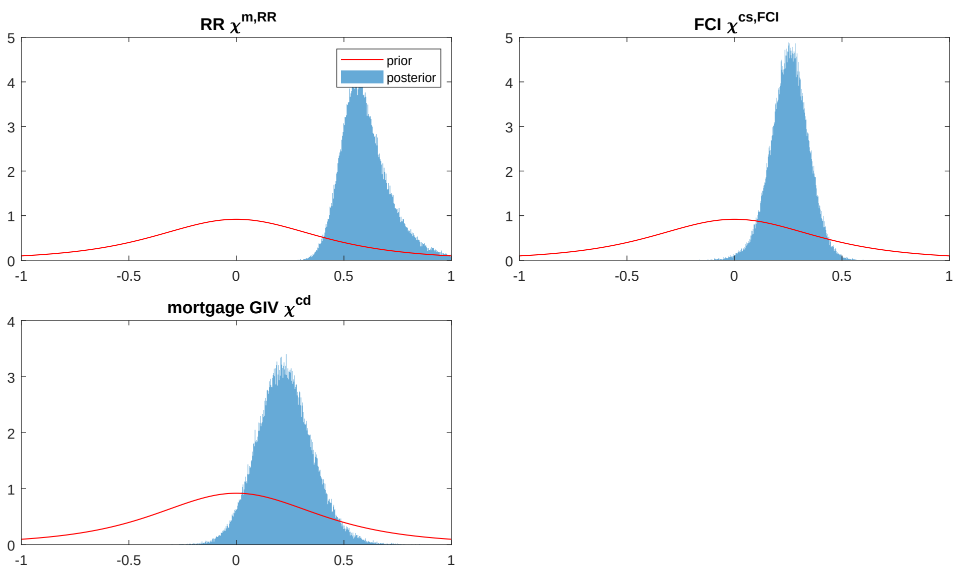


Figure D.9: Instrument coefficients, model with Romer-Romer instrument

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

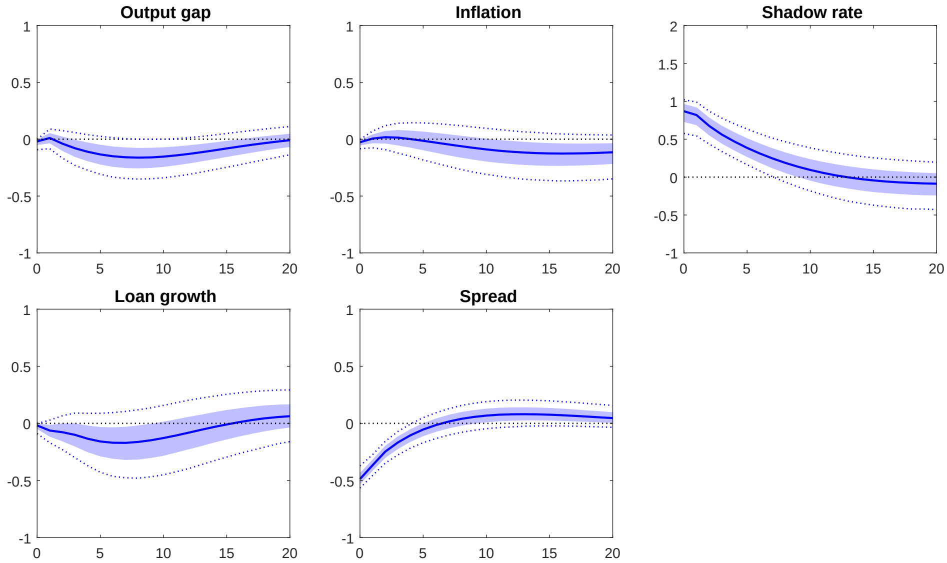


Figure D.10: Impulse response function, monetary policy shock identified using Romer-Romer instrument

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

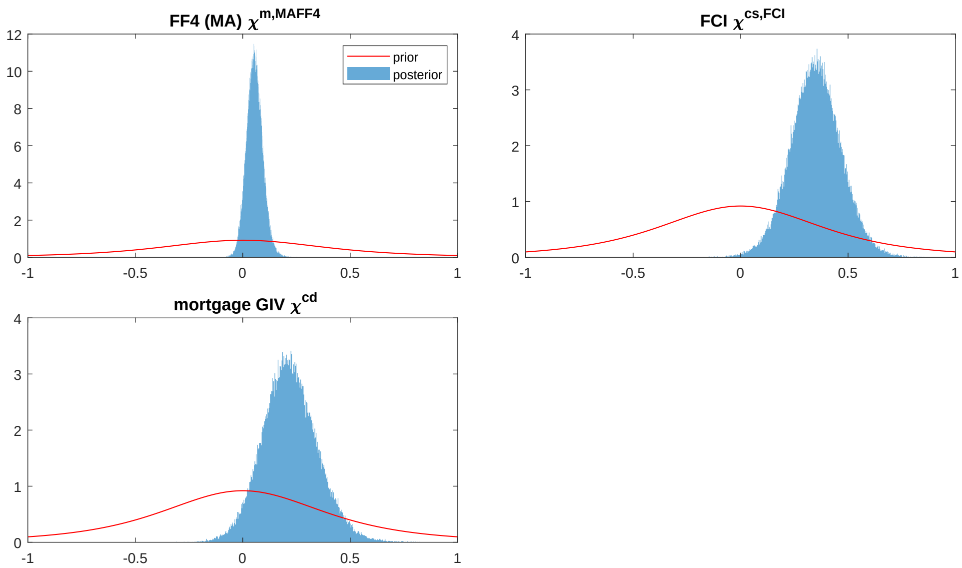


Figure D.11: Instrument coefficients, estimation sample 1994Q1 to 2016Q4

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

Table 8: Log Bayes factors, comparing a model with instrument vs. the model without

	$2log(B)$, 1973Q1-2019Q4	$2log(B)$, 1994Q2-2016Q4
$\chi^{mp} = 0$	-1.39	-0.86
$\chi^{cs} = 0$	3.17	11.96
$\chi^{cd} = 0$	-0.02	4.03
$\chi^{mp} = \chi^{cs} = \chi^{cd} = 0$	1.35	14.10

Note: Log Bayes factors are calculated as the difference between log prior and log posterior densities that instrument coefficients $\chi^{m}, \chi^{cs}, \chi^{cd}$ are individually or jointly zero, i.e. values in the first row are calculated as $2log(B) = 2log(p(\chi^i = 0)) - log(p(\chi^i = 0|\mathbf{Y}_T, \mathbf{Z}_T))$. Jeffrey's criteria indicate that values from 2 to 6 (6 to 10; above 10) provide positive (strong; very strong) evidence against the alternative model.