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Loans to Different Groups and Economic Activity at Times of Crisis and Growth*

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Abstract

We study the contribution of loans, granted to different borrower groups, to economic activity in the United States over the period 1971q1–2018q4. In general, loans to households emerge as the most important driver of economic activity when compared to other borrower groups. Meanwhile, for loans in terms of scope, consumer credit has a prime role. Deep economic recessions occurred during the period considered, we focus on the recent global financial crisis (GFC) to reveal the role of the credit crunch. The analysis confirms that loans had a large negative effect during the GFC when compared to other concurrent shocks. Furthermore, a comparison with other periods in post-war US history points to the specific role that loans played in this last crisis. The results are delivered through a historical decomposition analysis based on the estimation of a large VAR through Bayesian techniques.

I. Introduction

Access to credit is fundamental for economic activity and medium to long-term growth. Loans allow borrowers to achieve several economic goals, from consumption to investments. For this reason, particularly in modern advanced economies, the amount of credit has achieved remarkable levels compared to economic activity. In fact, its growth rate has been much higher than economic growth in the last few decades (Cecchetti, Mohanty and Zampolli, 2011; Schularick and Taylor, 2012; Justiniano, Primiceri and Tambalotti, 2019). However, credit also brings risk: excessive dependence on loans can cause distortions and make both households and firms vulnerable to adverse credit shocks.

The global financial crisis (GFC) and the Great Recession have brought to the fore the dependence of economic activity on credit availability. This connection may be well-known to economic theory (Schumpeter, 1912) but, perhaps, is underestimated in

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[Correction added on 20 May 2022, after first online publication: CRUI-CARE funding statement has been added.]

terms of its potential disruptive effects. In this regard, the GFC is an ideal case study because the turmoil generated in the financial market caused a reduction of credit availability, and this reduction impacted economic activity worldwide. The causality direction is clear for this crisis. In contrast, the role of credit is more blurred in other major historical events of income destruction that occurred after WWII.

Starting from this consideration, the objective of our research is to study the contribution of loans to economic activity. To understand the role that credit plays, we compare the GFC to other recessions and to periods of growth. In particular, we quantify the cumulative contribution of loans to economic activity (GDP) through a historical decomposition (Kilian, 2009; Kilian and Lee, 2014), which is based on the estimation of a vector autoregression (VAR). This topic has been partially investigated in other works (Hristov, Hülsewig and Wollmershäuser, 2012; Gambetti and Musso, 2017) in which, however, the focus was on the average effect of aggregate loans on economic activity. In contrast, we assess the effect of specific loan categories, as well as of other variables, during well-defined periods and not just on average. Furthermore, we exactly split the observed GDP variation across the variables included. We therefore add to the current literature results about the effect of loans to different groups, and for different scopes in general and during specific crises. We also clarify some technical details concerning the application of historical decomposition to estimations in growth rates.

The motivation of our research is rooted in results showing that loans respond differently to a monetary policy shock (den Haan, Sumner and Yamashiro, 2007; Barraza, Civelli and Zaniboni, 2019; Cafiso and Rivolta, 2021), and they are therefore likely to contribute with different intensities to economic activity. To this end, we split borrowers into households and firms. Firms are furthermore split into corporate and non-corporate business. We use disaggregated loans, such as consumer credit and mortgages; Justiniano *et al.* (2019) and Kaplan, Mitman and Violante (2020) have shown that mortgages had a prime role in the GFC. We would like to underline here that our approach, based on the historical decomposition of the GDP variation, is original with respect to other contributions in this branch of literature.

This paper is structured as follows. Section II introduces some recent literature on the effect of loans on economic activity. Section III provides the details on the estimation of the VAR using the Bayesian approach and on the historical decomposition built on the VAR estimation output. Section IV discusses the contribution of the different loan categories to economic activity as derived from the historical decomposition analysis. Finally, section V draws the conclusions of our research.

II. Loan shocks and economic activity: a short review of the literature

Credit availability influences the real economy in the short run via its capacity to expand aggregate demand components (Khan and Thomas, 2013; Guerrieri and Lorenzoni, 2017), household consumption and firms' investments in the first place (Cafiso, 2019). A large increase in credit to the economy in the last few decades has been observed and explained. Among the others, Justiniano *et al.* (2019) link this increase, particularly of mortgages, to reductions in lending constraints and financial innovation (i.e. securitization), which eased the flow of funds from savers to borrowers.

Apart from the monetary policy literature, recent research originated from the events of the GFC, has investigated the disruptive effects of credit shocks on economic activity (Mimir, 2016). In this context, shocks are defined through an unexpected variation of the quantity of loans granted (Busch, Scharnagl and Scheithauer, 2010; Hristov *et al*., 2012; Eickmeier and Ng, 2015), which may be accompanied/followed by a specific change of the interest rate; as it is often assumed in sign-identified VAR (Gambetti and Musso, 2017). Indeed, price shocks alone, alias interest-rate shocks, do not imply a credit reduction with certainty (Gilchrist and Zakrajšek, 2012, p. 1962).

Some research has focused specifically on understanding how the financial crisis managed to hit the economy so hard. Stock and Watson (2012) affirm that the GFC was characterized by shocks of unprecedented size but it was not a new typology of shocks, and therefore their impact on economic activity was largely foreseeable. Debt was truly at an unprecedented level at the time of the crisis, particularly household debt, and some of its features (such as its adjustable interest rate) made borrowers vulnerable to policy changes (Debelle, 2004). Furthermore, Ramcharan, Verani and van Den Heuvel (2016) assert that some novelties brought in by financial innovation, such as securitization, as well as the conjunction of high levels of household leverage during the boom with falling house prices during the bust, amplified the effect of the financial shock. Many researchers consider the housing market to be at the heart of the Great Recession and as important as the credit crunch, to which it is intertwined (for a synthesis of this view, see Guerrieri and Uhlig, 2016 and Mian and Sufi, 2016).

Research has proven that financial shocks are major drivers of economic fluctuations (Prieto, Eickmeier and Marcellino, 2016), probably more than other shocks of a different origin (Jordà, Schularick and Taylor, 2013; Furlanetto, Ravazzolo and Sarferaz, 2019), because of their interplay with uncertainty shocks (Caldara *et al*., 2016). Their consequences extend to different dimensions. Among the others, inequality is observed to increase (Menno and Oliviero, 2020).[1] Theoretical papers (such as Christiano, Motto and Rostagno, 2014; Mian and Sufi, 2014; Kaplan, Moll and Violante, 2018) have modelled the channels through which credit shocks impact economic activity and employment via consumer and firm behaviours. These studies suggest that their impact goes beyond what depends strictly on reduced credit availability because precautionary and forward-looking attitudes of households and firms trigger in and push both to save more to get ready against possible further adverse shocks (Khan and Thomas, 2013; Guerrieri and Lorenzoni, 2017). In addition, Kaplan *et al*. (2020) suggest that belief shifts about the future are the cause of the bust of the housing market, more than changes in credit conditions.

A first group of empirical papers has used macro and financial data to investigate different dimensions of the GFC. The contributions mentioned above (Stock and Watson, 2012; Caldara *et al*., 2016; Prieto *et al*., 2016; Furlanetto *et al*., 2019) are part of this literature. In the same group, Hristov *et al*. (2012) and Gambetti and Musso (2017) have specifically focused on the identification of supply-side loan shocks using

[1]Menno and Oliviero (2020) study the welfare effects of the Great Recession in the United States and their distribution between borrowers and savers. They find large welfare costs for the borrowers caused by the plunge in house prices.

sign restrictions (Uhlig, 2005) and checked their impact on economic activity. However, they only consider aggregate loans and do not differentiate across borrowers.[2] In some regards, this branch of research can be considered to be an evolution of the research on the credit channel (Bernanke and Gertler, 1995) but, unlike works on the credit channel, its focus is on shocks that originate in credit markets, and not from other sources and transmitted through credit markets.[3]

Other empirical contributions have used microdata, and have shown how the seeds and effects of the credit crunch can be detected along different dimensions. Mian and Sufi (2010) show that US counties with higher household leverage prior to 2007 reduced durable consumption by significantly more after the fall of 2008. They conclude that the leverage level is therefore a powerful statistical predictor of the severity of the 2007–09 recession. Ramcharan *et al*. (2016) use microdata from the housing and automobile markets to measure the real consequences of the credit shock. They show how the collapse of the ABS market affected the supply of credit to consumers and consumption as a consequence. Along the same line, Benmelech, Meisenzahl and Ramcharan (2016) discuss how frictions in short-term credit markets, such as those in which non-bank suppliers of auto loans get funds, impair their capacity to provide loans and this exacerbates the fall of economic activity, as shown by the fall of auto sales. As for the effect of credit shocks on firms, Dwenger, Fossen and Simmler (2020) provide results showing that when a firm's reference bank is hit by an adverse shock, the firm reduces investments and employment.

These contributions show neatly that heterogeneous agents, alias different groups of borrowers in a more empirical context, behave consistently in a different manner. Meanwhile, Bernanke and Gertler (1995), den Haan *et al*. (2007) document a different response of business loans with respect to household loans when a monetary shock occurs. Recently, Barraza *et al*. (2019) have suggested an explanation of such a divergence for which demand factors prevail before the GFC, while supply factors do afterwards. This was a further motivation to compare different periods of crisis and growth in our analysis. Furthermore, Cloyne, Ferreira and Surico (2016) split the household group into mortgagors, outright owners and renters in the United States and the United Kingdom. They show that differences emerge across those groups.[4] In brief, considering heterogeneous agents has revealed how different groups respond to the same shock, this motivates us to check how loans to different groups impact economic activity. This line of research was suggested by Gambetti and Musso (2017).

With respect to this literature, our research bridges two streams of research: the first on the role of credit shocks in recessions, the second centred on the use of

[2]We do not know whether this is an intentional choice but it is likely to be forced when identification is via sign restrictions. Indeed, it is hard to imagine a combination of signs effective to disentangle loan-to-households supply shocks from, for instance, loan-to-firms supply shocks. It would be necessary to add supplementary variables to the VAR that respond significantly and in an opposite direction to a shock to the two different groups of loans.

[3]In the literature about the credit channel of monetary policy, credit works more as a financial accelerator in propagating other shocks to the macro-economy (Cafiso, 2020).

[4]Coletta, De Bonis and Piermattei (2014), Christelis, Ehrmann and Georgarakos (2015) and Sufi (2015) define a relationship with the country of residence. Cloyne and Surico (2016), Bunn *et al*. (2017) assert the same too: agents respond differently and that depends on the country they reside in to some extent.

heterogeneous borrowers and of loans for different uses. Our scope is to assess the contribution of different loan categories to the evolution of economic activity during the GFC and other periods. We employ the analytical approach in Kilian (2009), Kilian and Lee (2014), which consists of a historical decomposition.

III. VAR estimation and historical decomposition

Our analysis is based on the estimation of a vector autoregression (VAR, Stock and Watson, 2001), the estimation is performed through the Bayesian approach. We identify the structural shocks from the reduced-form residuals using the Cholesky decomposition (recursive VAR, Wald causal chain). Instead of the well-known impulse response analysis, which returns the average effect of a variable on another over the entire estimation period, we opt for the *historical decomposition analysis* because it best suits our research objective given that it allows us to study specific points in time. After introducing the data that we have used, we explain the details of the VAR estimation. The last subsection provides information on the historical decomposition analysis whose results are presented in the next section IV.

Data

This analysis is based on US quarterly data and is developed around the loan series extracted from the Financial Accounts of the United States (Federal Reserve Board of Governors). The data are available starting from different dates and up to the end of 2018, the analysis is for the period 1971q1–2018q4. We conceptually group all of the variables needed for the analysis into five blocks: slow-moving price indices, loans, interest rates, fast-moving price indices and real variables.

The loan series are for the borrower groups: *Households and Non-Profit organizations* (HNP), *non-financial Corporate Business* (CBS) and *non-financial Non-Corporate Business* (NCB). Loans are from all sources, depository and non-depository institutions. This is most important for households because a large part of their loans are granted by non-depository institutions (Gambetti and Musso, 2017).[5] For each group, we have the following categories:

1. Total Mortgages (MTG). This category includes home, multifamily residential, commercial and farm mortgages granted by government and private institutions. The list of all components is in Table A2 in the appendix.
2. Consumer Credit (CCR). This is available only for households and it includes loans granted by depository (banks) and non-depository institutions, both public and private; some student loans are an example of consumer credit granted by government agencies, automobile loans are also part of this category.

[5]The loan data are made available non-seasonally adjusted, we have seasonally adjusted them by using the X-13ARIMA-SEATS program developed at the US Census Bureau. Loan series exhibit a strong seasonality on the fourth quarter.

3. Other Loans n.e.c. (OLN). This category is the sum of all loans by banks (i) and non-depository institutions (ii) granted for any purpose except mortgages and consumer credit, which are shown in the previous categories. The list of all components is given in Table A3 in the appendix.

Each loan category that we use is therefore uniquely identified by scope and borrower. Table 1 lists all of the loan categories available by borrower, a graph reporting their level for the three borrower groups is given in Figure 2 (first column).

As for the other variables, the block of *real variables* includes the gross domestic product (GDP; plotted in Figure 1), inventories and sales. GDP is the response variable on which we will assess the effect of all loan shocks, inventories and sales are included to account how loan shocks impact on aggregate demand and production.[6] The block of *slow-moving price indices* includes a world index of commodity prices, the consumer price index, the house price index. The world index of commodity prices aims to reduce the price puzzle observed in VAR estimations, the house price index accounts for the housing market evolution, the consumer price index is able to reflect domestic prices dynamics. The block of *fast-moving price indices* includes the crude oil price (West Texas Intermediate) and the Standard & Poors 500 index. These are fast moving because they are indices from high-frequency electronic trading, both are included to comprise important determinants of economic performance and potential causes of economic crisis. The separation between fast and slow price indices is functional to the structural identification (which will be discussed later on). The block of interest rates includes: the Federal Funds Rate, replaced with the shadow rate by Wu and Xia (2016) for the ZLB period (2009q1–2018q4), the interest rate spread on 3-month business loans, the interest rate spread on 24-month personal loans, the

TABLE 1

US loans by borrower

Households and non-profit ***(HNP)*** *(FL15 4123005.Q)*	*Corporate business* ***(CBS)*** *(FL10 4123005.Q)*	*Non-corporate business* ***(NCB)*** *(FL11 4123005.Q)*
MTG: total mortgages (FL15 3165005.Q)	**MTG**: total mortgages (FL10 3165005.Q)	**MTG**: total mortgages (FL11 3165005.Q)
CCR: consumer credit (FL15 3166000.Q)		
OLN: other loans (FL15 3168005.Q + FL15 3169005.Q)	**OLN**: other loans (FL10 3168005.Q + FL10 3169005.Q)	**OLN**: other loans (FL11 3168005.Q + FL11 3169005.Q)

Notes: This table reports all the loan categories used for the analysis grouped by borrower. The code in parenthesis identifies the series in the system of US Financial Accounts (BGFRS). Bold letters are for the acronyms identifying borrowers and loan categories throughout the paper.

[6]We constructed the inventory series in levels from variations (national accounts records) and made them directly comparable to the sales index series in levels released by the OECD. Inventory variations are indirectly compiled based on the identity: production is equal to sales plus inventory variation ($P_t = S_t + \Delta I_t$) (Ramey and West, 1999).

interest rate spread on 30-year mortgages. All spreads are with respect to the Treasury bill.[7] The Fed-funds rate accounts for the monetary stance, while the others reflect the cost of private loans.

Table 2 lists all of the variables with the respective source. The order of the variables in Table 2 reflects the order in the VAR, which is important because identification is based on the Wald causal chain (Cholesky decomposition). We will discuss this in more detail in the structural-identification subsection.

Some statistics on loans

The evolution of loans for each borrowing group is plotted in Figure 2. To gain information on the amount of each component over the total, we report weights in Table 3 and plot them in the second column of Figure 2. As for each borrower group's share over the total amount of loans in the economy (panel (a) in Table 3), loans to households amount to an average 62% and their share increases over the period considered, loans to corporate business amount to an average 18% with a constantly decreasing share, loans to non-corporate business to an average 20% with a fairly stable share.

As for the within-group composition, panel (b) in Table 3 reports each category's share; such weights are those plotted in Figure 2 (second column). The components of

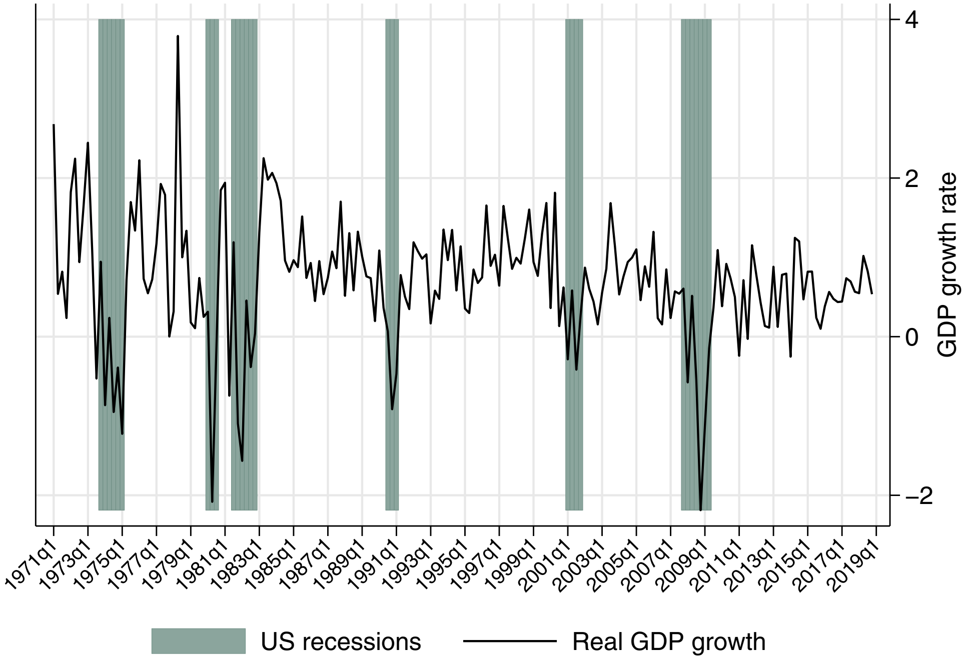


Figure 1. Real GDP growth rate

[7]For a discussion of the use of credit spreads, see Gilchrist and Zakrajšek (2012).

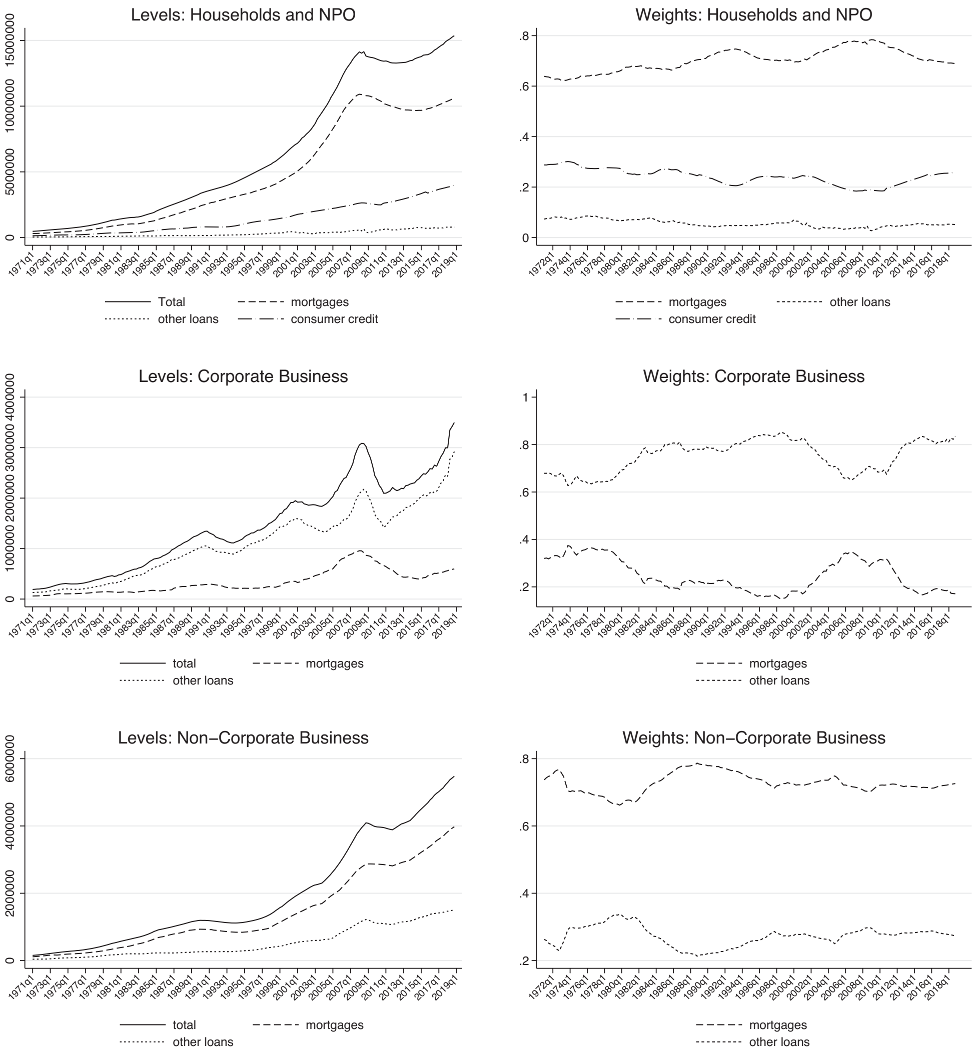


Figure 2. Loans by borrower, levels and weights

loans to households and non-corporate business are more stable over time than those of corporate business.

Estimation

We estimate the reduced-form VAR:

$$y_t = \alpha + \sum_{i=1}^{p} \beta_i y_{t-i} + \varepsilon_t$$

in which y_t is a 19-variable vector. Except for the credit spreads in first difference, all of the other variables are in log-differences. The choice for a VAR in differences is to

TABLE 2

List of variables

No.	*Block*	*Variable*	*Short*	*Source*	*Transf.*
1	(A) Slow-moving price indices	World index of commodity prices	WCP	Datastream	log-diff.
2		Consumer price index	CPI	OECD	log-diff.
3		House price index	HPI	FRED	log-diff.
4	(B1) Loans to households	Mortgages	HNP-MTG	BGFRS	log-diff.
5		Consumer credit	HNP-CCR	BGFRS	log-diff.
6		Other loans	HNP-OLN	BGFRS	log-diff.
7	(B2) Loans to corporate	Other loans	CBS-OLN	BGFRS	log-diff.
8	business	Mortgages	CBS-MTG	BGFRS	log-diff.
9	(B3) Loans to non-corporate	Mortgages	NCB-MTG	BGFRS	log-diff.
10	business	Other loans	NCB-OLN	BGFRS	log-diff.
11	(C) Interest rates	Fed funds rate	IR.FFR	FRED	diff.
12		Credit spread on 3-month business loans	IRS.B03m	FRED	diff.
13		Credit spread on 24-month personal loans	IRS.P24m	FRED	diff.
14		Credit spread on 30-year mortgages	IRS.M30y	FRED	diff.
15	(D) Fast-moving price	Crude oil price	COP	FRED	log-diff.
16	indices	Standard & Poors 500	SP500	Datastream	log-diff.
17	(E) Real variables	Gross domestic product	GDP	OECD	log-diff.
18		Sales	SALES	OECD	log-diff.
19		Inventories	INVEN	OECD	log-diff.

Notes: This table reports all the variables included in the VAR, grouped by bock. As for the sources, OECD stands for Organization for Economic Cooperation and Development, BGFRS for Board of Governors of the Federal Reserve System, FRED is the Saint Louis Fed's online application to extract data. The column 'short' reports the acronyms of the loan items (categories) used throughout the paper. COP is the West Texas Intermediate price, HPI is the All-Transactions House Price Index for the United States, WCP is the Commodity Research Bureau spot price index.

ensure stability to the VAR, which is necessary for historical decomposition analysis. The VAR includes one lag for each variable.[8] This results in 420 parameters (21 by equation) to estimate with approximately 144 observations. To deal with such over-parametrization (curse of dimensionality), which comes with the estimation of large systems (Bańbura, Giannone and Reichlin, 2010; Giannone, Lenza and Primiceri, 2015), we resort to the Bayesian approach that allows to shrink the parameter space. From this perspective, our analysis is similar to Giannone, Lenza and Reichlin (2019).

The posterior distribution is summarized by its median value. We specify the prior distribution as a Normal-InverseWishart (natural conjugate prior, see Dieppe, Legrand and van Roye, 2018):

[8]Other contributions in this branch of literature includes two lags when using quarterly data in log-levels (Hristov *et al*., 2012; Gambetti and Musso, 2017; Cafiso, 2020), we therefore opted for one lag only because we use first differences. The robustness checks discussed below show that inclusion of two lags does not change the results.

TABLE 3

Loan weights

Panel (a)	*HNP*			*CBS*		*NCB*	
1970q1–1979q4	56.7%			22.6%		20.7%	
1980q1–1989q4	55.8%			21.3%		22.9%	
1990q1–1999q4	63.9%			18.7%		17.5%	
2000q1–2009q4	67.7%			14.5%		17.8%	
2010q1–2018q4	66.7%			11.9%		21.4%	
1970q1–2018q4	62.0%			17.9%		20.0%	
Panel (b)	*-MTG*	*-OLN*	*-CCR*	*-MTG*	*-OLN*	*-MTG*	*-OLN*
1970q1–1979q4	63.9%	7.7%	28.4%	34.2%	65.8%	71.0%	29.0%
1980q1–1989q4	68.0%	6.3%	25.7%	23.1%	76.9%	73.6%	26.4%
1990q1–1999q4	72.1%	5.0%	22.8%	18.6%	81.4%	74.8%	25.2%
2000q1–2009q4	74.9%	4.1%	21.0%	27.4%	72.6%	72.3%	27.7%
2010q1–2018q4	72.1%	4.9%	23.0%	21.3%	78.7%	71.9%	28.1%
1970q1–2018q4	70.2%	5.6%	24.2%	25.0%	75.0%	72.7%	27.3%

Notes: HNP stands for households and non-profit, CBS for corporate business, NCB for non-corporate business. MTG for morgages, CCR for consumer credit, OLN for other loans. Panel (a) reports the shares of the aggregates by borrower over the total amount of loans in the economy, panel (b) reports the shares of each loan category over the total by borrower group.

1. prior for the mean $\beta \sim N(\beta_0, \Sigma \otimes \Phi_0)$,
2. prior for the variance-covariance matrix $\Sigma \sim IW(S_0, \alpha_0)$,

so that the posterior is also a Normal-InverseWishart. The prior hyperparameters are defined as follows: autoregressive coefficient equal to 0.5, overall tightness (λ_1) equal to 0.1, cross-variable weighting (λ_2) equal to 0.5, lag decay (λ_3) equal to 2. The total number of iterations is 1,000, the number of burn-in iterations is 500.[9]

Given the VAR structural form:

$$\Phi y_t = \Lambda_0 + \Lambda_1 y_{t-1} + \cdots + \Lambda_p y_{t-p} + u_t \tag{1}$$

the u_t innovations are identified through the Cholesky decomposition from the reduced-form residuals ε_t:

$$u_t = \Phi \varepsilon_t,$$

Φ is therefore lower triangular and the order of the variables reflects the Wald causal chain implicit to the recursive identification.

[9]To set the overall-tightness parameter (λ_1), we follow Bańbura *et al.* (2010) and define a shrinkage level based on the number of variables in the VAR. For $\lambda_1 = 0$ the posterior equals the prior and the data do not influence the estimates (maximum shrinkage), for $\lambda_1 \to \infty$ the posterior expectations coincide with the ordinary least squares estimates (no shrinkage). Then, when there are more coefficients to estimate, λ_1 should be closer to zero (higher tightness, Bańbura *et al.*, 2010, see Table I). We set λ_1 equal to 0.1, which is close to the 0.108 optimal value found by Bańbura *et al.* (2010) for a VAR of 20 variables. In their work, this optimal value is found as the one minimizing the in-sample mean squared forecast error. As a robustness check, we have used other values of the hyperparameters and the results remain very much stable. See the robustness-checks section.

Structural identification

Recursive identification requires that some variables are restricted to respond with a lag to a specific shock while others respond contemporaneously. In general, the timing of the across-variables effects chosen needs to be checked for robustness. Nonetheless, given our objective to assess the differential effect of shocks to specific loan categories on the GDP, this turned out to be the best approach because it allows us to identify separately all the shocks to the different loan categories at the same time.[10]

To define the order of the variables, we have conceptually grouped the variables in the VAR in blocks and regarded them as homogeneous groups in terms of their likely response to the shocks of interest (Christiano, Eichenbaum and Evans, 1999). The five blocks are those in the second column of Table 2: slow-moving price indices, loan aggregates, interest rates, fast-moving price indices and real variables. The order chosen derives from two specific considerations: first, we are primarily interested in the effect of credit shocks on GDP; second, we use quarterly data. Both induced us to allow for contemporaneous effects of the loan aggregates on the GDP, the interest rates and the financial variables. In contrast, ruling out contemporaneous effects of the loan aggregates on the real variables (by ordering the block of real variables first) would limit and bias the dynamics of the main effect in which we are interested, an effect which is likely to emerge within a 3-month horizon.[11]

For the same reason, the block of interest rates is also ordered after loans. Indeed, interest rates should be simultaneously determined with loan quantities at the equilibrium of the loanable-funds market. Within the group of interest rates, the monetary policy rate is imagined to impact loan aggregates with a lag because they are known to be sticky and need time to adjust. The two fast-moving price indices included (the Standard & Poors 500 stock-price index and the West Texas Intermediate crude oil price index) are generated through electronic trading and are known to be responsive to short-term economic dynamics. They are then positioned after the loan block. In contrast, we restrict the effect of loan shocks on the three price indices deemed as slow moving in relation to loan shocks. These are the world index of commodity prices, which is unlikely to respond promptly to shocks to the US loan

[10]Some contributions using quarterly data that study credit shocks as we do apply sign restrictions. The technique was pioneered by Uhlig (2005) and has a serious shortcoming with respect to the scope of our analysis: it makes feasible only credit shocks from one specific credit aggregate per time in applied applications. This happens because any combination of signs is unlikely to succeed in separating credit shocks to many different loan categories within the same VAR, the restrictions imposed fail. We have verified this by applying Arias, Rubio-Ramirez and Waggoner (2018)'s algorithm.

[11]In VAR analyses similar to ours, the interest often lies on monetary policy shocks, and then the monetary policy rate is set between two blocks of variables: the first block (positioned before the monetary policy rate) is said to be slow moving with respect to the monetary policy shock, while the second block (positioned after the monetary policy rate) is said to be fast moving. The first block typically includes real variables (such as GDP, sales and prices), which are imagined to respond with a lag reflecting the time for the transmission mechanism to operate. On the contrary, the second block includes fast-moving financial variables (such as stock prices and indices) that are imagined to respond contemporaneously to the MP shock. Reasoning in terms of monetary shocks, credit markets are part of the transmission mechanism, and then credit shocks have a direct effect on economic activity. Differently, monetary shocks have a lagged effect on economic activity because those have to transit first through credit markets before impacting economic activity. Based on this, our identification assumptions are consistent with the literature on the transmission mechanism (Albertazzi *et al.*, 2020).

market, the consumer price index and the house price index, which are plausibly sticky in a horizon such as a quarter.

The within-block order also has an indirect influence on the shocks, but we prove it to be irrelevant through the robustness checks in section 'Robustness of the estimations'.[12] In conclusion, the order defined is shown in Table 2.

Historical decomposition analysis

VAR modelling allows us to quantify the contribution of a specific-variable structural shocks to the observed evolution of the other variables in the VAR. This technique is known as *historical decomposition*; Burbidge and Harrison (1985), Kilian (2009), Kilian and Lee (2014) are prominent examples.

Let us use the following notation: k and i are two of the N variables included in the $\boldsymbol{y}$ vector of endogenous variables, k is the variable that we wish to decompose, while i is the variable whose contribution we want to assess. Historical decomposition analysis involves three steps (Kilian and Lütkepohl, 2017, chapter 4) and eventually it returns the *cumulative contribution* of variable i shocks to the evolution of variable k at time t, which we indicate as $cc_{i,t}^{k}$.[13]

For a given k variable, the sum of all the contributions (one for each of the N variables in the VAR) plus a residual component equals the value of variable k at time t, in notation:

$$k_t^* \approx \sum_{i=1}^{N} cc_{i,t}^{k}; \quad i = 1, \ \ldots, \ N$$

where $k_t^* = k_t - \text{exog}$ is the demeaned/detrended value of the variable k object of analysis at time t (exog = mean or trend).[14]

To assess the contribution of variable i to the evolution of k, the first option is to compare $cc_{i,t}^{k}$ against k_t^*: the closer $cc_{i,t}^{k}$ gets to k_t^*, the higher is its contribution compared to the other variables included.[15]

It is often convenient to reason in terms of the observed value of the variable of interest (not demeaned/detrended), alias k_t, because this allows a straight application to real-world data (e.g. the crude oil prices as in Kilian and Lee, 2014), then:

[12] As for the loan block, the different loan categories are ordered mainly for their size. Household loans amount to 62% of the total over the period considered, then we imagine them more likely to have an effect on the others. Corporate-business loans are slightly less than non-corporate, but they are more likely to respond with a lag to shocks to non-corporate loans than the other way around. Within the borrower groups, loans are ordered just for their relative size: the assumption is that larger categories are more likely to influence smaller ones at the impact.

[13] Those steps are the following. First, the estimation of the reduced-form VAR, which needs to be covariance-stationary $I(0)$, and in the identification of the structural shocks through the approach chosen (Cholesky in our case). Second, the computation of the moving-average coefficient matrices. Third, the matching of each structural shock with the appropriate impulse response weight, this is to form $T \times 1$ vectors of fitted values for each variable k, which we indicate as $cc_{i,t}^{k}$.

[14] If the VAR includes variables in level, then it is the detrended value, if the variables are in log-difference or deviations from the mean, then it is the demeaned value.

[15] Note that the N i variables counterbalance one another in shaping k. In a frequentist estimation, the sum of the components equals the value of the variable. In contrast, the reported values are the medians of the output distribution in a Bayesian estimation, so there is a small discrepancy (Dieppe *et al.*, 2018, chapter 3.2).

$$k_t \approx \sum_{i=1}^{N} cc_{i,t}^{k} + \text{exog}, \tag{2}$$

the portion of k_t explained by the cumulative contribution of variable i at time t, alias k_t^i, is:

$$k_t^i \approx cc_{i,t}^{k} + \text{exog} \times w_i, \tag{3}$$

in which w is a to-define weight necessary to split the exogenous component consistently across the N variables in a manner similar to Kilian and Lee (2014). We name k_t^i as *adjusted cumulative contribution*.

A first straight option is to split the exogenous component equally across the $Ncc_{i,t}^{k}$ contributions. However, we know that the contributions have a different role in shaping k_t. A more plausible alternative is to define the weight for the share of $cc_{i,t}^{k}$ over the total as follows:

$$w_i = \frac{\text{abs}(cc_{i,t}^{k})}{\sum_{i=1}^{N} \text{abs}(cc_{i,t}^{k})},$$

this is what we do in the applications in section ‘The global financial crisis’.[16]

Assessing the contribution to changes over time

It is possible to calculate the contribution of a variable to the variation of another across a specific period of analysis. This is of high interest to our analysis because we aim to check how much of the real GDP variation observed during a recession depends on specific variables. Let us consider two time points, T and s where $T > s$, from the previous equation (2) we know:

$$k_T - k_s = k_T^{*} - k_s^{*} \approx \sum_{i=1}^{N} \left(cc_{i,T}^{k} - cc_{i,s}^{k} \right), \tag{4}$$

it is important to note that $k_T - k_s = k_T^{*} - k_s^{*}$ because the exogenous component is deleted through differencing. The part of the observed variation $k_T - k_s$ depending on shocks to variable i over the same time period, alias $k_T^i - k_s^i$, is:

$$k_T^i - k_s^i \approx cc_{i,T}^{k} - cc_{i,s}^{k}. \tag{5}$$

Inconveniently, there is a complication with the application of equation (5) when the estimation is performed using log-differences, instead of simply log-transformed variables. Assuming that k_t is the log-transformed K_t variable, if we use log-diffs in the VAR, the values at hand are $d.k_t$, which are an approximation of growth rates. Then, $d.k_T - d.k_s$ is not the variation of the variable k_t between T and s but simply

[16]Conclusions are robust for alternative specifications of the weights, given the small size of the exogenous component when the variables are in log-differences.

the difference between the growth rates at those time points. To have that variation, we have to sum all the growth rates between T and s:

$$k_T - k_s = \sum_{t=s+1}^{T} d.k_t.$$

The variation obtained as sum of growth rates is more complex to decompose because the exogenous component is not deleted by differencing. Indeed, given $d.k_t = d.k_t^* + \text{exog}$, we have:

$$k_T - k_s = \sum_{t=s+1}^{T} d.k_t \approx \sum_{t=s+1}^{T} \left(\sum_{i=1}^{N} \left(cc_{i,t}^k + \text{exog} \times w_i \right) \right)_t .$$

Consequently, the portion of the k_t variation linked to variable i shocks, alias $k_T^i - k_s^i$, is:

$$k_T^i - k_s^i = \sum_{t=s+1}^{T} \left(cc_i^k + \text{exog} \times w_i \right)_t \tag{6}$$

where w is the previously introduced weight.

Given the need to ensure the VAR stability for historical decomposition to be consistent, we estimated the VAR in first difference. Then, we will apply equation (6) in the analysis of the GDP variation discussed in section ‘The global financial crisis’.

Historical decomposition as a counterfactual analysis

An alternative way to assess the contribution of each i variable is to use it to generate a counterfactual for the k variable (Kilian and Lee, 2014). This is simply obtained by subtracting $cc_{i,t}^k$ to the variable as originally introduced in the VAR; in our case, the first difference. In notation:

$$\hat{k}_{i,t} = k_t - cc_{i,t}^k, \tag{7}$$

$\hat{k}_{i,t}$ is the counterfactual series, k_t is the original series. $\hat{k}_{i,t}$ shows the evolution of k as if there were no shocks to the i variable.[17] Then, conclusions about the size and the direction of each i variable’s contribution can be drawn through a study of the deviations between the two series, $dev_{k-i,t} = (k_t - \hat{k}_{i,t})$, in particular: $dev_{k-i,t} > 0$, variable i has a positive effect on variable k because its exclusion makes k smaller; $dev_{k-i,t} < 0$, variable i has a negative effect on variable k because its exclusion makes k bigger.

Applications in the following analysis

Historical decomposition in terms of counterfactual shows how the variable of interest would have evolved if the i variable had no effect at all, while considering the cumulative contributions $cc_{i,t}^k$ shows the portion of the variable of interest explained by

[17]The plot of $\hat{k}_{i,t}$ against k_t is usually easier to read: the larger the difference between k_t and $\hat{k}_{i,t}$, the higher the contribution of i. If i had no contribution at all, then the two series would perfectly overlap.

shocks to variable i. These two methodologies are symmetrical and we will apply both in the following analysis. In detail, we use historical decomposition in terms of counterfactual to draw conclusions over the entire estimation period. In contrast, we opt for cumulative contributions to decompose the GDP variation over specific periods.

IV. The contribution of loan shocks to economic activity

We discuss now the contribution of shocks, particularly loan shocks, to economic activity. We are primarily interested in a comparative assessment of the different loan categories (those listed in Table 2), but we will also comment on the other variables included in the VAR. In addition to the results for each loan category included in the VAR, we also present results for the aggregation of those categories by borrower (HNP-ALL, CBS-ALL, NCB-ALL), by scope (ALL-MTG, ALL-OLN, HNP-CCR) and for the total loan aggregate (ALL-ALL).[18]

The period under investigation includes six US recessions, which are listed in Table 4; the GFC is the most recent event in our sample. After reviewing the contributions for the entire period in the next subsection by means of a counterfactual analysis, we will discuss the GFC and compare it to the Second Oil Shock in the 1980s, which was another important recession in US history. These two crises have different causes, and consequently they are interesting to compare. We will use the variations of the cumulative contributions for this part of the analysis.

An overview of the entire period 1971q1–2018q4

The contribution of loans to economic activity over the entire period available can be shown by means of counterfactual plots that display the evolution of the variables $\hat{k}_{i,t}$ and k_t (equation 7). The more the counterfactual diverges from the original series, the more the contribution made by the variable under consideration. Figure A1 in the appendix reports these plots for the aggregations of loans by borrower.[19] Because they cover a long time span and are in terms of growth rates, their interpretation is uneasy. Then, with the scope to show how they can be used to assess the effect of each variable, we have restricted the display to +/− 3 years around the GFC in the plots in the following Figure 3. On the whole, the only effect detectable is from household loans, at least during the GFC.

Although plots help to assess the relative weight of each loan category in driving GDP growth, the sum of the deviations (in absolute values) between the actual series and the counterfactual helps to clarify the ranking of the different variables. These values are given in Table 5 and are plotted in Figure 4; the bottom of Table 5 reports aggregations by borrower and by loan scope (mortgage/non-mortgage). Excluding GDP endogenous shocks, household loans are the largest contributor to the GDP evolution

[18]To wit: the HNP-ALL aggregate sums the contributions of mortgages, consumer credit and other loans to households.

[19]The counterfactual plots are directly comparable with those representing the cumulative contribution from which counterfactuals are obtained; the latter are in the second column of the same figure.

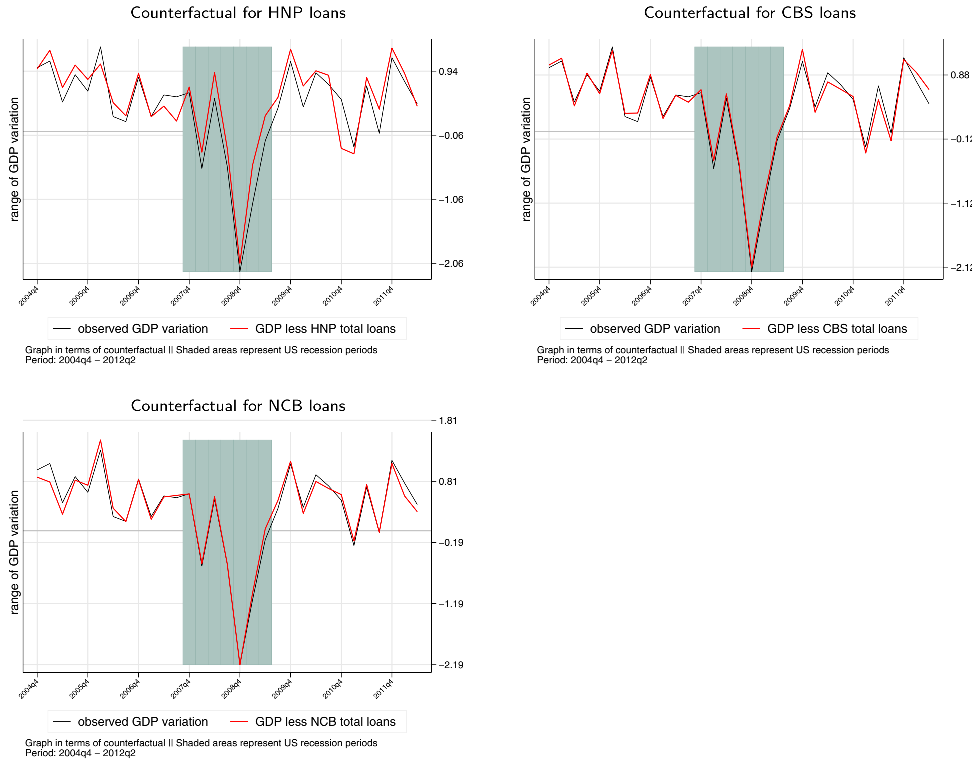


Figure 3. Counterfactual analysis plots, restricted to ±3 years around the GFC
Notes: These plots are for the observed GDP series versus its counterfactuals. HNP stands for households, CBS for corporate business, NCB for non-corporate business. These plots can be compared with those in Figure A1 in the appendix.

TABLE 4

US recessions in the period 1971q1–2018q4

No.	*Period*	*No. quarters*	*Name*
1	1973q4–1975q1	6	1st oil shock
2	1980q1–1980q3	3	Double-dip recession
3	1981q3–1982q4	6	2nd oil shock
4	1990q3–1991q1	3	Iraq war
5	2001q1–2001q4	4	Dot-com bubble
6	2007q4–2009q2	7	Global financial crisis

Notes: The recessions are triggered by the events in the column 'name', such events happen some time earlier than the following recession materializes. The 1st oil shock is linked to Israel's Yom Kippur War, the 2nd oil shock is related to the Iranian Revolution.
Source: The NBER.

(HNP-ALL), corporate and non-corporate loans have a much-smaller similar weight (CBS-ALL, NCB-ALL). Considering loans in terms of scope, consumer credit has had a prime role (HNP-CCR), mortgages follow (ALL-MTG), while other loans rank last (ALL-OLN). As for the other variables, particularly the slow-moving price indices have had a large effect. The interest-rate block ranks low, among these the Fed-funds rate has contributed the most. We recall that the Fed-funds rate should reflect monetary policy.

The entire period available covers a long time span in which structural variations, in terms of GDP driving forces, may have occurred. To wit, the role of some variables over a certain period might have structurally changed over the following. We focus now on shorter time spans centred around well-known periods of economic downturn (the GFC and the second oil shock) to reveal the role played by the variables of interest over these periods.

The global financial crisis

As for the role of lending on economic activity, the GFC is a case study of particular interest. Indeed, the narrative of the events is that the turmoil started in the financial markets and then impaired the capacity of lending institutions to extend credit. Consequently, intermediation fell and this undermined economic activity.[20] In this section we study the contribution of loans, as well as of the other variables, to the variation of

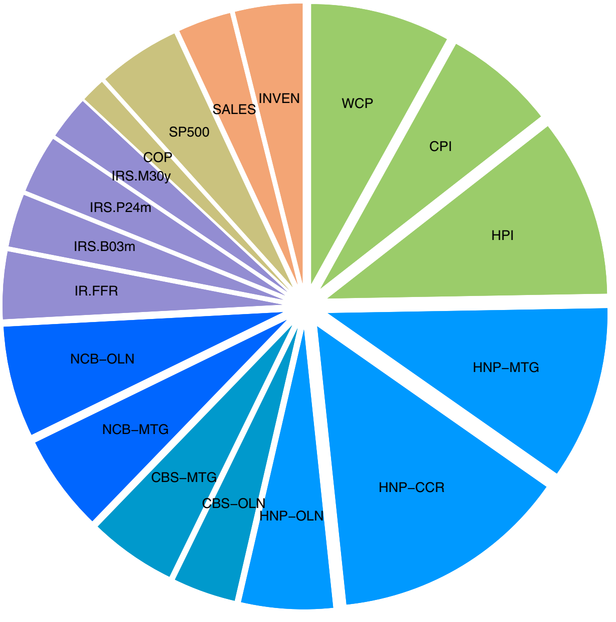


Figure 4. Counterfactual analysis, values in Table 5
Notes: Contributions (DEVsum) are grouped by block of variables marked by slices of the same colour. Blue coloured slices are for loans: light-blue for household loans (HNP), mid-blue for corporate-business loans (CBS), dark-blue for non-corporate business loans (NCB). Lavender coloured slices are for interest rate/spreads (IR). Beige coloured slices are for fast-moving price indices (COP, SP500). Orange coloured slices are for real variables (SALES, INVEN). Green coloured slices are for slow-moving price indices (WCP, CPI, HPI). The GDP contribution is not reported to deliver a better visual display.

[20]However, the problems were rooted in the real-estate sector and were triggered by a monetary policy change to a certain extent. Some recent research suggests that credit dynamics also depend on non-economic more-institutional determinants; among the others, see Castro and Martins (2019).

GDP during the GFC. Our intent is to check whether that matches the narrative of the events. We apply the same methodology as in Kilian and Lee (2014), we are therefore able to split the variation between two dates across the different variables included in the VAR.

GDP decreased about 4% in the period 2007q4–2009q2, the values in Table 6 show the decomposition of this variation across the variables in the VAR (based on equation (6)). These values are plotted in the top chart of Figure 5. As detailed in section 'Historical decomposition analysis', a convenient property of historical decomposition is that contributions can be aggregated. These aggregations are given in different columns of Table 6.

The house price index exhibits the largest negative influence on GDP growth (−1.98%), it ranks first in terms of contribution in all cases (columns 1.rank–4.rank in Table 6). Considering the aggregation of all loans by borrower and scope (ALL-ALL), they emerge to have an effect comparable to the house price index (−1.93%), so we can affirm that loans had really a deep influence in driving down economic activity during the GFC (column 1.rank). If we switch to loan aggregations by borrower (HNP-ALL, CBS-ALL, NCB-ALL), household loans appear to have driven much of the total loan effect, corporate and non-corporate business loans do play a role, but rank, respectively, 7 and 12 of 15 contributors (column 2.rank). Another point of interest is to consider the aggregation of loans by scope. In this case, it emerges that the aggregate loan effect depends largely on other loans, secondly on consumer credit and finally on mortgages (column 3.rank). This is somehow unexpected given the relative size of mortgages over the total. Eventually, when we assess each loan category separately, we can confirm what found at the aggregate level (column 4.rank): the

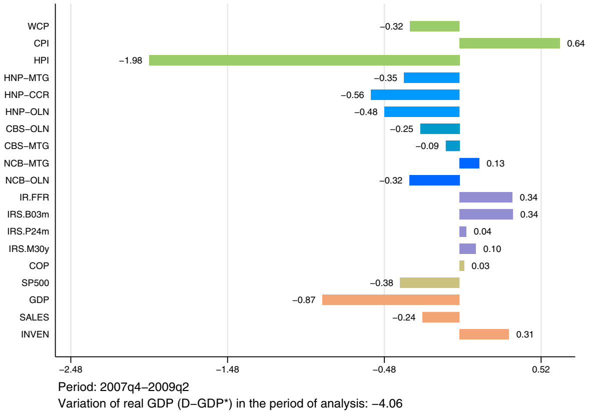
TABLE 5

Counterfactual analysis – Entire period

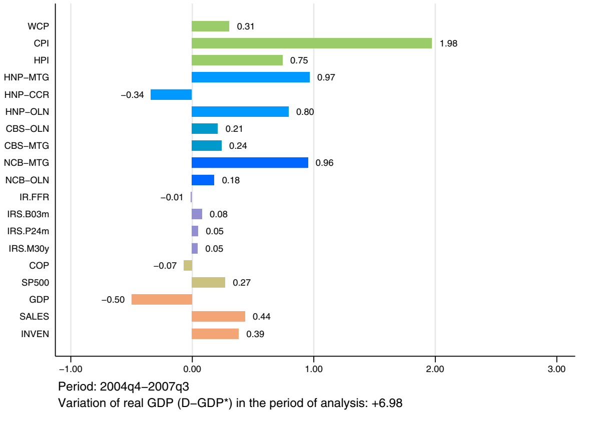
Block	*Variable*	*DEVsum*	*Rank*	*Block*	*Variable*	*DEVsum*	*Rank*
price.slow	WCP	17.91	5	int rate	IR.FFR	8.84	13
price.slow	CPI	14.20	7	int rate	IRS.B03m	6.63	17
price.slow	HPI	23.09	3	int rate	IRS.P24m	7.73	15
loans.hnp	HNP-MTG	22.64	4	int rate	IRS.M30y	5.09	18
loans.hnp	HNP-CCR	30.55	2	price.fast	COP	3.36	19
loans.hnp	HNP-OLN	12.08	9	price.fast	SP500	10.40	11
loans.cbs	CBS-OLN	8.03	14	real	GDP	74.13	1
loans.cbs	CBS-MTG	11.17	10	real	SALES	6.86	16
loans.ncb	NCB-MTG	12.19	8	real	INVEN	8.91	12
loans.ncb	NCB-OLN	14.45	6				
	HNP-ALL	42.07			ALL-MTG	27.32	
	CBS-ALL	14.54			ALL-OLN	20.23	
	NCB-ALL	18.51			HNP-CCR	30.55	
*D-GDP**	*127.45*				ALL-ALL	50.33	

Notes: DEVsum is the cumulated sum of time-specific deviations between the observed series and its counterfactual; Rank is the ranking of the variables based on DEVsum. The bottom panel reports aggregations of the values in the lines above for coherent groups: HNP-ALL is the sum of all loans to households, CBS-ALL is for all loans to corporate business, NCB-ALL is for all loans to non-corporate business, ALL-MTG is the sum of mortgages to any borrower, ALL-OLN is the sum of other loans to any borrower, ALL-ALL is the sum of all loans regardless of the borrower.

Global Financial Crisis, values in Table 6 (column 4.CC2).



Growth period before the GFC, values in Table 7 (column 4.CC2).



2nd Oil Shock, values in Table 8 (column 4.CC2).

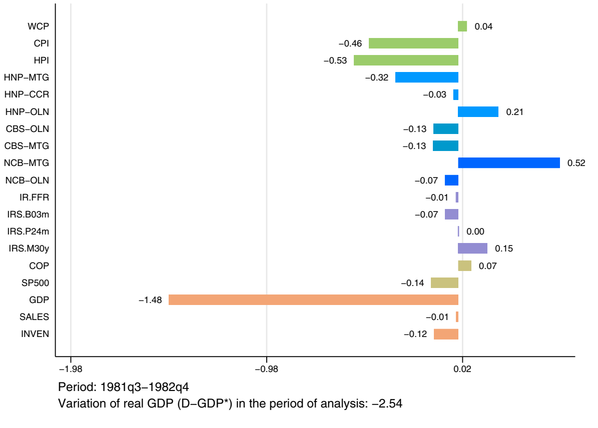


Figure 5. Contribution analysis plots *Notes*: Contributions are grouped by block of variables marked by bars of the same colour. Blue coloured slices are for loans: light-blue for household loans (HNP), mid-blue for corporate-business loans (CBS), dark-blue for non-corporate business loans (NCB). Lavender coloured slices are for interest rate/spreads (IR). Beige coloured slices are for fast-moving price indices (COP, SP500). Orange coloured slices are for real variables (GDP, SALES, INVEN). Green coloured slices are for slow-moving price indices (WCP, CPI, HPI).

different loans to households are those contributing the most, the category with the highest adverse effect is consumer credit.

As for the other variables, we have already mentioned that the house price index is the largest contributor to the GDP variation. Apart from that, it is of note that the CPI has instead a positive effect on GDP growth during that period, perhaps because of a slowdown in consumer prices during the recession. In contrast, the stock market contributes negatively and to a large extent. Interest rates contribute positively, perhaps because of their decline during the GFC. Note that the Fed-funds rate has an impact, not particularly high, as large as the interest rate on corporate loans (considerations based on column 1.rank).

Growth period before the global financial crisis

We can draw insights from the comparison of the GDP-growth drivers during the crisis with those in the period of growth preceding the crisis. We consider the 3-year period from 2004q4 to 2007q3, in which GDP growth is about 7%. Table 7 reports the values of the cumulative contributions, and these are plotted in the mid chart of Figure 5. By considering the aggregation of all loans, we realize that these have had the largest positive effect in such a growth period. This effect is relatively larger than what observed during the GFC. When looking at the aggregation of loans by borrower, household loans emerge again as the larger contributor. It should be noted that these three loan aggregations symmetrically switch sign from positive during this growth period to negative during the GFC. Loan aggregations by scope reveal that the total effect of loans depends mainly on mortgages, which is in contrast to what was observed during the GFC. Sales, inventories and the stock market have all contributed positively to GDP growth.

The Second Oil shock

The US recession in the period 1981q3–1982q4 is related to the oil shock triggered by the Iranian revolution, which caused increasing oil prices and eventually inflation, and to the monetary policies adopted by the FED to curb inflation. The observed GDP decrease was about 2.5%. Table 8 reports the values of the decomposition, and these are plotted in the bottom chart of Figure 5.[21]

The historical decomposition detects a relevant role neither for the Fed-funds rate nor for the crude oil price. Prices seem to have had a negative influence on GDP growth, but these prices are of consumption goods and houses. By comparing the GFC

[21]Across the different crises, we select the second oil shock because it has a length comparable the GFC, it happened in a period of time when the economy was structurally different, as well as the size of loans in the total economy, and because it is not at the beginning of our estimation sample because this can bias the computation of the historical decomposition (Kilian and Lütkepohl, 2017).

TABLE 6

Contribution analysis – Global financial crisis

Block	*Variable*	*1.CC2*	*1.rank*	*2.CC2*	*2.rank*	*3.CC2*	*3.rank*	*4.CC2*	*4.rank*
Period under consideration: 2007q4–2009q2									
price.slow	WCP	−0.32	8	−0.32	9	−0.32	9	−0.32	11
price.slow	CPI	0.64	4	0.64	4	0.64	4	0.64	3
price.slow	HPI	−1.98	1	−1.98	1	−1.98	1	−1.98	1
	ALL-ALL	−1.93	2						
loans.hnp	HNP-ALL			−1.4	2				
loans.cbs	CBS-ALL			−0.34	7				
loans.ncb	NCB-ALL			−0.19	12				
	ALL-MTG					−0.32	10		
	ALL-OLN					−1.05	2		
loans.hnp	HNP-CCR					−0.56	5	−0.56	4
loans.hnp	HNP-MTG							−0.35	7
loans.hnp	HNP-OLN							−0.48	5
loans.cbs	CBS-OLN							−0.25	13
loans.cbs	CBS-MTG							−0.09	17
loans.ncb	NCB-MTG							0.13	15
loans.ncb	NCB-OLN							−0.32	10
int rate	IR.FFR	0.34	7	0.34	8	0.34	8	0.34	9
int rate	IRS.B03m	0.34	6	0.34	6	0.34	7	0.34	8
int rate	IRS.P24m	0.04	12	0.04	14	0.04	14	0.04	18
int rate	IRS.M30y	0.1	11	0.1	13	0.1	13	0.1	16
price.fast	COP	0.03	13	0.03	15	0.03	15	0.03	19
price.fast	SP500	−0.38	5	−0.38	5	−0.38	6	−0.38	6
real	GDP	−0.87	3	−0.87	3	−0.87	3	−0.87	2
real	SALES	−0.24	10	−0.24	11	−0.24	12	−0.24	14
real	INVEN	0.31	9	0.31	10	0.31	11	0.31	12
*D-GDP**	−4.06								

Notes: This table reports the decomposition of the GDP variation (D-GDP*) across the different variables in the VAR, in terms of their adjusted cumulative contribution (CC2). Insightful aggregations of those contributions are in the different columns. Columns 1 are for the aggregation of all loans (ALL-ALL); CC2 is the cumulative contribution and 'rank' reports the ranking of the variables based on those contributions. Columns 2 are for the aggregations by borrower (HNP-ALL, CBS-ALL, NCB-ALL). Columns 3 are for the aggregations by loan scope (ALL-MTG, ALL-OLN, HNP-CCR). Columns 4 are for all the variables included (no aggregations).

with this recession, what emerges is the lack of a significant role played by total loans. In detail, aggregations by borrower show a difference between small firms and the other borrowers, which compensate one another at the aggregate level. The largest part of the GDP contraction is related to GDP endogenous shocks, which cannot be decoded in the framework of our model.

In conclusion, the GFC indicates the leading role played by loans and the real-estate sector, as accounted for by the house price index. Unsurprisingly, this leading role is also found in the growth period preceding the GFC, but it has coherently an opposite sign. The GFC started as a turmoil in the mortgage market. The results discussed show that the mortgage sector had indeed a leading role in the growth period before the GFC, but the evolution of mortgages does not seem to have influenced the GDP decrease during the GFC, it was more loans in general and particularly other loans.

TABLE 7

Contribution analysis – 3-year growth period before the GFC

Period under consideration: 2004q4–2007q3									
Block	*Variable*	*1.CC2*	*1.rank*	*2.CC2*	*2.rank*	*3.CC2*	*3.rank*	*4.CC2*	*4.rank*
price.slow	WCP	0.309	7	0.309	9	0.309	9	0.309	10
price.slow	CPI	1.976	2	1.976	1	1.976	2	1.976	1
price.slow	HPI	0.746	3	0.746	4	0.746	4	0.746	5
	ALL-ALL	3.029	1						
loans.hnp	HNP-ALL			1.43	2				
loans.cbs	CBS-ALL			0.458	6				
loans.ncb	NCB-ALL			1.141	3				
	ALL-MTG					2.17	1		
	ALL-OLN					1.195	3		
loans.hnp	HNP-CCR					−0.335	8	−0.335	9
loans.hnp	HNP-MTG							0.97	2
loans.hnp	HNP-OLN							0.796	4
loans.cbs	CBS-MTG							0.244	12
loans.cbs	CBS-OLN							0.214	13
loans.ncb	NCB-MTG							0.956	3
loans.ncb	NCB-OLN							0.185	14
int rate	IR.FFR	−0.008	13	−0.008	15	−0.008	15	−0.008	19
int rate	IRS.B03m	0.083	9	0.083	11	0.083	11	0.083	15
int rate	IRS.P24m	0.052	11	0.052	13	0.052	13	0.052	17
int rate	IRS.M30y	0.048	12	0.048	14	0.048	14	0.048	18
price.fast	COP	−0.066	10	−0.066	12	−0.066	12	−0.066	16
price.fast	SP500	0.275	8	0.275	10	0.275	10	0.275	11
real	GDP	−0.495	4	−0.495	5	−0.495	5	−0.495	6
real	SALES	0.438	5	0.438	7	0.438	6	0.438	7
real	INVEN	0.386	6	0.386	8	0.386	7	0.386	8
*D-GDP**	*6.98*								

Notes: This table reports the decomposition of the GDP variation (D-GDP*) across the different variables in the VAR, in terms of their adjusted cumulative contribution (CC2). Insightful aggregations of those contributions are in the different columns. Columns 1 are for the aggregation of all loans (ALL-ALL); CC2 is the cumulative contribution and 'rank' reports the ranking of the variables based on those contributions. Columns 2 are for the aggregations by borrower (HNP-ALL, CBS-ALL, NCB-ALL). Columns 3 are for the aggregations by loan scope (ALL-MTG, ALL-OLN, HNP-CCR). Columns 4 are for all the variables included (no aggregations).

Robustness of the estimations

The robustness of the results of the historical decomposition has been tested through several checks. Robustness has been evaluated in terms of stability of the contributions to the GDP evolution over the entire period available, we use contributions in terms of counterfactual as in section 'An overview of the entire period 1971q1–2018q4' for these checks.

As in any other VAR estimation, the results depend on the identification approach applied because it determines the structural parameters. To show robustness, we have reported the deviations between the actual series and its counterfactual for alternative causal orderings. The alternative orderings are shown in Table A1 in the appendix. The pie charts, which reflect the deviations, are in Figure A2 in the appendix; these are used to compare with Figure 4 in section 'An overview of the entire period 1971q1–

TABLE 8

Contribution analysis – Second oil shock

Period under consideration: 1981q3–1982q4									
Block	*Variable*	*1.CC2*	*1.rank*	*2.CC2*	*2.rank*	*3.CC2*	*3.rank*	*4.CC2*	*4.rank*
price.slow	WCP	0.045	10	0.045	12	0.045	10	0.045	15
price.slow	CPI	−0.456	3	−0.456	3	−0.456	3	−0.456	4
price.slow	HPI	−0.533	2	−0.533	2	−0.533	2	−0.533	2
	ALL-ALL	0.054	9						
loans.hnp	HNP-ALL			−0.141	7				
loans.cbs	CBS-ALL			−0.256	5				
loans.ncb	NCB-ALL			0.45	4				
	ALL-MTG					0.069	7		
	ALL-OLN					0.011	14		
loans.hnp	HNP-CCR					−0.025	11	−0.025	16
loans.hnp	HNP-MTG							−0.321	5
loans.hnp	HNP-OLN							0.205	6
loans.cbs	CBS-MTG							−0.129	9
loans.cbs	CBS-OLN							−0.127	10
loans.ncb	NCB-MTG							0.519	3
loans.ncb	NCB-OLN							−0.068	12
int rate	IR.FFR	−0.012	11	−0.012	13	−0.012	12	−0.012	17
int rate	IRS.B03m	−0.067	7	−0.067	10	−0.067	8	−0.067	13
int rate	IRS.P24m	0.003	13	0.003	15	0.003	15	0.003	19
int rate	IRS.M30y	0.149	4	0.149	6	0.149	4	0.149	7
price.fast	COP	0.066	8	0.066	11	0.066	9	0.066	14
price.fast	SP500	−0.138	5	−0.138	8	−0.138	5	−0.138	8
real	GDP	−1.478	1	−1.478	1	−1.478	1	−1.478	1
real	SALES	−0.011	12	−0.011	14	−0.011	13	−0.011	18
real	INVEN	−0.124	6	−0.124	9	−0.124	6	−0.124	11
*D-GDP**	−2.549								

Notes: This table reports the decomposition of the GDP variation (D-GDP*) across the different variables in the VAR, in terms of their adjusted cumulative contribution (CC2). Insightful aggregations of those contributions are in the different columns. Columns 1 are for the aggregation of all loans (ALL-ALL); CC2 is the cumulative contribution and 'rank' reports the ranking of the variables based on those contributions. Columns 2 are for the aggregations by borrower (HNP-ALL, CBS-ALL, NCB-ALL). Columns 3 are for the aggregations by loan scope (ALL-MTG, ALL-OLN, HNP-CCR). Columns 4 are for all the variables included (no aggregations).

2018q4' that refers to the baseline estimation. The comparison shows that, within the framework of the recursive identification approach, results are stable for different orderings of the variables, both within and across blocks.[22]

We have also estimated the VAR using alternative aggregations of the loan categories to have VARs of a different size. To wit, including only the aggregations of the loans by borrower. This alternative VAR has therefore 15 variables instead of 19, which is the number in the benchmark VAR. The estimation output of such a smaller VAR returns a ranking of the loan aggregates for the entire period available in line with what obtained from the benchmark VAR.

[22]As explained in the sub-section 'structural identification', an expected exception is when the effect of loans on the GDP is restricted to be null at the impact, the size of that effect changes in this case because a significant part of it is ruled out.

As a final check, we have estimated the benchmark VAR using different hyperparameters for the prior distribution (overall tightness $\lambda_1 = 0.12$ and autoregressive coefficient $ar = 0.7$), as well as using two lags instead of one. The ranking of loans remains comparable to the one in Table 5 in both cases.

V. Conclusions

In this research, we have investigated how loans to different groups, and for different scopes, have contributed to economic activity in the United States during the period 1971–2018. We focused on shorter periods along that time span, particularly on the recession triggered by the GFC. Indeed, our main objective was to verify the role of the credit crunch in the GDP fall observed during the Great Recession.

The analysis presented here shows that household loans exert the largest contribution on economic activity along the period 1971–2018, consumer credit has a larger influence than mortgages on average. During the GFC, the contribution of loans turned decisively negative, even though mortgages do not exhibit a leading role during the recession. In contrast, this role is evident in the period preceding the GFC. The specific role of loans during the GFC emerges clearer when compared to another severe crisis, such as the second oil shock in the 1980s. Generally speaking, loans to small firms have a contribution on economic activity that is larger than loans to corporations. This probably depends on the fact that corporations in the US raise funds internally through bonds or equity issuance. As for the other variables that we have used in our analysis, the house price index confirms a leading role of the real-estate sector on the GDP evolution.

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References

Albertazzi, U., Barbiero, F., Marques-Ibanez, D., Popov, A. A., DAcri, C. R. and Vlassopoulos, T. (2020). Monetary Policy and Bank Stability: The Analytical Toolbox Reviewed, Working Paper Series No. 2377, European Central Bank.

Arias, J. E., Rubio-Ramirez, J. F. and Waggoner, D. F. (2018). 'Inference based on structural vector autoregressions identified with sign and zero restrictions: theory and applications', *Econometrica*, Vol. 86, pp. 685–720.

Bańbura, M., Giannone, D. and Reichlin, L. (2010). 'Large Bayesian vector auto regressions', *Journal of Applied Econometrics*, Vol. 25, pp. 71–92.

Barraza, S., Civelli, A. and Zaniboni, N. (2019). 'Business loans and the transmission of monetary policy', *Journal of Financial and Quantitative Analysis*, Vol. 54, pp. 925–965.

Benmelech, E., Meisenzahl, R. R. and Ramcharan, R. (2016). 'The real effects of liquidity during the financial crisis: evidence from automobiles', *The Quarterly Journal of Economics*, p. qjw031.

Bernanke, B. S. and Gertler, M. (1995). 'Inside the black box: the credit channel of monetary policy transmission', *The Journal of Economic Perspectives*, Vol. 9, pp. 27–48.

Bunn, P., Le Roux, J., Reinold, K. and Surico, P. (2017). 'The consumption response to positive and negative income shocks', *Journal of Monetary Economics*.

Burbidge, J. and Harrison, A. (1985). 'An historical decomposition of the great depression to determine the role of money', *Journal of Monetary Economics*, Vol. 16, pp. 45–54.

Busch, U., Scharnagl, M. and Scheithauer, J. (2010). Loan Supply in Germany During the Financial Crisis, Discussion Paper No. 05/2010, Deutsche Bundesbank.

Cafiso, G. (2019). 'Gdp growth through private debt: the effect of monetary shocks', *CESifo Economic Studies*, Vol. 65, pp. 236–253.

Cafiso, G. (2020). The Loan Puzzle. A Study of Loans to Different Groups in the USA, CESifo Working Papers No. 8175, CESifo.

Cafiso, G. and Rivolta, G. (2021). Heterogeneous Loans and the Effect of Monetary Interventions, CESifo Working Papers No. 9194, CESifo.

Caldara, D., Fuentes-Albero, C., Gilchrist, S. and Zakrajšek, E. (2016). 'The macroeconomic impact of financial and uncertainty shocks', *European Economic Review*, Vol. 88, pp. 185–207.

Castro, V. and Martins, R. (2019). 'Political and institutional determinants of credit booms', *Oxford Bulletin of Economics and Statistics*, Vol. 81, pp. 1144–1178.

Cecchetti, S., Mohanty, M. and Zampolli, F. (2011). The Real Effects of Debt, Working Paper No. 352, BIS.

Christelis, D., Ehrmann, M. and Georgarakos, D. (2015). Exploring Differences in Household Debt Across Euro Area Countries and the United States, Working Paper No. 2015-16, Bank of Canada.

Christiano, L. J., Eichenbaum, M. and Evans, C. L. (1999). 'Monetary policy shocks: what have we learned and to what end?' *Handbook of Macroeconomics*, Vol. 1, pp. 65–148.

Christiano, L. J., Motto, R. and Rostagno, M. (2014). 'Risk shocks', *American Economic Review*, Vol. 104, pp. 27–65.

Cloyne, J. S. and Surico, P. (2016). 'Household debt and the dynamic effects of income tax changes', *The Review of Economic Studies*, Vol. 84, pp. 45–81.

Cloyne, J., Ferreira, C. and Surico, P. (2016). Monetary Policy when Households have Debt: New Evidence on the Transmission Mechanism, Staff Working Paper No. 589, Bank of England.

Coletta, M., De Bonis, R. and Piermattei, S. (2014). The Determinants of Household Debt: A Cross-Country Analysis, Working Papers No. 989, Banca d'Italia.

Debelle, G. (2004). 'Household debt and the macroeconomy1', *BIS Quarterly Review*, pp. 51–64.

den Haan, W. J., Sumner, S. W. and Yamashiro, G. M. (2007). 'Bank loan portfolios and the monetary transmission mechanism', *Journal of Monetary Economics*, Vol. 54, pp. 904–924.

Dieppe, A., Legrand, R. and van Roye, B. (2018). The Bayesian Estimation, Analysis and Regression (BEAR) Toolbox – Technical Guide, European Central Bank.

Dwenger, N., Fossen, F. M. and Simmler, M. (2020). 'Firms financial and real responses to credit supply shocks: evidence from firm-bank relationships in Germany', *Journal of Financial Intermediation*, Vol. 41, pp. 100773.

Eickmeier, S. and Ng, T. (2015). 'How do US credit supply shocks propagate internationally? A GVAR approach', *European Economic Review*, Vol. 74, pp. 128–145.

Furlanetto, F., Ravazzolo, F. and Sarferaz, S. (2019). 'Identification of financial factors in economic fluctuations', *The Economic Journal*, Vol. 129, pp. 311–337.

Gambetti, L. and Musso, A. (2017). 'Loan supply shocks and the business cycle', *Journal of Applied Econometrics*, Vol. 32, pp. 764–782.

Giannone, D., Lenza, M. and Primiceri, G. E. (2015). 'Prior selection for vector autoregressions', *Review of Economics and Statistics*, Vol. 97, pp. 436–451.

Giannone, D., Lenza, M. and Reichlin, L. (2019), Money, Credit, Monetary Policy and the Business Cycle in the Euro Area: What has Changed Since the Crisis? Working Paper Series No. 2226, ECB.

Gilchrist, S. and Zakrajšek, E. (2012). 'Credit spreads and business cycle fluctuations', *American Economic Review*, Vol. 102, pp. 1692–1720.

Guerrieri, V. and Lorenzoni, G. (2017). 'Credit crises, precautionary savings, and the liquidity trap', *The Quarterly Journal of Economics*, Vol. 132, pp. 1427–1467.

Guerrieri, V. and Uhlig, H. (2016). 'Housing and credit markets: booms and busts', in Taylor J. B. and Uhlig H. (eds), *Handbook of Macroeconomics*, Vol. 2, Amsterdam: Elsevier, chapter 2, pp. 1427–1496.

Hristov, N., Hülsewig, O. and Wollmershäuser, T. (2012). 'Loan supply shocks during the financial crisis: evidence for the Euro area', *Journal of International Money and Finance*, Vol. 31, pp. 569–592.

Jordà, Ò., Schularick, M. and Taylor, A. M. (2013). 'When credit bites back', *Journal of Money, Credit and Banking*, Vol. 45, pp. 3–28.

Justiniano, A., Primiceri, G. E. and Tambalotti, A. (2019). 'Credit supply and the housing boom', *Journal of Political Economy*, Vol. 127, pp. 1317–1350.

Kaplan, G., Moll, B. and Violante, G. L. (2018). 'Monetary policy according to HANK', *American Economic Review*, Vol. 108, pp. 697–743.

Kaplan, G., Mitman, K. and Violante, G. L. (2020). 'The housing boom and bust: model meets evidence', *Journal of Political Economy*, Vol. 128.

Khan, A. and Thomas, J. K. (2013). 'Credit shocks and aggregate fluctuations in an economy with production heterogeneity', *Journal of Political Economy*, Vol. 121, pp. 1055–1107.

Kilian, L. (2009). 'Not all oil price shocks are alike: disentangling demand and supply shocks in the crude oil market', *American Economic Review*, Vol. 99, pp. 1053–1069.

Kilian, L. and Lee, T. K. (2014). 'Quantifying the speculative component in the real price of oil: the role of global oil inventories', *Journal of International Money and Finance*, Vol. 42, pp. 71–87.

Kilian, L. and Lütkepohl, H. (2017). *Structural Vector Autoregressive Analysis*, Cambridge: Cambridge University Press.

Menno, D. and Oliviero, T. (2020). 'Financial intermediation, house prices, and the welfare effects of the US Great Recession', *European Economic Review*, Vol. 129, p. 103568.

Mian, A. and Sufi, A. (2010). 'Household leverage and the recession of 2007–09', *IMF Economic Review*, Vol. 58, pp. 74–117.

Mian, A. and Sufi, A. (2014). 'What explains the 2007–2009 drop in employment?' *Econometrica*, Vol. 82, pp. 2197–2223.

Mian, A. and Sufi, A. (2016). 'Who bears the cost of recessions? The role of house prices and household debt, in Taylor J. B. and Uhlig H. (eds), *Handbook of Macroeconomics*, Vol. 2, Amsterdam: Elsevier, chapter 2, pp. 255–296.

Mimir, Y. (2016). 'Financial intermediaries, credit shocks and business cycles', *Oxford Bulletin of Economics and Statistics*, Vol. 78, pp. 42–74.

Prieto, E., Eickmeier, S. and Marcellino, M. (2016). 'Time variation in macro-financial linkages', *Journal of Applied Econometrics*, Vol. 31, pp. 1215–1233.

Ramcharan, R., Verani, S. and van Den Heuvel, S. J. (2016). 'From wall street to main street: the impact of the financial crisis on consumer credit supply', *The Journal of Finance*, Vol. 71, pp. 1323–1356.

Ramey, V. A. and West, K. D. (1999). 'Inventories', *Handbook of Macroeconomics*, Vol. 1, pp. 863–923.

Schularick, M. and Taylor, A. M. (2012). 'Credit booms gone bust: monetary policy, leverage cycles, and financial crises, 1870–2008', *American Economic Review*, Vol. 102, pp. 1029–1061.

Schumpeter, J. A. (1912). *Theorie der wirtschaftlichen Entwicklung*, Leipzig: Dunker & Humblot.

Stock, J. H. and Watson, M. W. (2001). 'Vector autoregressions', *The Journal of Economic Perspectives*, Vol. 15, pp. 101–115.

Stock, J. H. and Watson, M. W. (2012). 'Disentangling the channels of the 2007–09 recession', *Brookings Papers on Economic Activity*, pp. 81–135.

Sufi, A. (2015). 'Out of many, one? Household debt, redistribution and monetary policy during the economic slump', in Andrew Crockett Memorial Lecture. https://www.bis.org/events/agm2015/sp150628.htm

Uhlig, H. (2005). 'What are the effects of monetary policy on output? Results from an agnostic identification procedure', *Journal of Monetary Economics*, Vol. 52, pp. 381–419.

Wu, J. C. and Xia, F. D. (2016). 'Measuring the macroeconomic impact of monetary policy at the zero lower bound', *Journal of Money, Credit and Banking*, Vol. 48, pp. 253–291.

Appendix

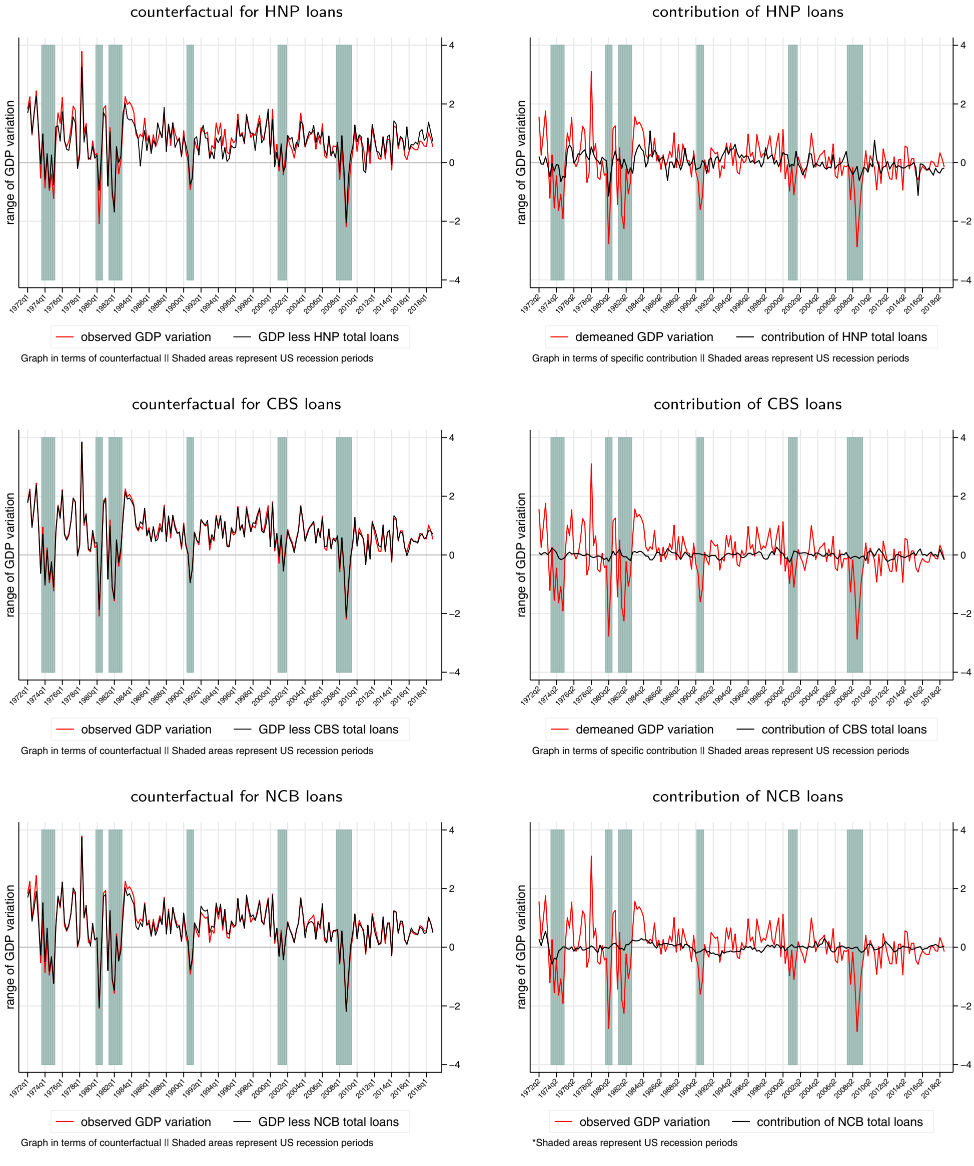

Figure A1. Counterfactual analysis plots: entire period (1971q1–2018q4)
Notes: The charts in the first column report the counterfactuals for the entire period available for the three borrower groups, the charts in the second column report the cumulative contributions from which those counterfactuals are constructed. HNP stands for households, CBS for corporate business, NCB for non-corporate business.

TABLE A1

Robustness checks, alternative orderings

Order B		*Order C*		*Order D*	
1	WCP	1	HNP-MTG	1	WCP
2	CPI	2	HNP-CCR	2	CPI
3	HPI	3	HNP-OLN	3	HPI
4	IR.FFR	4	CBS-OLN	4	NCB-MTG
5	IRS.B03m	5	CBS-MTG	5	NCB-OLN
6	IRS.P24m	6	NCB-MTG	6	CBS-OLN
7	IRS.M30y	7	NCB-OLN	7	CBS-MTG
8	HNP-MTG	8	WCP	8	HNP-MTG
9	HNP-CCR	9	CPI	9	HNP-CCR
10	HNP-OLN	10	HPI	10	HNP-OLN
11	CBS-OLN	11	IR.FFR	11	IR.FFR
12	CBS-MTG	12	IRS.B03m	12	IRS.B03m
13	NCB-MTG	13	IRS.P24m	13	IRS.P24m
14	NCB-OLN	14	IRS.M30y	14	IRS.M30y
15	COP	15	COP	15	COP
16	SP500	16	SP500	16	SP500
17	GDP	17	GDP	17	GDP
18	SALES	18	SALES	18	SALES
19	INVEN	19	INVEN	19	INVEN

Notes: This table reports alternative orderings of the variable in the VAR implying different causal relationships across the variables in accordance with the recursive identification approach.

TABLE A2

Total mortgages: components by borrower

FRB code	*Component*
Households and non-profit organizations	
FL153165105	Households and non-profit organizations; home mortgages; liability
FL163165505	Non-profit organizations; commercial mortgages; liability
Corporate business	
FL103165105	NF corporate business; home mortgages; liability
FL103165405	NF corporate business; multifamily residential mortgages; liability
FL103165505	NF corporate business; commercial mortgages; liability
FL183165605	Corporate farm business; farm mortgages; liability
Non-corporate business	
FL233165605	Non-corporate farm business; farm mortgages; liability
FL113165003	NF non-corporate business; total mortgages, excluding non-corporate farms; liability

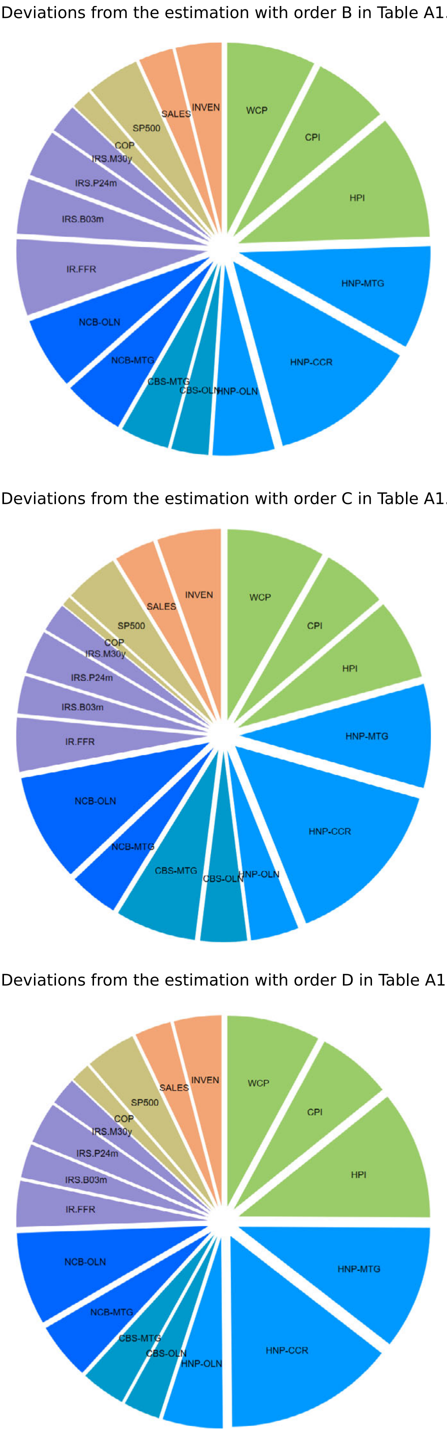

Figure A2. Deviations between the original series and the counterfactual, robustness checks
Notes: The pie charts reflect the size of the deviations between the GDP actual series and its counterfactuals: the larger the slice, the deeper the contribution of the variable in question. These charts are to compare with the one in Figure 4 for robustness.

TABLE A3

Other Loans: components by borrower

Other Loans (OLN): Depository-Institution Loans + Advances and Other Loans	
Depository-Institution loans	
FRB code	*Component*
Households and non-profit organizations	
FL763068213	US-chartered DIs; other bank loans to households and non-profit organizations; asset
FL753068213	Foreign banking offices in the United States; other bank loans to households and non-profit organizations; asset
FL713068303	Monetary authority; DI loans n.e.c. to households (Term Asset-Backed Securities Loan Facility); asset
Corporate business	
FL763068105	US-chartered DIs; DI loans n.e.c. to NF business; asset
FL753068110	Foreign banking offices in the United States ; commercial and industrial loans and leases to US addressees; asset
FL753069603	Foreign banking offices in the United States; bankers' acceptances; asset
FL743068005	Banks in US-affiliated areas; DI loans n.e.c.; asset
FL473068005	Credit unions; DI loans n.e.c.; asset
FL113168005	NF non-corporate business; DI loans n.e.c.; liability
Non-corporate business	
FL233168005	Non-corporate farm business; DI loans n.e.c.; liability
FL113168003	NF non-corporate business; DI loans n.e.c., excluding non-corporate farms; liability

Advances and other loans	
FRB code	*Component*
Households and non-profit organization	
FL 15 31692 03	Households and non-profit organizations; U.S. government loans; liability
FL 15 31694 05	Households and non-profit organizations; policy loans; liability
FL 15 31693 05	Households and non-profit organizations; Sallie Mae loans; liability
FL 66 30670 03	Security brokers and dealers; margin accounts at brokers and dealers; asset
Corporate business	
FL 10 31692 05	Corporate business; US government loans, including loans to automakers; liability
FL 10 31695 35	Corporate business; finance companies loans; liability
FL 10 31697 05	Corp. bus.; customers' liability on acceptances outstanding to commercial banking; liability
FL 26 30695 00	Rest of the world; US NF business loans; asset
FL 10 31698 03	Corporate business; syndicated loans; liability
FL 18 31693 05	Corporate farm business; Farm Credit System loans; liability
FL 73 30690 13	Holding companies; other loans and advances due from U.S. addressees; asset
Non-corporate business	
FL 11 31692 05	Non-corporate business; US government loans; liability
FL 11 31695 35	Non-corporate business; finance companies loans; liability
FL 11 31693 05	Non-corporate business; Farm Credit System loans; liability