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The Contribution of Loans to Economic Activity.

Abstract

We study the contribution of loans, granted to different borrower groups, to economic activity in the USA over the period 1971q1-2018q4. Significant economic recessions occurred along the period considered, we center our discussion around the recent Global Financial Crisis. Results are delivered through a historical decomposition analysis based on the estimation of a large VAR through Bayesian techniques. Loans to households emerge as the most important driver of economic activity when compared to other groups, mortgages contribute the most with respect to other typologies. The analysis shows that loan shocks have truly undermined economic activity during the Global Financial Crisis.

JEL-Codes: E440, E510, G200, G210, C110.

Keywords: loans, economic activity, households, corporate business, non-corporate business, Bayesian VAR, historical decomposition.

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Contents

1 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/debt has achieved remarkable levels compared to economic activity. In fact, its growth rate has been much higher than economic growth in the last decades (Schularick & Taylor 2012, Cecchetti et al. 2011). At the same time, however, credit brings risk: excessive dependence on loans can cause distortions and make both households and firms particularly vulnerable to adverse loan shocks.

The Global Financial Crisis (GFC) and the Great Recession after that have brought to the fore the dependence of economic activity on credit availability; a connection well known to economic theory (Schumpeter 1912) but, perhaps, underestimated in terms of 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, such a reduction impacted economic activity worldwide. Then, the causality direction is quite clear for this crisis. Differently, the role of credit is more blurred in other major historical events of income destruction occurred after WWII.

Starting from this consideration, the objective of our research is to study the contribution of loans to economic activity. To this end, we compare the GFC to other crises, but we compare also to periods of sustained economic growth, in order to understand the role credit plays. In terms of analysis, we quantify the cumulative contribution of loans to economic activity (GDP); this is achieved through a historical decomposition based on the estimation of a vector auto-regression (Kilian 2009, Kilian & Lee 2014). This topic has been partially object of investigation in other works (Hristov et al. 2012, Gambetti & Musso 2017) in which, however, the objective was to assess the average effect of loans on economic activity. Differently, we assess the effect of loans during well-defined time periods and not on average, and we add to the current literature results about the effect of loans to different groups and for different scopes. The idea comes from observing that loans respond differently to a monetary policy shock (Den Haan et al. 2007, Cafiso 2020), 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. Moreover, we use disaggregated loans, such as consumer credit and mortgages, from banks and other financial institutions. We like to underline that our approach, based on historical decomposition, is original with respect to other contribution in this branch of literature.

The paper is structured as follows. Section 2 introduces to same recent literature on the effect of loans on economic activity. Section 3 provides the details on the estimation of the vector auto-regression using the Bayesian approach and on the historical decomposition built on the VAR estimation output. Section 4 discusses the contribution of the different loan categories to economic activity as derived from the historical decomposition analysis. Section 5 draws the conclusions of our research.

2 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 some aggregate demand components (Khan & Thomas 2013, Guerrieri & Lorenzoni 2017), household consumption and firms' investments in the first place (Cafiso 2019). Credit is driven to some extent by monetary policy and it is considered as a conductor of monetary interventions in the *credit channel* literature or, in Bernanke & Gertler (1995)'s words, as a financial accelerator of monetary policy to the real economy. Apart from the monetary policy literature, recent research, originated from the events of the Global Financial Crisis (GFC), investigates the disruptive effects of credit shocks on economic activity. Much effort has been made to understand how the financial shock hit the economy so hard. Stock & Watson (2012) affirm that the GFC was characterized by shocks of unprecedented size but it was not a new typology of shocks, then its impact on economic activity was largely foreseeable. Nonetheless, debt was at an unprecedented level at the time of the crisis, particularly household debt, and some of its features (such as its adjustable interest rate) make borrowers more vulnerable to policy changes (Debelle 2004). Furthermore, Ramcharan et al. (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.

On the whole, research has proved that financial shocks are major drivers of economic fluctuations (Prieto et al. 2016), probably more than other shocks of a different origin (Jordà et al. 2013, Furlanetto et al. 2019), perhaps, partially because of their interplay with uncertainty shocks (Caldara et al. 2016). Theoretical papers (such as Khan & Thomas 2013, Mian & Sufi 2014, Christiano et al. 2014, Guerrieri & Lorenzoni 2017) have modeled the channels through which credit shocks impact economic activity and employment via consumer and firm behaviors. Interestingly, these theoretical contributions suggest that the impact of the credit shocks goes beyond what depends strictly on reduced credit availability, since precautionary and forward looking attitudes of households and firms trigger in and push them to save more to get ready against possible further adverse shocks (Khan & Thomas 2013, Guerrieri & Lorenzoni 2017).

A first group of empirical papers has used macro and financial data to investigate different dimensions of the GFC. The contributions mentioned above (Stock & Watson 2012, Prieto et al. 2016, Caldara et al. 2016 and Furlanetto et al. 2019) are part of this literature. In the same group, Hristov et al. (2012) and Gambetti & Musso (2017) have specifically focused on the identification of supply-side loan shocks using sign restrictions (Uhlig 2005) and checked their impact on economic activity; however, they just consider aggregate loans and do not differentiate across borrowers.[1] In some regards, such branch of research can be considered as an evolution of the reseach on the credit channel (Bernanke & Gertler 1995) but, unlike works on the credit channel, its focus is on shocks originated into credit markets and not from other sources and transmitted through credit markets.[2]

Other empirical contributions have used micro data and shown how the seeds and effects of the credit crunch can be detected along different dimensions. Mian & 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 2007-2009 recession. Ramcharan et al. (2016) use micro data from the housing and automobile markets to measure the real consequences of the credit shock, their goal is to show how

[1] We do not know whether this is an intentional choice, but it is almost 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.

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

the collapse of the ABS market affected the supply of credit to consumers and those two good markets as a consequence. Along the same line, Benmelech et al. (2016) discuss how illiquidity in short-term credit markets, such as those in which non-bank suppliers of auto loans get funds, impairs 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 et al. (2018) provide results showing that when a firm's reference bank is hit by an adverse shock, such firm reduces investments and employment.

Easy to learn from the research papers above-mentioned is the need to consider heterogeneous agents or, in a more empirical context, different groups of borrowers. First evidence in this direction is in Bernanke & Gertler (1995) and den Haan (2011), among the others, both discuss why households and firms respond differently to a monetary shock. Surico et al. (Cloyne et al. 2016, Cloyne & Surico 2016, Bunn et al. 2017) too show that agents are highly heterogeneous in terms of their response to a shock when debt is involved and assert a relationship with the country of residence.[3] Furthermore, Cloyne et al. (2016) split the household group into mortgagors, outright owners and renters in the USA and the UK, they show that differences emerge between these groups. Along the same line, Guerrieri & Lorenzoni (2017) develop a model that highlights differences across different groups of households; a point discussed also by Kaplan et al. (2018). In conclusion, considering heterogeneous agents allows to check how different groups respond to the same shock, to quantify the weight of each group in the aggregated result and, by the same token, motivate to check whether loans to different groups impact differently on economic activity; a research development suggested by Gambetti & Musso (2017).

With respect to the above-mentioned literature, our research bridges two streams of research: the first on the role of debt shocks in recessions, the second centered on the use of heterogeneous borrowers. Our scope is to assess the contribution of different loan categories to the evolution of economic activity observed during the GFC and other periods. We employ the analytical approach in Kilian (2009), Kilian & Lee (2014) which consists of a historical decomposition.

[3] Also Coletta et al. (2014), Christelis et al. (2015) and Sufi (2015) affirm that, from an across-countries perspective, agents respond differently and that dependes to some extent on the country they reside.

3 VAR estimation and historical decomposition

The analysis is based on the estimation of a Vector Auto-Regression (VAR, Stock & Watson 2001), the estimation is performed through the Bayesian approach. The choice in favor of Bayesian techniques is to avoid some drawbacks of frequentist estimations. First and foremost, Bayesian techniques allow the estimation of large VARs with a standard number of observations because they shrink the parameter space and consequently overcome the over-parametriziation problem (Bańbura et al. 2010). We identify the structural shocks from the reduced-form residuals using the Choleski decomposition (recursive VAR, Wald causal chain). Instead of the more known impulse-response analysis, which returns the average effect of a variable on another over the entire estimation period, we focus on the *historical decomposition analysis* that suits best our research objective since it allows studying specific points in time. After introducing the data used, we explain the details of the VAR estimation and of the robustness checks performed. The last subsection provides information on the historical decomposition analysis whose results are presented in the next section 4.

3.1 Data

The 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 loan series are for the borrower groups: *Households and Non-Profit organizations* (HNP), *non-financial Corporate Business* (CBS), *non-financial Non-Corporate Business* (NCB).

Loans are from all sources, depository and non-depository institutions; this is most important for households since a large part of their loans are granted by non-depository institutions (Gambetti & Musso 2017). For each group we have the following categories:

- Total Mortgages (TM). This category includes home, multifamily residential, commercial and farm mortgages granted by government and private institutions. The list of all components is in Table 7 in the appendix.

- Consumer Credit (CC). This is available only for households and it includes loans granted by depository (banks) and non-depository institutions (non-bank firms), both public and private;

Table 1: US loans by borrower group

Households and Non-Profit **-HNP-** (FL15 4123005.Q)	Corporate Business **-CBS-** (FL10 4123005.Q)	Non-Corporate Business **-NCB-** (FL11 4123005.Q)
TM: Total Mortgages	**TM**: total mortgages	**TM**: Total Mortgages
(FL15 3165005.Q)	(FL10 3165005.Q)	(FL11 3165005.Q)
CC: consumer credit		
(FL15 3166000.Q)		
DI: Depository Institution loans	**DI**: Depository Institution loans	**DI**: Depository Institution loans
(FL15 3168005.Q)	(FL10 3168005.Q)	(FL11 3168005.Q)
AO: Advances and Other loans	**AO**: Advances and Other loans	**AO**: Advances and Other loans
(FL15 3169005.Q)	(FL10 3169005.Q)	(FL11 3169005.Q)

Notes: The code in parenthesis identifies the series in the system of US Financial Accounts (FRBG). Bold letters are for the acronyms of the loan items used throughout the paper.

some student loans are an example of consumer credit granted by government agencies, also automobile loans are part of this category.

- Depository Institution loans n.e.c. (DI). This category includes all loans by banks except for open market papers, mortgages and consumer credit, which are shown in other categories. The list of all components is in Table 8 in the appendix.

- Advances and Other loans (AO). These are mainly loans from non-bank institutions, the US government and the rest of the world. The list of all components is in Table 9 in the appendix.

Table 1 lists all the categories available by borrower.[4] A graph reporting the level of the loan aggregates for the three borrower groups is in Figure 2 (first column).

The other variables are: the gross domestic product (plotted in Figure 1), inventories, sales, a world index of consumer prices, the consumer price index, the federal funds rate and a group of interest rates applied to private loans. We construct the inventories series in levels from variations (national accounts records), we made it directly comparable to the sales index series in levels released by the OECD.[5] The Federal Funds Rate accounts for the monetary stance. The other interest rates included are meant

[4]The loan series data are made available non-seasonally adjusted, we have seasonally adjusted them by using the X-13ARIMA-SEATS program developed at the U.S. Census Bureau; loan series exhibit a strong seasonality on the 4th quarter.

[5]Inventory variations are indirectly compiled based on the identity: production is equal to sales plus inventory variation $(P_t = S_t + \triangle I_t)$ (Ramey & West 1999).

to reflect the cost of private loans: an average interest rate on short-term business loans (bank prime loan rate), an average interest rate on personal loans with 24 months maturity, an average interest rate on automobile loans with 48 months maturity, an average interest rate on mortgages with 30 years maturity. Table 2 lists all the variables with the respective source. To sum up, variables 1-2 are price indices, variables 3-7 are the interest rate variables, variables 8-17 are the loan categories, variables 18-20 are real-economy variables.

The order of the variables in Table 2 reflects the order in the VAR. This is important because identification is based on the Wald causal chain (Choleski decomposition). Reasoning in terms of groups, prices are imagined to respond with a lag to a monetary policy shock, while interest rates on private loans, loan volumes and real variables respond contemporaneously (within the same quarter) to a monetary policy shock. More generally, real variables respond within the same quarter to all the other variables in the system, in relation to the scope of our research, this implies that economic activity is imagined to respond to loan shocks within the same quarter.

Data are available starting from different dates and up to the end of 2018, the analysis is for the period 1971q1-2018q4.

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.

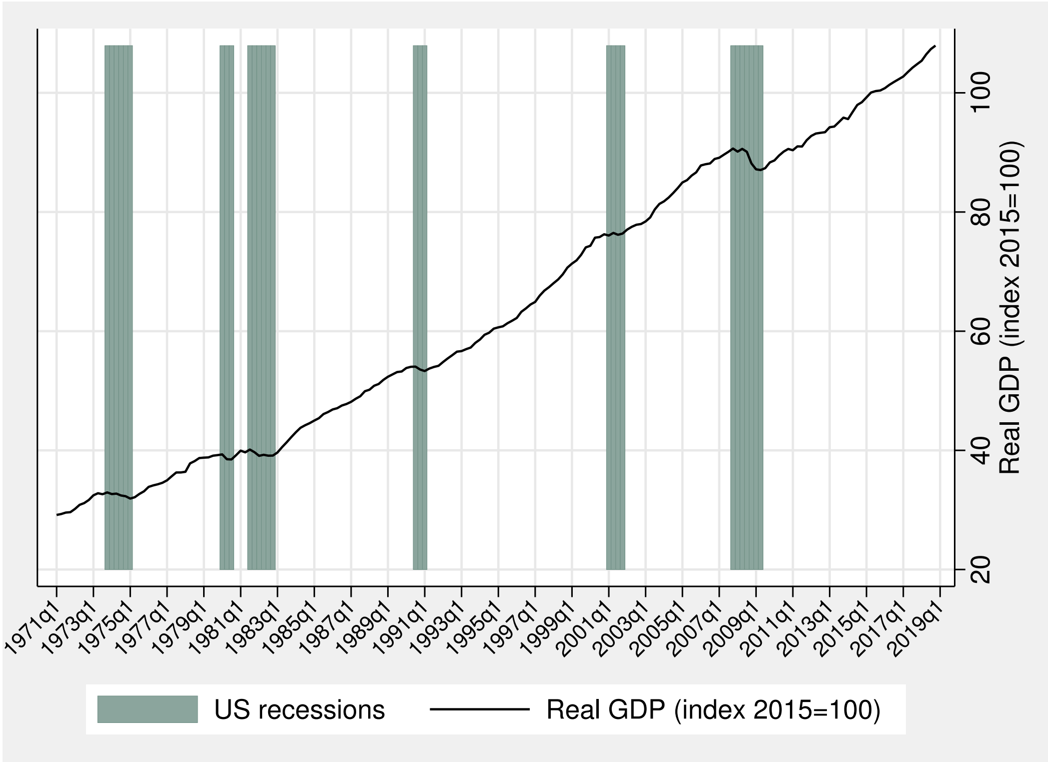
As for the within-group composition, Panel B in Table 3 reports each component's share; such weights are those plotted in Figure 2. Loans to households and non-corporate business are stable overtime. Differently, loans to corporate business exhibit a structural change well before the GFC and the Geat Recession, as shown by the decreasing weight of loans from depository institutions; this is linked to the growing importance of non-bank lenders in the US financial system.

Table 2: List of variables

#	group	name	short	source	code
1		World index of commodity prices	WICP	Datastream	wicp
2		Consumer Price Index	CPI	OECD	cpi
3		Fed funds rate	FFR	FRED	ir_fedfunds
4		Interest rate on short-term business loans	IRBPL	FRED	ir_mprime
5		Interest rate on 24 months personal loans	IR24M	FRED	ir_pers24m
6		Interest rate on 48 months automobile loans	IR48M	FRED	ir_auto48m
7		Interest rate on 30 years mortgages	IR30Y	FRED	ir_mort30y
8	Households and Non-Profit	Total Mortgages	HNP-TM	BGFRS	hnp_tm
9		Consumer Credit	HNP-CC	BGFRS	hnp_cc
10		Depository Institutions Loans nec	HNP-DI	BGFRS	hnp_di
11		Advances and Other Loans	HNP-AO	BGFRS	hnp_ao
12	Corporate Businesses	Total Mortgages	CBS-TM	BGFRS	nfc_tm
13		Depository Institutions Loans nec	CBS-DI	BGFRS	nfc_di
14		Advances and Other Loans	CBS-AO	BGFRS	nfc_ao
15	Non-corporate Businesses	Total Mortgages	NCB-TM	BGFRS	nfNc_tm
16		Depository Institutions Loans nec	NCB-DI	BGFRS	nfNc_di
17		Advances and Other Loans	NCB-AO	BGFRS	nfNc_ao
18		Gross Domestic Product	GDP	OECD	gdp
19		Sales	SALES	OECD	sales
20		Inventories	INVENT	OECD	inven

Notes: 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 used throughout the paper.

Figure 1: GDP evolution



3.2 Estimation

We estimate the reduced-form VAR:

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

in which y_t is a 20-variable vector. All variables are in first differences; except for the interest rates, those were log-transformed first. The choice for a VAR in differences is to ensure stability to the VAR (covariance-stationary), this is a necessary requirement for historical decomposition analysis (see below). The VAR includes 1 lag for each variable.[6] This results in 420 parameters (21 by equation) to estimate with approximately 144 observations.[7] In order to deal with such over-parametrization (curse of dimensionality), which comes with the estimation of large systems (Bańbura et al. 2010, Giannone

[6]Other contributions in this branch of literature includes 2 lags when using quarterly data in log-levels (Hristov et al. 2012, Gambetti & Musso 2017, Cafiso 2020), we therefore opted for 1 lag only since we use first differences. The robustness checks discussed below show that inclusion of two lags does not change the results.

[7]$(n \times p + 1) \times n$ is the formula for the number of parameters in the VAR according to the number of n variables and the number of p lags.

Figure 2: Loans by component, levels and weights

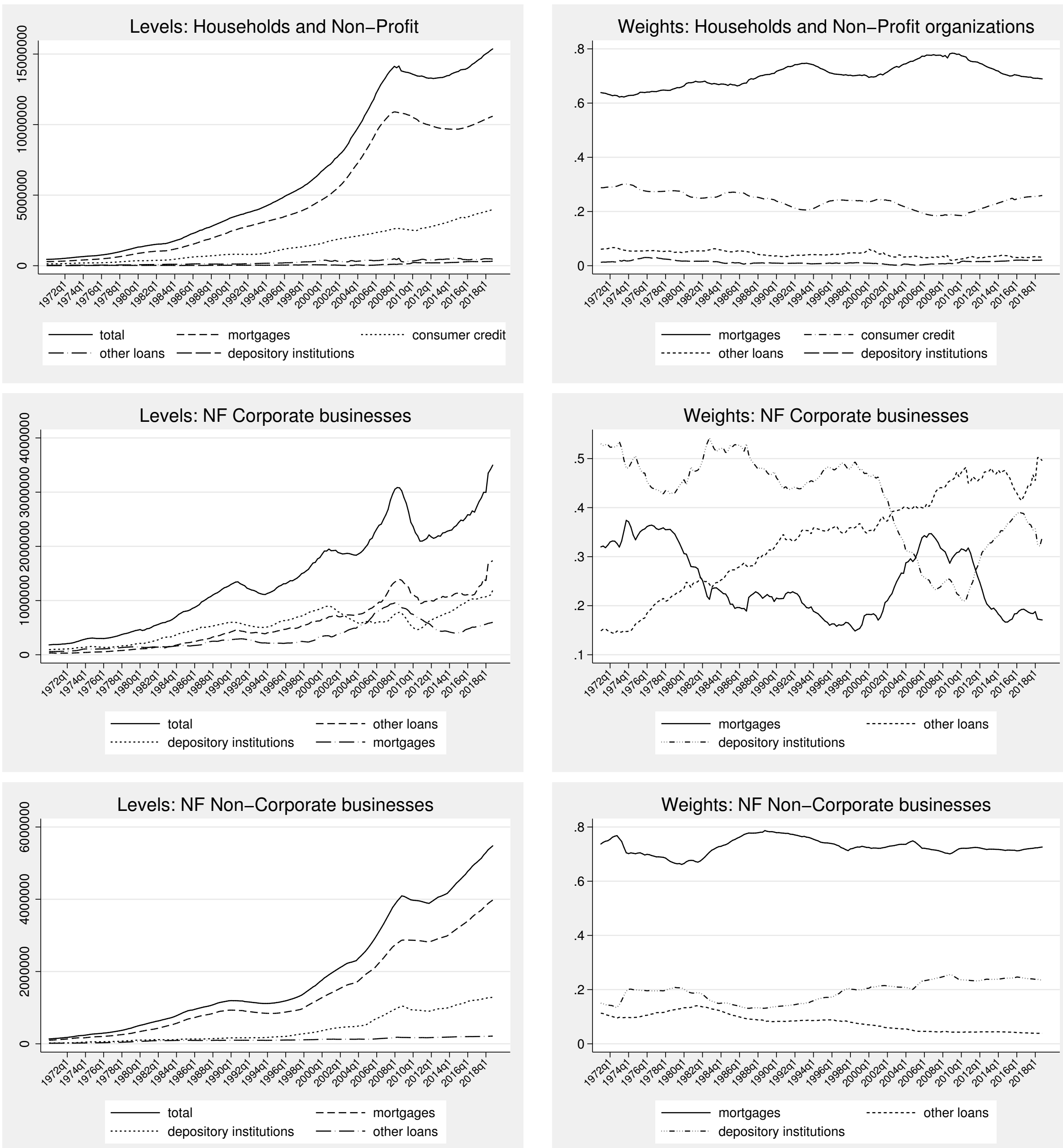


Table 3: Loan weights

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	**-TM**	**-CC**	**-DI**	**-AO**	**-TM**	**-DI**	**-AO**	**-TM**	**-DI**	**-AO**
(1970q1,1979q4)	63.9%	28.4%	2.0%	5.7%	34.2%	48.1%	17.8%	71.0%	18.1%	10.9%
(1980q1,1989q4)	68.0%	25.7%	1.2%	5.1%	23.1%	49.9%	27.0%	73.6%	15.3%	11.1%
(1990q1,1999q4)	72.1%	22.8%	0.9%	4.1%	18.6%	46.4%	35.0%	74.8%	16.9%	8.3%
(2000q1,2009q4)	74.9%	21.0%	0.6%	3.5%	27.4%	32.0%	40.6%	72.3%	22.4%	5.2%
(2010q1,2018q4)	72.1%	23.0%	1.8%	3.2%	21.3%	32.6%	46.1%	71.9%	23.8%	4.2%
(1970q1,2018q4)	70.2%	24.2%	1.3%	4.3%	25.0%	42.0%	33.0%	72.7%	19.2%	8.0%

HNP stands for households and non-profit, CBS for corporate business, NCB for non-corporate business. TM for morgages, CC for consumer credit, DI stands for depository institution loans, AO for advances and other loans. Panel A reports the shares of the aggregates by group over the total amount of loans in the economy, Panel B reports the shares of each loan category within each borrower group.

et al. 2015), we resort to the Bayesian approach that allows to shrink the parameter space; in this perspective our analysis is similar to Giannone et al. (2019).[8]

The posterior distribution is summarized by its median value. We specify the prior distribution as a Normal-InverseWishart (natural conjugate prior, among the others, see Dieppe et al. 2018):

- Prior for the mean: $\beta \sim N\left(\beta_0, \Sigma \otimes \Phi_0\right)$
- Prior for the variance-covariance matrix: $\Sigma \sim IW\left(S_0, \alpha_0\right)$

so that the posterior is also a Normal-InverseWishart. The hyperparameters for the prior 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 1000, the number of burn-in iterations is 500.

As for the overall-tightness parameter (λ_1), we follow Bańbura et al. (2010) and set 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, the more the coefficients to estimate, the

[8] Giannone et al. (2019) estimate a VAR with 28 variables and include 7 lags, this sums to 5516 parameters to estimate with around 190 observations.

closer to zero λ_1 should be (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.[9]

Given the VAR structural-form:

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

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

$$u_t = \Phi \epsilon_t,$$

Φ is therefore lower triangular and the order of the variables reflects the Wald causal chain implicit to the recursive identification; the order of the variables is the one in Table 2.

3.3 Robustness of the estimation

The robustness of the conclusions, drawn from the historical decomposition analysis discussed in the next section, has been tested through a couple of robustness checks. First, we have re-estimated the VAR using two lags, instead of one. The ranking of the different loan-category contributions reported in Table 5 remains very much the same when we use two lags instead of one. Secondly, we have estimated a VAR using only the aggregations of the loan categories by borrower group, this VAR has therefore 13 variables instead of 20, which is the number in the benchmark VAR; for this VAR we used a overall tightness parameter (λ_1) equal to 0.16 given the fewer variablies used. The estimation output of such a smaller VAR returns a ranking of the loan aggregates for the entire time period in line with what obtained from the benchmark VAR; namely, HNP loans exert the largest contribution, NCB loans follow, CBS loans have the smallest effect. Thirdly, we have re-estimated the benchmark VAR using a different order of the variables for the Choleski decomposition. In this case, as we imagined, the ranking of the loan-category contributions changes. Quite unsurprisingly, conclusions are influenced by the specific Wald causal chain defined. As a last check, we have also re-estimated the benchmark VAR using different hyperparameters for the prior distribution (overall tightness $\lambda_1 = 0.12$ and autoregressive

[9] In their work, such optimal value is found as the one minimizing the in-sample mean squared forecast error.

coefficient $ar = 0.7$), results remain very much comparable in this case.

3.4 Historical decomposition analysis

A matter of interest with VAR models is to establish the contribution of each structural shock to the historical dynamics of the data series. The technique is known as *historical decomposition*, Burbidge & Harrison (1985), Kilian (2009), Kilian & Lee (2014) are prominent examples. It allows to decompose the value of each variable into its different components, each component linked to one structural shock in the model, for every time point.

Historical decomposition analysis involves three steps. First, the estimation of the reduced-form VAR, which needs to be covariance-stationary $I(0)$, and the identification of the structural shocks through the approach chosen (Choleski 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 $c^k_{i,t}$. Eventually, $c^k_{i,t}$ is the cumulative contribution of variable i shocks at time t to the evolution of variable k; both k and i are one of the N variables included in the VAR.[10]

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 observed k variable, in notation:

$$y^*_{k,t} \approx \sum_{i=1}^{N} c^k_{i,t} + res;\ i = 1, ..., N$$

where $y^*_{k,t}$ is the demenead/detrended value of variable k object of analysis at time t, $c^k_{i,t}$ is the contribution of variable i at time t; y is the vector of dependent variables in the VAR which includes k and i.[11] To notice 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. Differently, 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).

To assess the contribution of variable i to the evolution of k one first option is to plot $c^k_{i,t}$ against

[10] This brief presentation of the basis of historical decomposition is taken from Kilian & Lütkepohl (2017) (chapter 4), we refer the reader to it for the more technical details.

[11] As for $y^*_{k,t}$, if the variables in the VAR are in levels then it is the detrended value, if it the variables are in first difference then it is the demeaned value.

$y^*_{k,t}$ (visual display option A): the more $c_{i,t}$ gets close to $y^*_{k,t}$ the higher its contribution compared to the other variables; this is shown in Figure 6 in the appendix. An alternative, somehow more convenient method is described below.

Historical decomposition as a counterfactual analysis

As matter of fact, the visual display described above (option A) is somehow difficult to read. An alternative more convenient way to assess the contribution of each i variable is to use it to generate a counterfactual for the k variable (Kilian & Lee 2014). This is simply obtained by subtracting $c^k_{i,t}$ to the variable as originally introduced in the VAR; first difference in our case. In notation:

$$\hat{y}^i_{k,t} = y_{k,t} - c^k_{i,t},$$

$\hat{y}^i_{k,t}$ is the counterfactual series, $y_{k,t}$ is the original series. $\hat{y}^i_{k,t}$ shows the evolution of k as if there were no shocks to the i variable. The plot of $\hat{y}^i_{k,t}$ against $y_{k,t}$ (visual display option B) is usually easier to read: the larger the difference between $y_{k,t}$ and $\hat{y}^i_{k,t}$, the higher the contribution of i. If i had no contribution at all, then the two series would perfectly overlap. Nevertheless, also the plot of $\hat{y}^i_{k,t}$ against $y_{k,t}$ gets difficult to read when the period considered has many time observations. Then, in this case, 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 $y_{k,t}$ and $\hat{y}^i_{k,t}$: $dev_{k-i,t} = \left(y_{k,t} - \hat{y}^i_{k,t}\right)$.

As for **the size of the contribution**, conclusions for a specific sub-period $T-s$ can be simply achieved through the average of such deviations in absolute value:

$$AVdev_{k-i,T-s} = \frac{\sum\limits_{t=s}^{T} abs\left(dev_{k-i,t}\right)}{T-s}, \tag{2}$$

the higher the value of $AVdev$, the larger the contribution of variable i to k in the period $T-s$. Considering the deviations in this way allows to draw conclusions across variables, but also for the same variable across different periods. As for **the direction of the contribution**, if $dev_{k-i,t} > 0$ $(y_{k,t} > \hat{y}^i_{k,t})$ the i variable exerts a positive effect on k, if $dev_{k-i,t} < 0$ otherwise. Coherently, a simple way to draw conclusions is to count either the positive or negative deviations over the total, if the fraction of (let us say) positive deviations is substantially larger than 50%, then the i variable exerts a positive effect, the opposite if the fraction is significantly lower than 50%:

$$PSdev_{k-i,T-s} = \frac{num.\ of\ \ (dev_{k-i,t} > 0)\ \ in\ T-s}{T-s}. \tag{3}$$

This is a simple way to synthesize the distribution of the deviations and has the advantage to get straight to the point.[12]

4 The contribution of loan shocks to economic activity

Based on what discussed in section 2, we study now the cumulative contribution of loan shocks to economic activity. As already affirmed, we are primarily interested in a comparative assessment of the different loan categories (those listed in Table 2). The analysis is inspired also by the conclusions in Gambetti & Musso (2017), in which the authors encourage to analyze separately credit to non-financial corporations and loans to households. The results discussed here are from the historical decomposition presented in terms of counterfactual analysis as described in the previous section.

The contribution of loans by borrower group is shown through [A] the plot of economic activity ($y_{k,t}$) as included in the VAR (GDP growth rate) against its counterfactual ($\hat{y}^i_{k,t}$), and as summarized by [B1] the average of the deviations (eq. 2) and by [B2] the fraction of positive deviations (eq.3). Furthermore, we report also [C] the plot of economic activity (demeaned, $\overset{*}{y}_{k,t}$) against some contributions of interest ($c^k_{i,t}$) in the appendix. In addition to the results for each loan category in Table 1, we present results also for the aggregation of all those categories by borrower group (*ALL*).[13]

4.1 An overview of the entire period 1971q1-2018q4

Figure 3 shows respectively the contributions of household, corporate business and non-corporate business loans to economic activity in terms of counterfactual [A]; these are the by-borrower aggregations. The plots for the entire period are not easy to read because we cover a long time span, which includes several economic recessions. The more the counterfactual diverges from the original series, the more the

[12] Alternatively, one could plot the quantile distribution and/or test whether that fraction is statistically significant from zero, but for presentation convenience the method mentioned above is what we opt for.

[13] To wit: the household *ALL* aggregate sums the contributions of mortgages, consumer credit, depository-institution loans and advances-and-other loans.

contribution of the variable under consideration on the GDP evolution is; we synthesize such divergence through the average of the deviations further on. With the same scope, it can be convenient to compare the plots in Figure 3 with the same in Figure 6 in the appendix; the latter show how economic activity would have evolved if shaped only by shocks to the i variable under consideration [C].

Table 5 (Panel A) reports the average of the deviations [B1, $AVdev$ in eq. 2] and the fraction of positive deviations [B2, $PSdev$ in eq. 3]; the average of the deviations is displayed also in Figure 4. Overall, expect for endogenous shocks to the GDP series itself, household loans have contributed the most to the GDP evolution, non-corporate business loans and corporate business loans follow respectively in order. At a more disaggregated level, consumer credit and total mortgages (both to households) are at the first place in terms of contribution. After those, it is again mortgages (to corporate business and to non-corporate business) to have the largest weight. The predominance of mortgages is likely to signal the weight of the construction sector in the GDP. All the other categories follow. It is interesting to notice that bank loans (DI) contribute more to the GDP evolution when granted to firms than to corporations. As for the non-loan variables, commodity prices and the fed-funds rate have contributed more than many loan categories (except for consumer credit and household mortgages); we recall that the fed-funds rate should reflect monetary policy.

If we look at the fraction of positive deviations, a positive deviation suggesting that shocks to the variable under consideration push economic growth upwards, almost all the variables had a balanced influence on economic growth over the long time period considered, only the fed-funds rate shows a more positive effect.

4.2 A comparison of two crises

The period under investigation includes six US recessions, these are listed in Table 4; the GFC is the most recent event in our sample. 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 impaired the capacity of lending institutions to extend credit. Consequently, intermediation fell and this undermined economic activity. In this section we study the contribution of loans during the GFC, also with the intent to check whether that matches the narrative of the events. To this end, we will compare the GFC with the 2nd oil shock in the eighties, another great recession in US history; these two crises have different causes and for this reason are interesting to compare. The values of $AVdev$ and $PSdev$ for both crises are in Table 5, respectively in Panel B and Panel C; the same $AVdev$ values are plotted in Figure 4 for ease of comparison.[14]

As for the GFC, comparing the values in Panel B with those for the entire period in Panel A shows that almost all loan categories switch to an adverse effect on economic activity; this meaning that loan shocks have decreased economic activity. At the aggregated level, household loans gain weight and overcome GDP shocks, but during the GFC those exert a markedly negative effect; particularly mortgages to households are adverse. Interesting to notice that corporate-business loans have a larger contribution than non-corporate business loans during the crisis (both are much negative), while it is the opposite over the entire period. At a disaggregated level, we have already pointed out the negative contribution of almost all loan categories, among those, household mortgages stand out, but also mortgages to corporations exert a negative contribution. The GFC started as a turmoil in the mortgage market, these findings therefore meet the narrative of the events. As for the other variables, commodity prices gained weight and increased their positive contribution to economic activity; probably, their fall during the recession had somehow a positive influence on economic performance. The contribution of sales compared to inventories is also consistent with what expected during an economic recession.

During the crisis following the 2nd oil shock (Panel C), the contribution of aggregated loans seems in general comparable with what observed over the entire period (Panel A); that is almost neutral and never adverse. Then, a remarkable difference is to notice with respect to the GFC. At a disaggregated level, mortgages to different categories do not contribute homogeneously, as well as bank and non-bank loans. Difficult to understand why commodity prices loose weight since that was an oil shock, but the sign of their contribution turns negative as expected. It is important to notice the stronger influence of the fed-funds rate. In accordance with Kilian & Lewis (2011), we believe this depends on a more active role of monetary policy to counterbalance inflationary pressures linked to higher oil prices. In line with this interpretation, the sign of the FFR positive deviations dramatically drops during the second oil shock.

[14] To better study the dynamics of the events, we added a quarter at the beginning and at the end of the recession period defined by the NBER.

Table 4: List of US recessions in the period 1971q1-2018q4.

#	Period	# 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

Source: the NBER.

4.3 A comparison of two growth periods

The comparison of growth periods can return useful insights as well, particularly when such periods are at different stage of economic development and sufficiently far apart in time. Then, we like to compare the two 4-year periods of significant economic growth that preceded the crises discussed in the previous section: the first period is the one leading to the GFC, 2003q4-2007q3 (GDP growth around 10.75%); the second period is 1977q3-1981q2 (GDP growth around 9.3%), this the period before the 2nd oil shock.[15] The study of the deviations for such periods ($AVdev$ and $PSdev$), a way to synthesize the counterfactual analysis based on the historical decomposition, is reported in the following Table 6, in Panel B for the period 2003q4-2007q3 and in Panel C for the period 1977q3-1981q2; the results for the entire period are again reported in Panel A to ease the comparison (these are the same as in Table 5).

At the aggregated level, the contribution of loans to the different groups is stable in terms of ranking across the two periods, also when compared to the entire period under investigation: household loans come first, non-corporate and corporate business loans follow in order. It is to signal, however, that the contribution of household loans during the period 2003q4-2007q3 is more negative at such a level of aggregation.

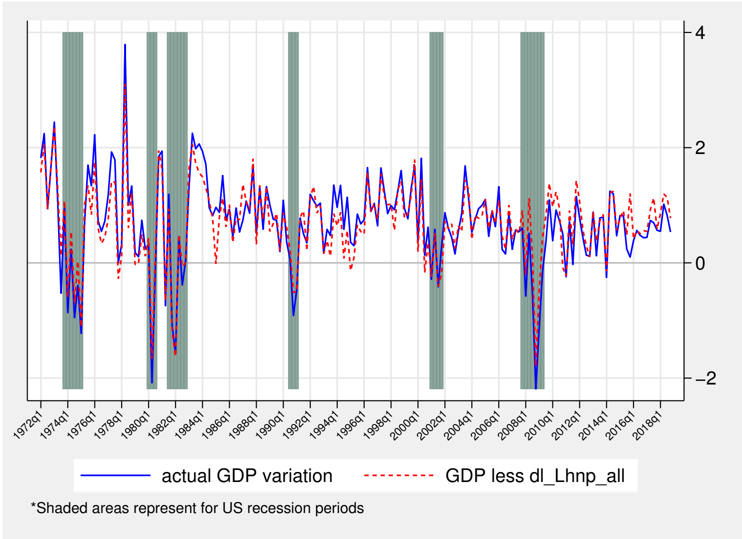
Focusing on the period before the GFC, the positive contribution of household mortgages stands out; this meets quite well the narrative of the GFC for which the excessive expansion of mortgages towards non-creditworthy borrowers (sub-prime) was one of the main causes of the crisis. Consumer credit exerts a large contribution too but, difficult to explain, it is mainly negative. Also mortgages to small firms contribute positively to economic activity. Nothing of particular interest emerges with respect to

[15] The period 1977q3-1981q2 includes the double-dip recession occurred in 1980q1-1980q3. This lasted only three quarters and was quite soft so we did not worry about its inclusion in the much longer period of growth discussed.

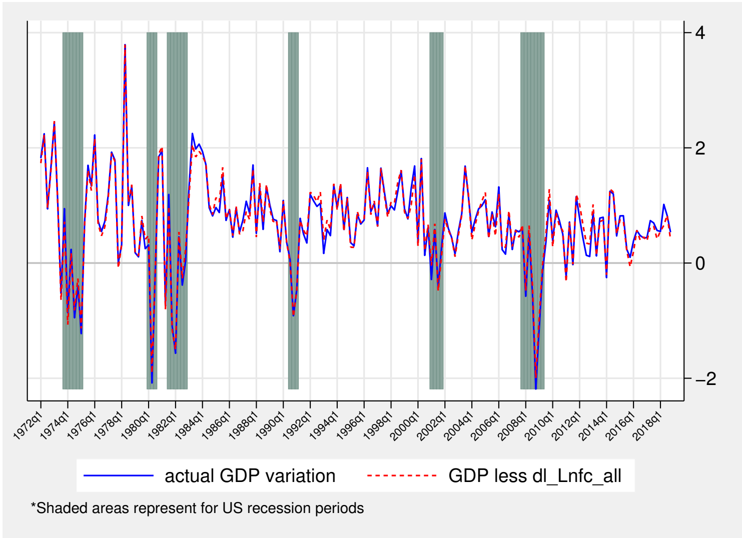
the other loan categories. As for the period before the 2nd oil shock, household mortgages rank still high and exert a markedly positive contribution in that period too as well as consumer credit. Apart for advances and other loans, all other loan categories seem to exert a positive influence on economic growth. When comparing the two periods, it is to notice that monetary policy (the fed-funds rate) exerts a larger contribution in the eighties than in the 2000s. This might be linked to the more negative effect of prices (CPI) during that period, an effect which the FED might have tried to counterbalance through an active monetary policy.

Figure 3: Counterfactual analysis, plots: entire period (1971q1-2018q4)

counterfactual for HNP loans



counterfactual for CBS loans



counterfactual for NCB loans

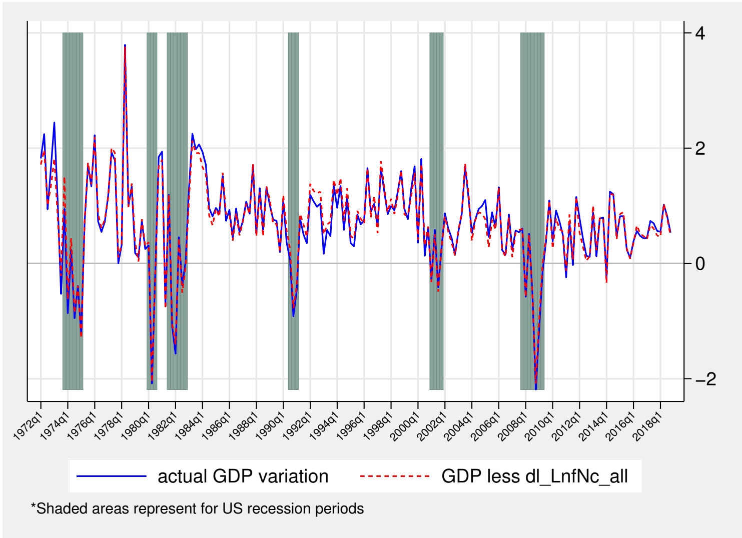
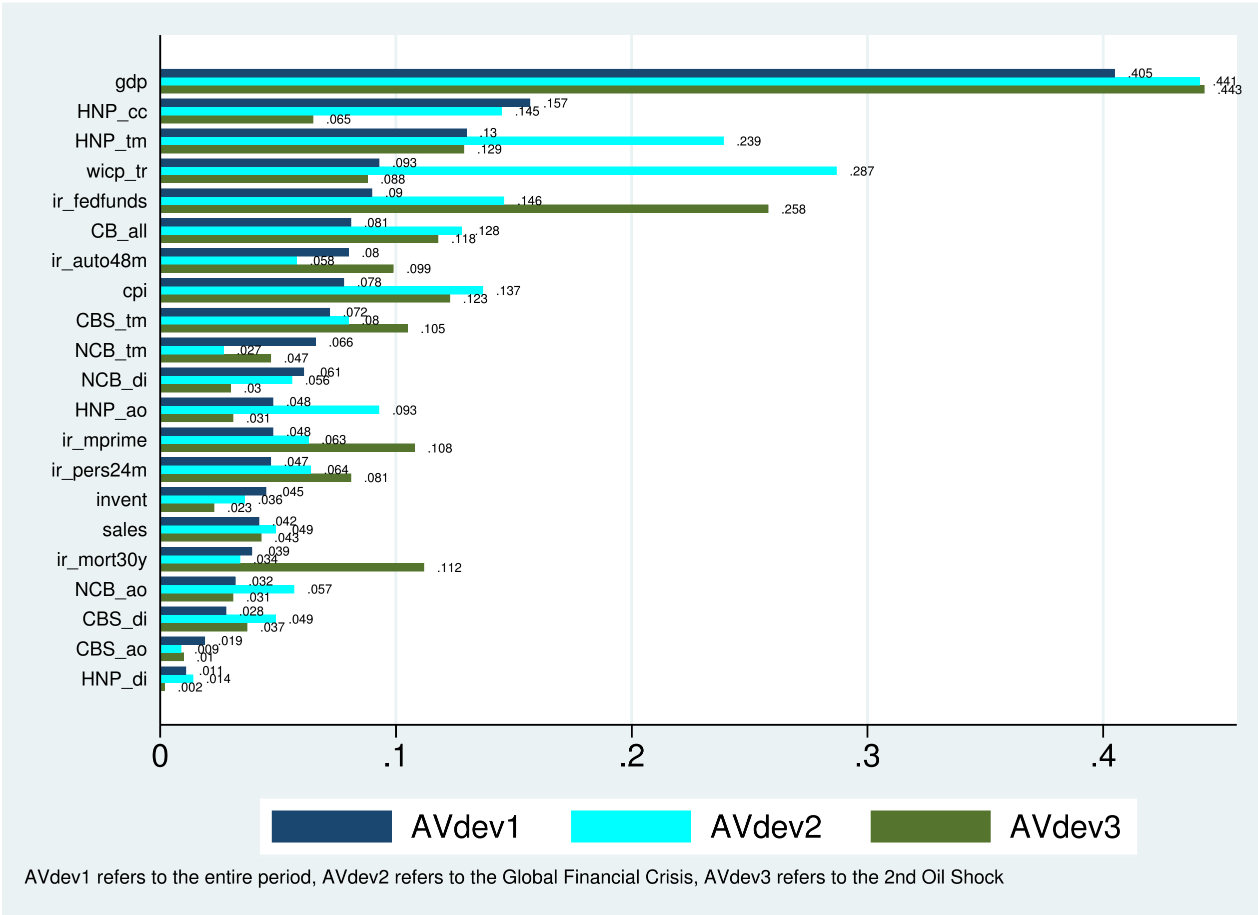


Table 5: Counterfactual analysis, study of the deviations: entire period against crisis periods

	Panel A				Panel B				Panel C			
	Entire period: 1972q2-2018q4				Global Fin. Crisis: 2007q3-2009q3				2nd oil shock: 1981q2-1983q1			
Rank	*Variable*	*#Q*	*AVdev*	*PSdev*	*Variable*	*#Q*	*AVdev*	*PSdev*	*Variable*	*#Q*	*AVdev*	*PSdev*
					*HNP_all	9	0.448	11.1%				
1	gdp	187	0.405	47.5%	gdp	9	0.441	33.3%	gdp	8	0.443	12.5%
	*HNP_all	187	0.218	49.2%								
2	HNP_cc	187	0.157	47.0%	wicp	9	0.287	66.6%	ir_fedfunds	8	0.258	25.0%
									*HNP_all	8	0.154	50.0%
3	HNP_tm	187	0.130	50.2%	HNP_tm	9	0.239	0.0%	HNP_tm	8	0.129	12.5%
	*NCB_all	187	0.094	50.2%								
4	wicp	187	0.093	50.8%	ir_fedfunds	9	0.146	55.5%	cpi	8	0.123	25.0%
									*CBS_all	8	0.118	50.0%
5	ir_fedfunds	187	0.090	57.7%	HNP_cc	9	0.145	11.1%	ir_mort30y	8	0.112	50.0%
	*CBS_all	187	0.081	50.2%								
6	ir_auto48m	187	0.080	50.8%	cpi	9	0.137	55.5%	ir_mprime	8	0.108	37.5%
					*CBS_all	9	0.128	11.1%				
7	cpi	187	0.078	52.4%	HNP_ao	9	0.093	33.3%	CBS_tm	8	0.105	50.0%
8	CBS_tm	187	0.072	49.2%	CBS_tm	9	0.080	11.1%	ir_auto48m	8	0.099	50.0%
9	NCB_tm	187	0.066	55.6%	ir_pers24m	9	0.064	33.3%	wicp	8	0.088	37.5%
									*NCB_all	8	0.084	62.5%
10	NCB_di	187	0.061	49.2%	ir_mprime	9	0.063	55.5%	ir_pers24m	8	0.081	37.5%
					*NCB_all	9	0.059	33.3%				
11	HNP_ao	187	0.048	49.7%	ir_auto48m	9	0.058	22.2%	HNP_cc	8	0.065	75.0%
12	ir_mprime	187	0.048	45.9%	NCB_ao	9	0.057	22.2%	NCB_tm	8	0.047	87.5%
13	ir_pers24m	187	0.047	52.4%	NCB_di	9	0.056	22.2%	sales	8	0.043	50.0%
14	invent	187	0.045	56.6%	CBS_di	9	0.049	11.1%	CBS_di	8	0.037	37.5%
15	sales	187	0.042	50.8%	sales	9	0.049	22.2%	HNP_ao	8	0.031	100.0%
16	ir_mort30y	187	0.039	51.8%	invent	9	0.036	88.8%	NCB_ao	8	0.031	50.0%
17	NCB_ao	187	0.032	49.7%	ir_mort30y	9	0.034	11.1%	NCB_di	8	0.030	62.5%
18	CBS_di	187	0.028	51.3%	NCB_tm	9	0.027	44.4%	invent	8	0.023	37.5%
19	CBS_ao	187	0.019	50.2%	HNP_di	9	0.014	55.5%	CBS_ao	8	0.010	37.5%
20	HNP_di	187	0.011	47.0%	CBS_ao	9	0.009	55.5%	HNP_di	8	0.002	25.0%

HNP stands for households and non-profit, CB for corporate business, NCB for non-corporate business. DI stands for depository institution loans, AO for advances and other loans, TM for morgages, CC for consumer credit; ALL sums all the loan categories by group.

Figure 4: AVdev, as from Table 5.



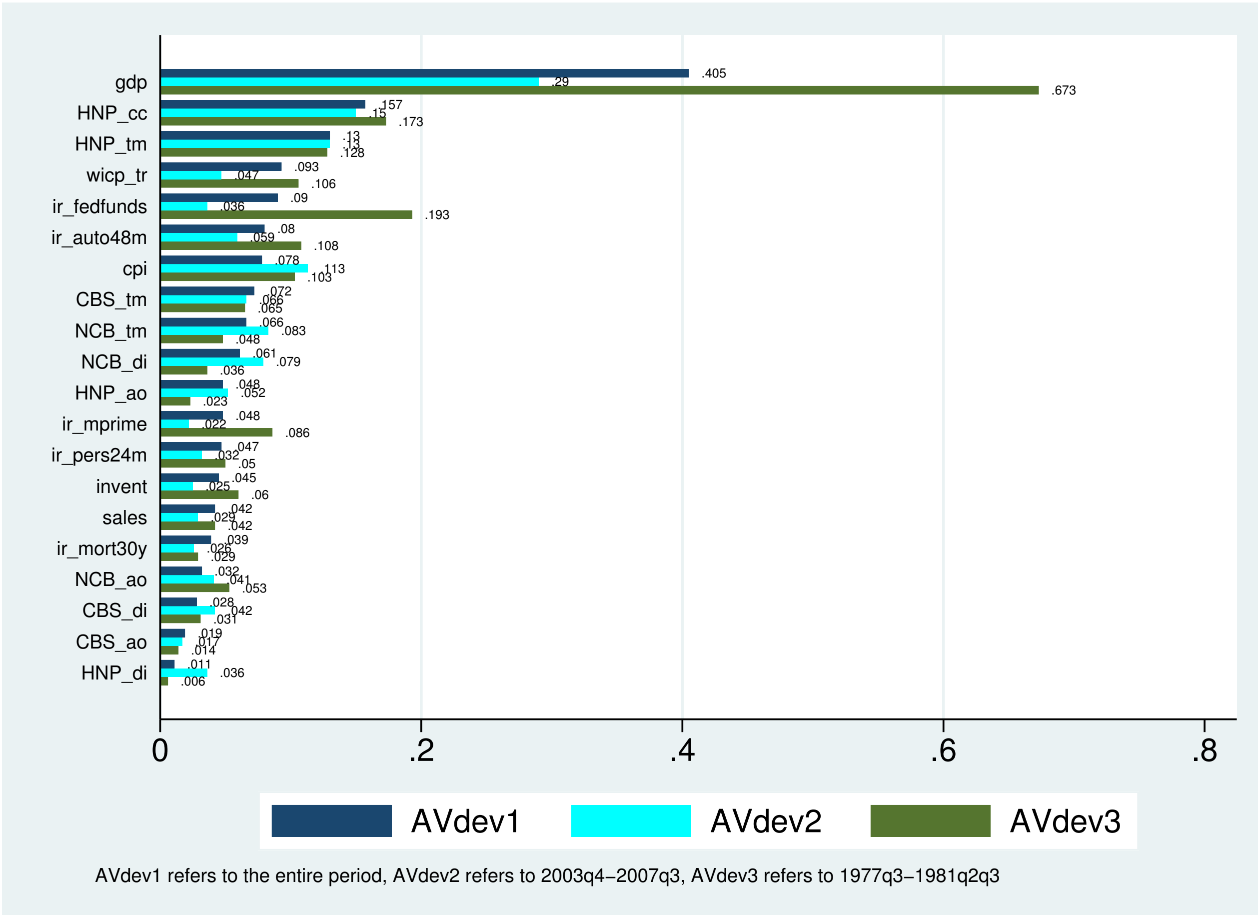
HNP stands for households and non-profit, CB for corporate business, NCB for non-corporate business. DI stands for depository institution loans, for advances and other loans, TM for morgages, CC for consumer credit. Ranked for the values of AVdev1 (from highest to lowest).

Table 6: Counterfactual analysis, study of the deviations: comparison of growth periods

	Panel A				Panel B				Panel C			
	Entire period: 1972q2-2018q4				Growth period 1: 2003q4-2007q3				Growth period 2: 1977q3-1981q2q3			
Rank	Variable	#Q	AVdev	PSdev	Variable	#Q	AVdev	PSdev	Variable	#Q	AVdev	PSdev
1	gdp	187	0.405	47.6%	gdp	16	0.290	31.3%	gdp	16	0.673	37.5%
	*HNP_all	187	0.218	49.2%					*HNP_all	16	0.251	68.8%
2	HNP_cc	187	0.157	47.1%	HNP_cc	16	0.150	25.0%	ir_fedfunds	16	0.193	50.0%
3	HNP_tm	187	0.130	50.3%	HNP_tm	16	0.130	68.8%	HNP_cc	16	0.173	62.5%
					*HNP_all	16	0.114	31.3%				
	*NCB_all	187	0.094	50.3%								
4	wicp	187	0.093	50.8%	cpi	16	0.113	75.0%	HNP_tm	16	0.128	87.5%
					*NCB_all	16	0.089	81.3%				
5	ir_fedfunds	187	0.090	57.8%	NCB_tm	16	0.083	93.8%	ir_auto48m	16	0.108	68.8%
	*CBS_all	187	0.081	50.3%								
6	ir_auto48m	187	0.080	50.8%	NCB_di	16	0.079	43.8%	wicp	16	0.106	68.8%
					*CBS_all	16	0.076	56.3%				
7	cpi	187	0.078	52.4%	CBS_tm	16	0.066	43.8%	cpi	16	0.103	25.0%
8	CBS_tm	187	0.072	49.2%	ir_auto48m	16	0.059	50.0%	ir_mprime	16	0.086	43.8%
									*NCB_all	16	0.072	43.8%
9	NCB_tm	187	0.066	55.6%	HNP_ao	16	0.052	56.3%	CBS_tm	16	0.065	37.5%
									*CBS_all	16	0.063	31.3%
10	NCB_di	187	0.061	49.2%	wicp	16	0.047	62.5%	invent	16	0.060	68.8%
11	HNP_ao	187	0.048	49.7%	CBS_di	16	0.042	56.3%	NCB_ao	16	0.053	18.8%
12	ir_mprime	187	0.048	46.0%	NCB_ao	16	0.041	56.3%	ir_pers24m	16	0.050	75.0%
13	ir_pers24m	187	0.047	52.4%	ir_fedfunds	16	0.036	56.3%	NCB_tm	16	0.048	62.5%
14	invent	187	0.045	56.7%	HNP_di	16	0.036	62.5%	sales	16	0.042	50.0%
15	sales	187	0.042	50.8%	ir_pers24m	16	0.032	31.3%	NCB_di	16	0.036	56.3%
16	ir_mort30y	187	0.039	51.9%	sales	16	0.029	68.8%	CBS_di	16	0.031	43.8%
17	NCB_ao	187	0.032	49.7%	ir_mort30y	16	0.026	37.5%	ir_mort30y	16	0.029	75.0%
18	CBS_di	187	0.028	51.3%	invent	16	0.025	81.3%	HNP_ao	16	0.023	37.5%
19	CBS_ao	187	0.019	50.3%	ir_mprime	16	0.022	43.8%	CBS_ao	16	0.014	37.5%
20	HNP_di	187	0.011	47.1%	CBS_ao	16	0.017	56.3%	HNP_di	16	0.006	43.8%

HNP stands for households and non-profit, CB for corporate business, NCB for non-corporate business. DI stands for depository institution loans, AO for advances and other loans, TM for morgages, CC for consumer credit; ALL sums all the loan categories by group.

Figure 5: AVdev as from Table 6.



HNP stands for households and non-profit, CB for corporate business, NCB for non-corporate business. DI stands for depository institution loans, for advances and other loans, TM for morgages, CC for consumer credit. Ranked for the values of AVdev1 (from highest to lowest).

5 Conclusions

In this research we have investigated how loans to different groups have contributed to economic activity in the US during the period 1971-2018. We have considered also shorter periods along that time span, such as the Global Financial Crisis. Indeed, one of our objectives was to verify the role of the credit crunch in the GDP fall observed during the Great Recession.

The analysis presented in the previous section shows that household loans exert the largest contribution on economic activity, in that group mortgages and consumer credit rank first. During the Global Financial Crisis, the contribution of loans turned decisively negative with mortgages leading the negative effect as the narrative of the events suggests. The specific role of loans during the GFC is even clearer when compared to another severe crisis such as the 2nd oil shock in the eighties. As for that crisis, we confirm that monetary policy seems to worsen the scenario as suggested by Kilian & Lewis (2011).

Loans to small firms have had a contribution on economic activity larger than loans to corporations. This is likely proof of the fact that large corporations in the USA manage to raise funds internally through bonds or equity issuance. Non-bank loans do not emerge as major contributors even if their share over total loans has increased. This does not mean that such other sources of funds are not important for the borrowers, but simply that their impact on aggregate economic activity is low compared to the other variables considered.

In conclusion, results show relevant heterogeneity across the different loan categories, this motivates research that considers not just the aggregates but also the single loan categories as we do in this research work.

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Appendix.

Other Tables and Figures

Table 7: total mortgages: components by borrower

FRB code	component
	Households and nonprofit organizations
FL153165105	Households and nonprofit organizations; home mortgages; liability
FL163165505	Nonprofit 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	Noncorporate farm business; farm mortgages; liability
FL113165003	NF noncorporate business; total mortgages, excluding noncorporate farms; liability

Table 8: depository-institution loans: components by borrower

FRB code	component
	Households and nonprofit organizations
FL763068213	U.S.-chartered DIs; other bank loans to households and nonprofit organizations; asset
FL753068213	Foreign banking offices in the U.S.; other bank loans to households and nonprofit organizations; asset
FL713068303	Monetary authority; DI loans n.e.c. to households (Term Asset-Backed Securities Loan Facility); asset
	Corporate business
FL763068105	U.S.-chartered DIs; DI loans n.e.c. to NF business; asset
FL753068110	Foreign banking offices in the U.S.; commercial and industrial loans and leases to U.S. addressees; asset
FL753069603	Foreign banking offices in the U.S.; bankers' acceptances; asset
FL743068005	Banks in U.S.-affiliated areas; DI loans n.e.c.; asset
FL473068005	Credit unions; DI loans n.e.c.; asset
FL113168005	NF noncorporate business; DI loans n.e.c.; liability
	Non-corporate business
FL233168005	Noncorporate farm business; DI loans n.e.c.; liability
FL113168003	NF noncorporate business; DI loans n.e.c., excluding noncorporate farms; liability

Note: DI stands for depository institution

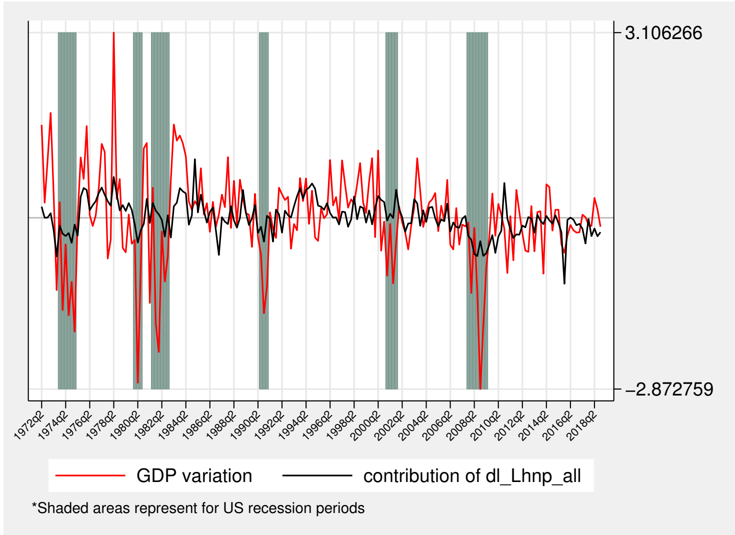
Table 9: advances and other loans: components by borrower

FRB code	component	weight
	Households and nonprofit organization	
FL 15 31692 03	Households and nonprofit organizations; U.S. government loans; liability	11%
FL 15 31694 05	Households and nonprofit organizations; policy loans; liability	47%
FL 15 31693 05	Households and nonprofit organizations; Sallie Mae loans; liability	0%
FL 66 30670 03	Security brokers and dealers; margin accounts at brokers and dealers; asset	42%
	Corporate business	
FL 10 31692 05	corporate business; U.S. government loans, including loans to automakers; liability	4%
FL 10 31695 35	corporate business; finance companies loans; liability	60%
FL 10 31697 05	corp. bus.; customers' liability on acceptances outstanding to commercial banking; liability	8%
FL 26 30695 00	Rest of the world; U.S. NF business loans; asset	17%
FL 10 31698 03	corporate business; syndicated loans; liability	4%
FL 18 31693 05	Corporate farm business; Farm Credit System loans; liability	1%
FL 73 30690 13	Holding companies; other loans and advances due from U.S. addressees; asset	3%
	Non-corporate business	
FL 11 31692 05	noncorporate business; U.S. government loans; liability	46%
FL 11 31695 35	noncorporate business; finance companies loans; liability	23%
FL 11 31693 05	noncorporate business; Farm Credit System loans; liability	31%

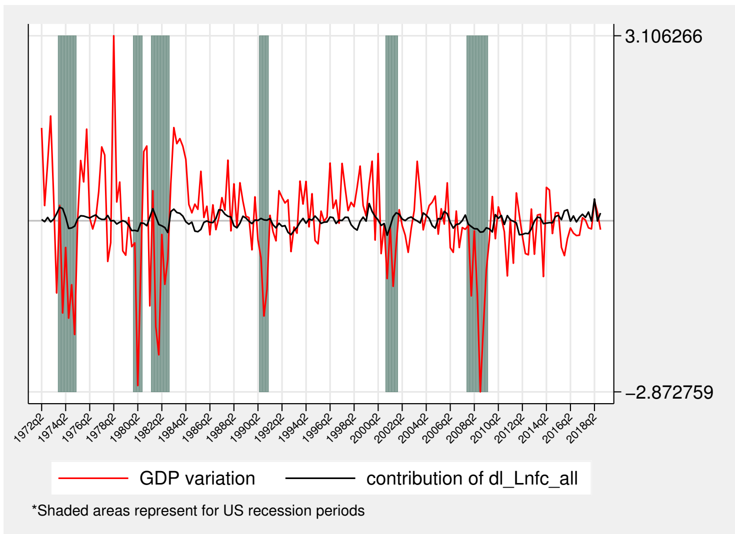
Notes: weights are over the total for the period 1971q1-2007q4.

Figure 6: Contributions against demeaned GDP growth

contribution of HNP loans



contribution of CBS loans



contribution of NCB loans