Credit Supply Decomposition and Real Activity [*]

Maximillian Littlejohn[†]

University of California, Irvine

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Abstract

This paper investigates the implications of sector-specific credit supply shocks on real economic activity in the United States during the past 66 years. These sectors include private households, non-financial corporations, and banks. Within a structural vector autoregression (SVAR) framework, I employ a unique sign-restriction strategy to identify one monetary policy shock, two aggregate macroeconomic shocks, and three credit supply shocks. I find evidence that credit supply shocks not only vary by the sectors in which they arise, but also by their consequences for business cycle dynamics. Credit shocks originating in the banking sector can explain up to 25% of output fluctuations while those arising in the household and corporate sectors can explain up to 15%. In addition, household and bank credit shocks may hold long-run consequences for inflation explaining up to 15% of its fluctuations. Within a historical context, the model identifies several periods where credit supply has been a significant driver of GDP. With respect to the recent financial crisis, the model uncovers a smaller role for credit shocks relative to aggregate supply shocks than is typically found in the literature. This supports recent empirical evidence suggesting that the early stages of the crisis were more reminiscent of an oil price shock recession.

[†]Mailing address: 3208 Social Science Plaza B, Irvine, CA 92697. Email: mlittlej@uci.edu

1 Introduction

In recent years, the importance of credit markets for economic activity and their connection with business cycle dynamics have gained considerable attention. In accordance with key economic indicators such as consumption, investment, and aggregate output, credit markets also experience various disruptions and cyclic fluctuations. Between 1952-2018, the US economy witnessed many episodes of credit supply expansions and contractions within the private sector. While some of these episodes can be linked to common observables such as stock market fluctuations and policy rate changes by the Federal Reserve, others are associated with less obvious exogenous disturbances. These disturbances can take the form of changes in financial regulation, credit risk aversion, bank liquidity funding costs, or new technology and innovation.[1]

Credit supply and bank lending growth are typically regarded as critical drivers for economic activity and development. Unexpected financial market disruptions can interfere with the flow of credit to borrowers and hold significant economic consequences. This was witnessed recently by the 2008 financial crisis with the collapse of the mortgage-backed security market and subsequent, prolonged credit crunch that ensued. Depending on their timing, magnitude, and severity, credit supply fluctuations can interfere with an economy's ability to properly allocate its financial resources directly impacting GDP growth. However, when investigating the relationship between aggregate credit and growth for developed countries, recent studies find nuanced results suggesting the true underlying relationship may be sector-dependent. That is, instead of using broad measures of total credit to the private sector, one may need to study credit cycles at the sector-specific level to determine the credit-growth relationship.

While many credit sectors exist in the US that can be decomposed by geographic region, borrower demographics, or the credit instrument traded, this paper focuses on the following three: households, non-financial corporations, and banks. Considering these sectors each serve a unique economic role, changes to their credit supply would likely hold heteroge-

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[1]According to the October 2019 Senior Loan Officer Opinion Survey, banks cited concerns over borrower repayment ability, a less favorable economic outlook, and a general decrease in risk tolerance as most important for reduced willingness to approve new loans.

neous consequences for real activity. For example, a sudden contraction in credit supply to households may elicit a stronger impact on aggregate consumption than a contraction in corporate credit supply. The converse might be true for an adverse corporate credit shock and investment. In turn, these shocks would likely not hold the same consequences for GDP and should be studied separately.

The primary objective of this paper is twofold: to accurately identify credit supply shocks based upon the sectors in which they arise, and to assess their implications and relative importance for economic activity. Within an SVAR framework, I employ a unique set of sign restrictions to identify an aggregate demand, aggregate supply, monetary policy, and three credit supply shocks: household, corporate, and bank. Household and corporate credit refers to the credit supplied to households and firms from all lenders, while bank credit refers to the credit supplied only by banks to those same borrowers. The purpose of including bank credit is to separate shocks inherent to the lending sector from those inherent to the borrowing sectors. When a credit supply contraction is observed in the data, the underlying shock might be a sudden change in borrower net worth or in bank capital requirements. However, regardless of the source, each shock's impact on credit supply may be indistinguishable in the data while their transmission to GDP can vary. It's not unreasonable to assume a banking sector shock could suggest fundamentally different economic conditions than a household sector shock. Hence, the shock source should be accounted for to properly investigate credit supply disruptions.

A baseline model is estimated initially that includes only the household and corporate credit shocks. This serves as a benchmark to study the economic implications from any type of change in household and corporate credit supply. The model is then extended with bank credit to determine if credit supply's economic impact is contingent on the sector in which the shock originates. The paper makes two key contributions to the literature. The first is from an empirical and methodological standpoint with respect to the strategy employed to identify three credit supply shocks within the same VAR. In the literature, using aggregate measures of private credit to identify a single credit supply shock is common practice. However, if credit cycles can vary by sector, then estimating a model with shocks to aggregate credit supply could provide misleading results and obfuscate the true relationship

between credit and the macroeconomy. To address this, I decompose private credit and study its implications at the sector-specific level. The empirical strategy entails assigning sign restrictions on the impulse responses for a vector of macroeconomic indicators, interest rates, spreads, and credit ratios to identify six mutually exclusive shocks. The ratios, known as "mix" variables, are employed specifically to distinguish the three credit supply shocks.

The paper's second contribution comes from the estimation results and empirical analysis. Throughout the 66-year sample, I find credit supply shocks have not only varied by sector, but also by their consequences for GDP and inflation. The results show how in one sector, an adverse credit supply shock suppressing GDP growth can be accompanied by credit expansions in another promoting growth. The model estimates that bank credit shocks can explain up to 25% of unforecasted GDP fluctuations while household and corporate credit shocks can explain up to 15% on a one-year horizon. In addition, the model suggests household and bank credit shocks may hold long-run consequences for inflation and explain up to 15% of its fluctuations. However, the direction in which inflation responds to credit supply shocks is sector-dependent. While theoretical models often disagree on the inflation response to financial shocks due to opposing demand and supply channel effects, some SVAR studies assign a procyclical inflation response to credit shocks. I take an agnostic stance and leave the inflation response unrestricted.

Further evidence provided by historical decompositions identifies several periods throughout the sample where credit shocks have been significant drivers of GDP fluctuations. These periods include the early 1950s and 60s; the 1973, early 80s and 90s recessions; the 2000s housing bubble; and the last several years. When assessing the model's empirical validity, many credit supply disturbances identified by the SVAR can be matched with well-known credit events documented in the literature. Examples include the Carter Administration's 1980 credit controls and the rapid expansion in mortgage lending during the early 2000s housing bubble. Also, in contrast to recent studies emphasizing the importance of credit markets during the 2008 financial crisis and downturn, the model uncovers only a minor role for credit supply shocks during the onset of the crisis. This suggests the recessionary effects from credit market distress beginning in late 2007 may have been more predictable than previously thought. Instead, adverse supply shocks are most responsible for the large

contractions in GDP during this period supporting evidence in Hamilton (2009) finding the recession to be highly reminiscent of an oil price shock recession. Additionally, historical decomposition analysis for inflation provides evidence on the possible role for credit supply in explaining the "missing disinflation" observed during the crisis.

The paper is organized as follows. Section 2 reviews the related empirical and theoretical literature. Section 3 details the econometric methodology and identification strategy. Section 4 presents results from the model's baseline and extended specifications while section 5 interprets them in a historical context and analysis. Section 6 concludes.

2 Related literature

The ratio of total private sector credit-to-GDP is commonly used to measure a country's level of financial development or depth. King and Levine (1993) is one of the first studies finding the ratio to be a strong predictor for economic growth. Using a variety of econometric techniques, Beck et al. (2000a,b) also identify a positive relationship between financial development and GDP. More recently, SVAR frameworks have gained popularity as a tool to further investigate the credit-growth relationship. One area of the literature applies recursive techniques to identify credit shocks separating the time series into macro and financial blocks. This approach relies on the assumption that macroeconomic disturbances such as aggregate demand and supply shocks impact financial variables contemporaneously while financial shocks impact macro variables with a one-period lag. Following this methodology, Gilchrist and Zakrajšek (2012) isolate the excess bond premium from corporate bond spreads and find that exogenous shocks to the premium can lead to significant contractions in bank lending, equity valuations, and real activity. Using various measures of credit, other papers studying this relationship within recursive SVAR frameworks include Lown and Morgan (2006), Gilchrist and Zakrajšek (2011), Bassett et al. (2014), and Boivin et al. (2018).

When using data at a quarterly frequency, the timing restrictions imposed for recursive identification may not be entirely plausible in all contexts. Alternative identification strategies such as sign restrictions attempt to circumvent this issue by taking a more agnostic approach. This entails assigning restrictions on impulse response functions to uniquely iden-

tify various shocks as in Faust (1998) and Uhlig (2005). Recent studies employing variations of this methodology in constant Bayesian VAR frameworks with credit shocks include Busch et al. (2010), Helbling et al. (2011), Hristov et al. (2012), Meeks (2012), Fornari and Stracca (2013), Eickmeier and Ng (2015), Abbate et al. (2016), Fadejeva et al. (2017), Furlanetto et al. (2017), and Mumtaz et al. (2018). Other related models modify the sign identification strategy by using combinations of sign, timing, and zero restrictions.[2] Despite the variation across identification methods, a procyclic relationship between credit shocks and output growth is consistent across these studies, especially in the short-run. This relation serves as a critical component for justifying within-quarter sign restrictions on measures of real activity.

Considering SVARs require a priori assumptions regarding the behavior of the endogenous variables, their imposed restrictions should be supported both in theory and empirically. In particular, evidence from DSGE models have provided theoretical foundations upon which sign restriction-based approaches to credit shock identification are grounded. Gerali et al. (2010) estimate a DSGE model with financial frictions and identify credit supply shocks with loan-to-value ratios and lending spreads for households and firms. Using Euro Area data, they find credit shocks were most responsible for the 2008 economic downturn and recession. Curdia and Woodford (2010) assess the implications of a modified Taylor Rule that adjusts to fluctuations in credit spreads and aggregate credit volumes for mitigating the contractionary economic effects of credit shocks. Gilchrist and Zakrajšek (2012) perform a similar analysis but with a Taylor Rule incorporating their excess bond premium as a proxy for credit supply conditions. Additional theoretical contributions investigating these relationships include Christensen and Dib (2008), De Graeve (2008), Gertler and Karadi (2011), Carlstrom et al. (2014) and Christiano et al. (2014).

While it's well established throughout the empirical literature that credit growth fosters future economic growth in less developed economies, the same is not necessarily true for advanced economies. Among others, Rioja and Valev (2004) and Arcand et al. (2015) suggest there may exist a financial development threshold at which the credit-growth relationship

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[2]Examples include Bean et al. (2010), Canova and Paustian (2011), Peersman (2011), Houssa et al. (2013), Barnett and Thomas (2014), Moccero et al. (2014), Peersman and Wagner (2014), and Duchi and Elbourne (2016).
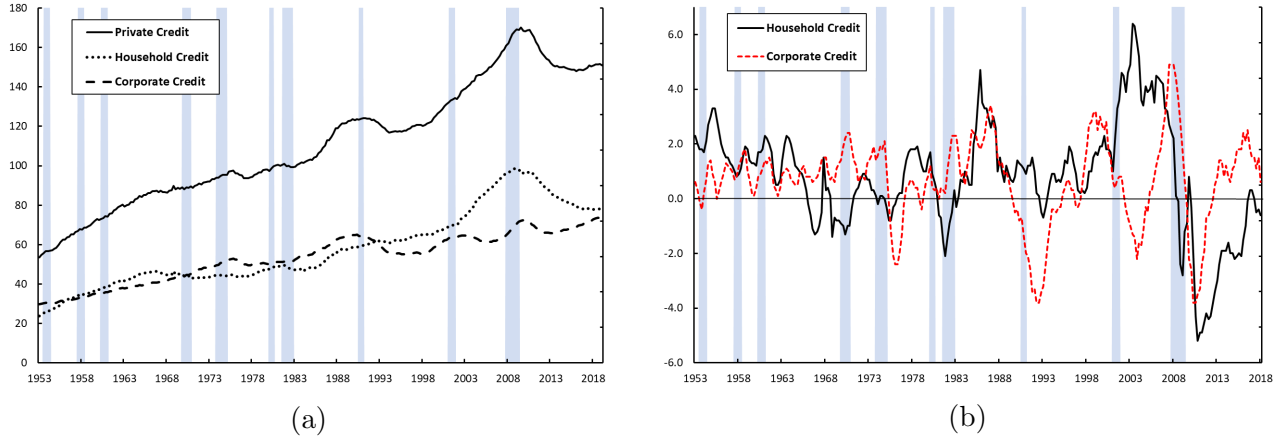
Figure 1: Panel (a) is total private, household, and non-financial corporate credit as shares of GDP. Panel (b) is the year-on-year change. Y-axis units are percentage points.

turns negative. Arcand et al. (2015) find the relationship is positive and statistically significant until private credit-to-GDP reaches 72% before turning negative once exceeding 110%. While a range of explanations for this non-linearity exist, the one of particular interest in this study pertains to borrowing sector composition. Within the context of credit supply shocks, a sudden contraction in private credit may be concentrated among one specific type of borrower or multiple. Therefore, aggregate credit measures may be too broad and should be decomposed by sector to properly explore credit supply's economic consequences. When private credit is split between households and non-financial corporations, empirical studies find nuanced results regarding the credit-growth relationship. According to Sassi and Gasmi (2014), more financially developed countries exhibit higher shares of household credit and the credit-growth relationship depends on borrower composition.

Figure 1a plots the time series for total private credit, household credit, and non-financial corporate credit as shares of GDP. While each series displays an overall upward trend throughout the sample, household and corporate credit growth appear to follow distinct cycles. Corporate credit made up the larger share of GDP during the early 1950s, 70s, and 80s, while the late-50s, 60s, and last 25 years have witnessed a larger share of household credit. A more detailed display of these cycles is provided in Panel b which plots the year-on-year change for the household and corporate credit shares. While the time series vaguely follow similar trends on occasion, they vary substantially throughout the majority of the sample. Looking at the 1990 and 2001 stock market crashes, corporate credit growth

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slows significantly while household credit maintains positive growth. Household credit then experiences a rapid expansion during the early 2000s housing bubble with corporate credit expanding soon after until the recession hits and growth contracts in both sectors.

Within the empirical literature, Mian et al. (2017) find that growth in household and non-financial corporate credit predict a negative credit-to-GDP relationship in the long-run, while household credit is expansionary on shorter horizons. The predictive power of corporate credit for growth is not robust in the long-run. Using data on a panel of 143 countries, Leon (2016) also finds the relationship to be negative. In contrast, Beck et al. (2014) and Sassi and Gasmi (2014) find corporate credit growth to be expansionary with household credit eliciting contractionary or insignificant effects. Attempts to alleviate this ambiguity involve identifying the specific channels through which credit markets impact real activity such as consumption behavior, savings decisions, and human capital investment.[3] However, explaining the channels through which credit shocks may propagate and transmit to real activity is beyond the scope of this paper.

The literature most closely related to this study involves the identification of sector-specific credit shocks within VAR frameworks. Using a recursive SVAR, Walentin (2014) studies the impact of mortgage spread shocks on consumption, residential investment, and output. While he does focus on shocks to the non-corporate private sector, the model does not include measures for credit supply other than rates, spreads, and outstanding mortgage debt. Brunnermeier et al. (2018) include measures of business, real estate, and consumer loans along with various credit spreads and time-variation across shock volatilities. They identify ten independent shocks of which several closely resemble shocks to household credit, corporate credit, inter-bank stress, and monetary policy. Another study decomposing credit supply by sector but applied to the Dutch economy is Duchi and Elbourne (2016). Using sign and zero restrictions, they use total private lending with corporate bond spreads before estimating two separate VARs to analyze the impact of credit supply shocks on consumption, investment, and inflation. Following a credit shock, they find investment responds and recovers quickest while household lending and consumption respond less but with greater

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[3]Several studies include Galor and Zeira (1993), Jappelli and Pagano (1994), De Gregorio (1996), Levine (1997), Borio et al. (2015), Gopinath et al. (2017), and Charles et al. (2018).

persistence. The key distinction between their approach and mine is that I identify multiple credit shocks within one VAR without imposing zero restrictions or isolating the components of GDP.

3   Empirical methodology

3.1   The model

The econometric analysis begins with estimating the reduced-form of the VAR model. This involves regressing each dependent variable at time t on its own lags and lags of the remaining dependent variables. Consider the model's reduced-form in vector notation:

$$y_t = c_a + \sum_{i=1}^{p} A_i y_{t-i} + u_t, \tag{1}$$

where y_t is an $(n$ x $1)$ vector containing n endogenous variables, c_a is an $(n$ x $1)$ vector of constants, A_i with $i = 1, ..., p$ represents the $(n$ x $n)$ coefficient matrices, and u_t is the $(n$ x $1)$ reduced-form vector of residuals with $u_t \sim N(0, \Sigma)$ and Σ denoting the $(n$ x $n)$ residual variance-covariance matrix. The number of lags is denoted by p. The reduced-form of the model is sufficient for performing forecast analysis, but due to correlation across the error terms in u_t, structural identification is required to isolate the exogenous structural innovations, ϵ_t. The vector of residuals can then be expressed as a linear combination of the structural innovations, $u_t = B_0^{-1} \epsilon_t$, where B_0 is a non-singular parameter matrix and $\epsilon_t \sim N(0, I_n)$ where I_n is an $(n$ x $n)$ identity matrix. The structure of the variance-covariance matrix is $B_0^{-1} B_0^{-1'} = \Sigma$ which implies symmetry. The structural form can now be written as

$$B_0 y_t = c_b + \sum_{i=1}^{p} B_i y_{t-i} + \epsilon_t.$$

Given the symmetry of the variance-covariance matrix, $n(n-1)/2$ restrictions are required to derive B_0 and identify the SVAR. One of the most common ways for imposing the necessary restrictions to identify B_0 is the Cholesky decomposition which leaves the parameter matrix with a lower triangular structure. This implies a recursive ordering of the variables with

zero restrictions to separate the fast and slow-moving variables. However, theory typically provides a stronger consensus on the directions and comovement between variables than the amount of time it takes for one variable to respond to others, especially for macrofinance SVARs. Following Uhlig (2005), I take a more theoretically consistent approach to identification by imposing sign restrictions on the impulse responses. While the sign restriction approach will not identify B_0 exactly, it will restrict B_0 to a credible range from which informative estimates can be derived from. Further details and support regarding the choice of sign over zero restrictions are provided in section 3.3.

To impose the sign restrictions, I employ the methodology developed in Arias et al. (2018) which allows for combinations of sign, zero, and magnitude restrictions to be assigned on impulse responses in any given period. Remaining consistent with the recommendation outlined in Canova and Paustian (2011), all restrictions are imposed only on impact. The algorithm works as follows. The first step is to draw a vector β of reduced-form coefficients for $A_1, A_2, ..., A_p$ and a residual variance-covariance matrix Σ from their posterior distributions. From this, the reduced-form of the model in (1) can be recovered. The next step is to form combinations of the structural innovations derived from the recursively identified model. This is achieved by drawing a random orthogonal matrix Q from a uniform distribution such that $B_0^{-1}QQ'B_0^{-1'} = \Sigma$ holds. To successfully obtain matrix Q, an (n x n) random matrix X is drawn containing entries drawn from an independent standard normal distribution. A QR decomposition of X is then performed so that $Q = XR$ where R is an upper triangular matrix. Now, candidate impulse response functions are generated from BQ and A_i for $i = 1, 2, ..., p$ and checked to determine if they satisfy the restrictions. If they are satisfied, the proposed matrix Q is kept. If not, Q is discarded, a new matrix X is drawn, and the procedure is iterated over until a valid matrix Q is obtained.[4]

3.2   Data and estimation

The model's baseline specification includes the demand, supply, monetary, household, and corporate credit shocks to establish a benchmark before introducing bank credit. A

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[4]Additional details regarding the estimation procedure and strategy using sign restrictions can be found in Arias et al. (2018) and Dieppe et al. (2016).

sample of quarterly US data beginning in 1952 Q1 and ending in 2018 Q1 is used. The sample begins in 1952 due to the availability of private sector credit data. The vector of endogenous variables include real GDP, the GDP price deflator, the Federal Funds rate, the spread between the bank prime lending rate and 3-month Treasury bill rate, the non-financial private credit mix, and the household credit mix.

The private credit mix is the ratio between total credit to the non-financial private sector and GDP.[5] Private credit includes credit to households, non-profit institutions serving households, and all non-financial corporations public and privately owned. It's measured as the sum of all non-government loans and debt securities outstanding, which includes the market value of bonds and short-term commercial paper. Trade credit is excluded from the corporate credit measure due to globally poor underlying data. The lenders include domestic and foreign banks, residents, governments, and all other credit-providing sectors such as credit unions, pension funds, and various financial institutions. The household credit mix is the ratio between total household credit and non-financial private credit. It follows that the sum of household and non-financial corporate credit comprises total private credit. Section 3.3 provides a detailed discussion on the implementation and significance of mix variables for shock identification.

As for the policy rate, since the zero lower bound (ZLB) period is included in the sample, data for the shadow federal funds rate from Wu and Xia (2016) is used from 2009 Q1 through 2015 Q4. Since the shadow funds rate retains a similar relationship with macro variables as the federal funds rate does historically, it provides a more accurate measure for the monetary policy stance during the ZLB period. The shadow rate is also appealing with respect to its low volatility and absence of sharp drops in accordance with the Federal Reserve's gradualist approach to monetary policy adjustments.[6] A list of the data series used in all estimation exercises along with their sources can be found in Table 4 of Appendix A.

The endogenous variables enter the VAR in terms of their natural logarithm except for

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[5]According to Mian et al. (2017), when measuring private debt fluctuations, it's important to normalize debt by GDP, because it's the growth in debt relative to the size of the economy that matters. Without normalizing, periods of real debt growth may appear large from a small base without being economically significant.

[6]During a 2004 speech at an economics luncheon in Seattle, Ben Bernanke detailed the Federal Reserve's gradualist approach to policy rate adjustments and its benefits for financial stability.

the interest rates and spreads which enter in levels. Each equation of the model includes two lags and a constant term.[7] The reduced-form is estimated using Bayesian methods which requires specifying a prior distribution. Following the methodology introduced by Banbura et al. (2010), the dummy observation prior is used which performs particularly well when dealing with large VARs and many identified shocks. While matching the moments of the Minnesota prior via pseudo observations instead of placing direct restrictions on Σ, the prior allows covariance between the VAR coefficients and makes for a more tractable computation procedure. As is common throughout the literature, hyperparameter values are chosen such that the prior distribution is sufficiently informative. Robustness to prior specification is assessed in Appendix B.[8] All estimations are conducted using the European Central Bank's Bayesian Estimation, Analysis, and Regression (BEAR) toolbox in MATLAB developed by Dieppe et al. (2016).

3.3   Identification

There exists a strong consensus within the theoretical and empirical literature regarding the response of output, inflation, and the short-term interest rate to aggregate demand, supply, and monetary policy shocks. For demand shocks, output, prices, and the policy rate should move in the same direction, while for monetary policy shocks, output and prices move in the opposite direction as the policy rate. Supply shocks are identified with output and prices moving in opposite directions. The policy rate's response is less clear as it depends on whether monetary policy reacts stronger to output or inflation fluctuations. This ambiguity arises from DSGE theory and Taylor rules that assign a negative interest rate response to rises in inflation and the output gap. Due to this uncertainty, I remain agnostic and leave the federal funds rate unrestricted for supply shocks.

Assigning credible restrictions to identify credit supply shocks is less straightforward. While choices for credit market indicators vary in the literature, there is consensus on the response of credit volume and price. Within the context of credit supply shocks, credit price,

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[7]For comparability I present the results for both models with two lags, however, the paper's key results are robust to the choice of lag length. All robustness exercises can be found in Appendix B.

[8]See Banbura et al. (2010), Dieppe et al. (2016), Miranda-Agrippino and Ricco (2018), and Appendix B for more detailed discussions on the dummy observation prior.

typically measured with lending rates or spreads relative to risk-free government rates, is assumed to move in the opposite direction as volume. While for credit demand, price and volume are expected to move in identical directions. However, the significance and frequency of credit demand shocks in the data are more difficult to justify than credit supply and are therefore not included in the VAR.[9]

One attractive feature of credit spreads is that they do not rule out periods of non-price credit rationing. Since credit spreads may increase with a rise in the lending rate or decline in the risk-free rate, credit supply shocks can be identified absent any changes to lending rates. Instead, higher spreads may result from looser monetary policy in response to depressed GDP following a credit contraction. They may also result from a flight-to-quality as banks shift their portfolios toward more government debt during periods of increased uncertainty, tight money, or liquidity shortages as discussed in Bernanke and Blinder (1988).[10] When using lending rates alone, they are restricted to rise with adverse supply shocks, making it difficult to identify periods of non-price rationing. I use the spread between the prime lending rate and 3-month Treasury yield as a proxy for credit price and the general willingness to bear private sector risk. The credit mix is used to measure credit volume. While corporate bond spreads such as the BAA-10 year Treasury are often used, I argue in favor of using the prime rate for studying household and corporate credit, considering banks often use it as a benchmark for charging both their household and corporate customers.

The unique identification of sector-specific credit supply shocks is a leading contribution of this paper. Mix variables were introduced in Kashyap et al. (1993) to identify a bank lending channel for the transmission of monetary policy, and have been employed in other credit VAR frameworks by Ludvigson (1998), Iacoviello and Minetti (2008), Milcheva (2013), and Halvorsen and Jacobsen (2014). In a monetary policy context, a drop in the ratio of bank lending-to-total lending following a monetary contraction would indicate a reduction in credit supply through a bank lending channel. In contrast, a decrease in overall credit

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[9]According to Bernanke and Blinder (1988), "we find it difficult to think of or identify major shocks to credit demand, that is, sharp increases or decreases in the demand for loans at given interest rates and GNP. But shocks to credit supply are easy to conceptualize and find in actual history." Wojnilower (1980) finds credit demand to be inelastic with respect to the general level of interest rates and credit growth to be supply-determined.

[10]Andolfatto and Spewak (2018) find Treasury debt holdings increase in response to recent regulatory changes with respect to the shadow banking sector.

supply not exclusive to banks, should have a larger impact on the ratio's denominator and either increase the mix or leave it unaltered. Following this intuition, the household mix is used to disentangle household and corporate credit supply shocks. The mix is restricted to respond negatively to adverse household shocks and positively to adverse corporate shocks.

A common approach taken to disentangle credit supply from macro and monetary shocks is through recursive identification and the Cholesky decomposition. This requires the block of credit or financial variables to be labeled as fast-moving and is placed second after the macro-variable block. The ordering restricts shocks originating in financial markets from impacting the macro variables contemporaneously, while macro shocks impact all variables within the period. This assumption may be plausible when using monthly or weekly data, but becomes significantly more difficult to justify using quarterly data. Additionally, the specific variable orderings within each block matters for contemporaneous relations, and therefore identification becomes ambiguous when using multiple fast-moving financial variables. In this study, it would be a stretch to assume that household consumption habits remain unchanged following household credit shocks for an entire quarter.

Within the sign-restriction literature, many models use a combination of sign and zero restrictions while others have imposed magnitude restrictions to separate macro and financial shocks. Consider the task of separating an adverse aggregate demand and credit supply shock. Both shocks would likely decrease GDP and credit growth within the quarter. However, the demand shock should have a stronger impact on GDP, while the credit shock should have a stronger impact on credit. Therefore, restrictions can be placed such that the initial response of one variable must be smaller in magnitude than the other. Furlanetto et al. (2017) use the ratio of private sector credit to real estate value for separating credit and housing sector shocks. In line with this intuition, I use the credit mix to separate the macro and credit shocks as in Eickmeier and Ng (2015). Following an adverse demand or supply shock, the mix is restricted to increase on impact with the opposite response imposed for credit shocks. This assumption can be supported by the time series in Figure 1b. During many of the recessions, household and corporate credit as shares of GDP rise before dropping. This suggests a stronger reduction in GDP initially following the aggregate-level disturbances associated with demand and supply shocks during recessions, before credit markets begin to

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Table 1

Sign Restrictions for the Baseline Model

	Demand	Supply	Monetary	Household	Corporate
GDP	−	−	−	−	−
Prices	−	+	−		
Policy Rate	−		+		
Prime Spread			−	+	+
Credit Mix	+	+		−	−
Household Mix				−	+

contract.

The final restriction separates the monetary policy and credit shocks. Identifying these to be mutually exclusive and justifiable is not trivial considering exogenous changes in the federal funds rate may have an immediate impact on credit markets. I exploit the direction in which the prime spread initially responds to uniquely identify these shocks. The spread is restricted to decrease for contractionary monetary shocks and increase for contractionary credit shocks. Considering the prime and federal funds rates are highly correlated, these restrictions assume the prime rate reacts quicker and stronger to credit market disruptions than it would to policy rate shocks. Theoretical and empirical studies find imperfect pass through from policy rates to lending rates.[11] Other studies explicitly applying this assumption to identify credit shocks with spreads and sign restrictions include Helbling et al. (2011), Eickmeier and Ng (2015), Fadejeva et al. (2017), and Baurle and Scheufele (2018).

Restrictions for the five shocks in the baseline model are summarized in Table 1.[12] All restrictions are imposed on impact and last one quarter. Each shock is specified as contractionary with a negative sign placed on GDP. However, the VAR estimation identifies both the contractionary and expansionary form of each shock.

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[11]Using the financial accelerator model developed by Christiano et al. (2014), Cesa-Bianchi and Sokol (2017) show how the spread between loan and policy rates responds stronger than the policy rate to financial shocks. The opposite holds for aggregate demand shocks. Leaving the response of credit spreads unrestricted, Furlanetto et al. (2017) find that financial shocks generate countercyclical movements in credit spreads.

[12]While identifying a total of n shocks for an n-variable SVAR is common practice, the sixth shock is left unidentified. This serves as a residual shock and picks up any remaining disturbances unaccounted for. The residual shock is not included in Table 1.
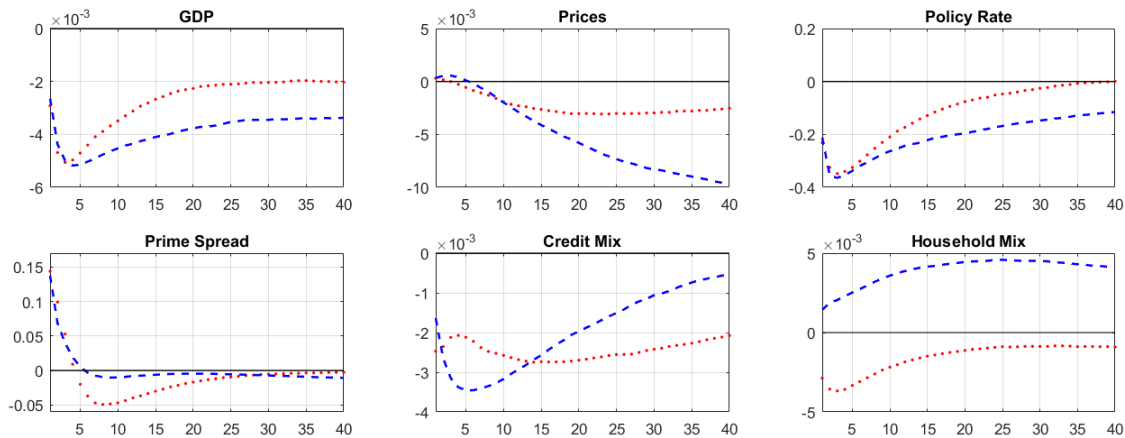
Figure 2: Impulse responses to a one standard deviation adverse household (dotted red) and corporate credit supply shock (dashed blue) for the baseline model. Estimates based on median response.

4   Results

4.1   Baseline model

Results for the baseline estimation are presented first to study the implications of household and corporate credit supply for real activity. While the paper's focus pertains to credit supply, results for the demand, supply, and monetary policy shocks are referenced for comparison and evaluation of the model's performance. Figure 2 displays the median impulse responses for the six endogenous variables to a one standard deviation adverse household and corporate credit shock.[13] For both shocks, GDP declines to about -0.5% before beginning its recovery after three quarters. The drop is more persistent following the corporate shock with GDP at -0.2% and -0.35% after ten years for the household and corporate shocks, respectively. Impulse responses are similar yet negligible for inflation within the first two years before prices drop and level out for household credit, but decline further to -1% for corporate credit. While this suggests credit shocks may matter more for long-run price levels, some studies find procyclical responses on shortened horizons.[14] The policy rate declines by about 35 basis points following both shocks in accordance with the drops in output and inflation, but is more persistent for corporate credit. This complies with Taylor rules and the interest

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[13]See Appendix A for median impulse responses and corresponding credible intervals.

[14]Bean et al. (2010), Busch et al. (2010), Ciccarelli et al. (2010), and Gambetti and Musso (2017) document procyclical inflation responses to loan supply shocks within the first two years. Analyzing loan supply shocks for the Netherlands, Duchi and Elbourne (2016) document a near-zero inflationary response.

rate reaction to inflation and output gap fluctuations. The stronger responses by output and inflation following the corporate shock likely account for the policy rate's slower recovery.

Moving to the financial block, the prime spread rises nearly 15 basis points and returns to steady state within five quarters for both shocks. However, it levels out slightly below steady state for corporate credit yet continues to decline another year for household credit. Around the same horizon, a divergence develops with the response of the credit mix. Corporate credit induces the larger decline with the mix reaching -0.35% after five quarters. However, the drop in the mix following the household shock is much more persistent and rests around -0.2% after ten years. The quick recovery following corporate shocks supports evidence regarding the alternative sources of corporate financing options not available to households during economic downturns.[15]

Comparing with the IRFs for the macro and monetary shocks in Figure 6 of Appendix A, credit shocks produce the largest contractions in GDP. Demand shocks elicit the weakest impact at -0.25% that fully recovers after three years. The supply and monetary shocks are stronger and more persistent with GDP dropping to -0.3% after two years and remaining depressed for the following eight. The inflation response to supply and monetary shocks is minimal while for demand it resembles the corporate shock with prices gradually decreasing to almost -0.9%. The policy rate is also more responsive to demand shocks while remaining near its steady-state level for supply. This complies with the literature's uncertainty regarding the policy rate reaction to supply shocks and gives credence to leaving it unrestricted.

Table 2 reports the forecast error variance decomposition (FEVD) for each endogenous variable. The FEVD provides the share of forecast error variation explained by a given shock. Estimates are based on the median draw satisfying the sign restrictions at the 1, 4, 16, and 32-quarter horizons. For comparability, the decompositions are rescaled so they sum to one at each horizon.[16] Supply and credit shocks serve as the leading drivers of output fluctuations within the first quarter, while credit shocks dominate at all horizons

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[15]Giesecke et al. (2014) find banks increase their lending to firms shortly after bond default crises. With respect to the 2008 Lehman Brothers collapse, Ivashina and Scharfstein (2010) discuss how corporations increased borrowing by drawing on unused bank credit lines.

[16]According to Fry and Pagan (2011), using the median values from impulse responses to compute the FEVD combines information across different models allowing the decompositions to not necessarily sum to one. For clearer interpretation, the values can be rescaled so the variance is exhaustively accounted for without sacrificing quantitative significance.

Table 2
Median Forecast Error Variance Decomposition for the Baseline Model

	Horizon	Demand	Supply	Monetary	Household	Corporate	Residual
GDP	1	0.15	0.21	0.14	0.21	0.18	0.12
	4	0.09	0.13	0.11	0.28	0.28	0.11
	16	0.07	0.14	0.14	0.22	0.31	0.11
	32	0.09	0.15	0.16	0.19	0.30	0.11
Prices	1	0.17	0.23	0.14	0.13	0.16	0.17
	4	0.23	0.24	0.10	0.13	0.15	0.16
	16	0.40	0.12	0.07	0.12	0.18	0.12
	32	0.38	0.09	0.06	0.10	0.26	0.10
Policy Rate	1	0.21	0.11	0.18	0.17	0.17	0.16
	4	0.30	0.08	0.09	0.19	0.22	0.12
	16	0.34	0.09	0.07	0.18	0.22	0.11
	32	0.31	0.10	0.08	0.16	0.24	0.11
Prime Spread	1	0.16	0.11	0.22	0.19	0.17	0.16
	4	0.16	0.14	0.16	0.20	0.16	0.17
	16	0.24	0.14	0.11	0.20	0.15	0.16
	32	0.26	0.13	0.11	0.19	0.15	0.16
Credit Mix	1	0.22	0.22	0.12	0.19	0.08	0.17
	4	0.24	0.16	0.12	0.13	0.20	0.15
	16	0.18	0.11	0.13	0.17	0.26	0.15
	32	0.16	0.12	0.13	0.22	0.21	0.15
Household Mix	1	0.12	0.12	0.13	0.40	0.10	0.14
	4	0.12	0.11	0.14	0.37	0.12	0.13
	16	0.17	0.11	0.14	0.18	0.27	0.13
	32	0.16	0.13	0.12	0.12	0.34	0.12

beyond the first year. After one year, both credit shocks explain 28% of GDP fluctuations with corporate credit as the leading long-run driver explaining 30-31% after the fourth. Demand shocks make significant contributions to output on impact, but explain very little variation beyond one quarter. The short-lived decline in output following demand shocks reinforces this result. As for prices, demand shocks make modest contributions in the short-run but become increasingly more important explaining up to 40% of their fluctuations after four years. Supply shocks make similar contributions for prices as they do for output, but household and corporate shocks contribute less.

The FEVD for credit shocks are broadly in line with those found for various financial sector shocks, but contribute more than what is typically found for credit supply shocks. The literature typically assigns around 20-40% of GDP variation to financial shocks and 10-20% to credit supply shocks. As for inflation, studies assign an even wider range between 10-40% to credit shocks at various horizons. The FEVD for prices and the macro shocks in this study also broadly agree with the literature finding supply shocks to matter most for short-run fluctuations while demand shocks dominate for the long-run. However, I refrain from closely comparing my estimates to this literature as it varies widely with respect to variable

choice, identification methods, and datasets. Also, many models identify financial shocks as disturbances exclusive to the financial or banking sectors. Considering this, the household and corporate credit shocks here would not necessarily be considered financial shocks since they may be responding to financial or non-financial conditions. To further address this issue, I now extend the model with bank credit to determine whether the impact from banking sector shocks differ from the household and non-financial corporate sectors.

4.2   Extended model

In the baseline specification, household and corporate credit shocks may arise in response to credit conditions among borrowers or lenders. If perceived credit risk associated with a specific group of borrowers rises, lenders would likely respond by restricting credit to that group regardless of lender type. Alternatively, if the shock is concentrated among a specific lending sector such as a bank balance sheet disturbance, then bank lenders would be most likely to respond with tighter credit initially. To circumvent this potential ambiguity, I disentangle credit shocks propagating in response to borrowers and banks. The key assumption is that borrowing sector shocks reflect credit supply contractions from all lenders (bank and non-bank) due to borrower-specific reasons.

Banking sector shocks may arise as exogenous changes in risk preference, regulation, liquidity funding costs, or new financial technology and innovation. Consider a regulatory change that raises capital requirements forcing banks to increase their liquid assets. Depending on the costs and availability of short-term liquidity, their lending behavior may be adversely affected. Since banks possess superior knowledge, skills, and technology for assessing borrower risk, changes in their willingness to extend credit may suggest more severe issues underlying the economy. Hence, bank and non-bank credit shocks displaying similar effects on aggregate credit in the data don't necessarily imply similar levels of health and risk in the economy. For these reasons, bank credit shocks may elicit a GDP response heterogeneous to those found in the baseline estimation.

Bank credit is measured as the sum of all domestic bank claims on the private non-financial sector. This consists of all outstanding loans and debt securities provided by the
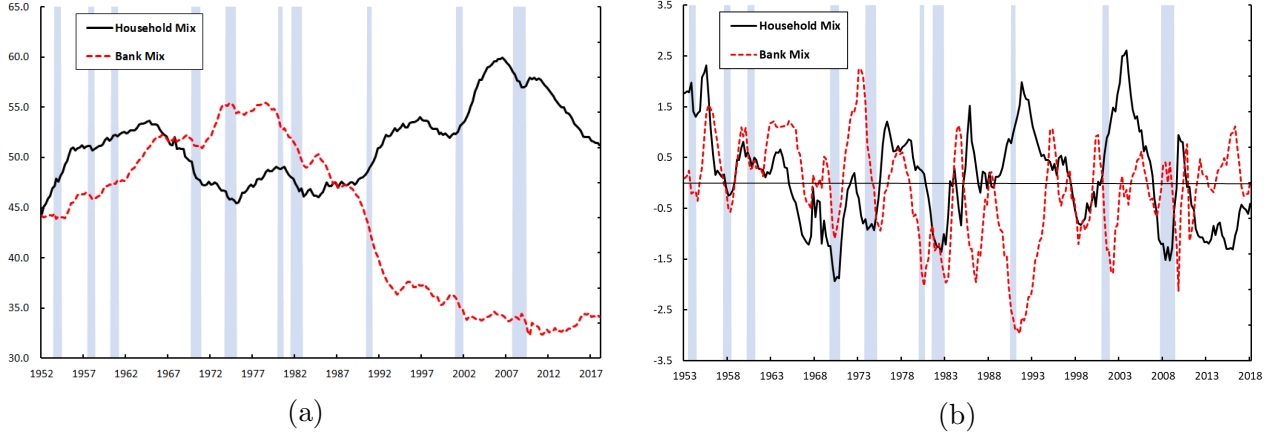
Figure 3: Panel (a) is total credit to households and credit supplied by banks as shares of total credit to the non-financial private sector. Panel (b) is the year-on-year change. Y-axis units are percentage points.

sectoral balance sheets of US depository institutions, excluding the Federal Reserve.[17] Following the same approach for household and corporate credit, I use a bank credit mix variable to separate bank and non-bank sector shocks. The bank mix is the ratio of total bank-issued credit to total private credit. Using this mix, Halvorsen and Jacobsen (2014) identify a VAR with sign restrictions to compare the effects between bank credit supply and monetary policy shocks on real activity in the UK and Norway. Iacoviello and Minetti (2008) isolate bank credit shocks within a recursive VAR to study their impact on GDP and prices, but within the context of mortgage lending and the housing market. Adverse credit shocks exclusive to banks should lower the bank mix while adverse household or corporate shocks should raise it.

The bank mix is plotted alongside the household mix in panel a of Figure 3, with its year-on-year change in panel b. Early in the sample, both mixes follow upward trends until the mid-1960s when corporate credit begins to dominate the household mix while bank credit continues expanding relative to non-bank lenders. This pattern begins to change around the mid-1970s and completely reverses by 1990. On further inspection, Figure 3b reveals specific episodes such as the late-70s expansion and early 2000s housing bubble in which positive

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[17]One issue for bank credit data is securitization. Derecognized securitized loans are not reported on banks' balance sheets under traditional accounting rules and should not be included in the measure even though banks often support their loan portfolios with off-balance sheet claims as demonstrated by the recent financial crisis. However, total private credit is unaffected by this issue since it covers credit from all sectors including special purpose vehicles to which banks sell their loan portfolios. Additional details are provided in Dembiermont el al. (2013).

Table 3

Sign Restrictions for the Extended Model

	Demand	Supply	Monetary	Household	Corporate	Bank
GDP	−	−	−	−	−	−
Prices	−	+	−			
Policy Rate	−		+			
Prime Spread			−	+	+	+
Credit Mix	+	+		−	−	−
Household Mix				−	+	
Bank Mix				+	+	−

growth in one may not be accompanied by positive growth in the other. This suggests a nonlinearity as to whether the sources for household and corporate credit fluctuations are driven by factors akin to the banking or borrowing sectors.

The full set of sign restrictions for the extended model are presented in Table 3 and the impulse responses for credit shocks are displayed by Figure 4. The extended model's FEVD and non-credit impulse responses can be found in Appendix A. The IRFs for demand and supply shocks follow similar patterns as in the baseline, except now GDP recovers quicker and prices respond less for demand. Monetary policy shocks elicit larger drops in inflation and now account for 24% of long-run GDP fluctuations, making it the largest non-credit shock contributer. Bank credit shocks cause the largest GDP contraction at -0.43% while the impact from household and corporate shocks are around -0.32%. In response to depressed output, the policy rate displays the largest and most persistent decline following the bank shock at -35 basis points after three quarters. Unlike the baseline, the policy rate now only drops by 18 basis points before turning positive after three years following the household and corporate shocks.

The inflation response is negligible initially, but household and bank shocks appear to matter for the long-run, while corporate shocks leave prices almost unchanged in line with Christiano et al. (2010) regarding the low levels of inflation observed during US stock market booms.[18] These results depart from the baseline which predicted a .25% and 1% long-run price decline following household and corporate shocks, respectively. Also, household

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[18]Christiano et al. (2010) discuss how inflation was relatively low during all 18 of the stock market booms that occurred in the US throughout the last two centuries. This was also observed for Japan during their 1980s stock market boom.
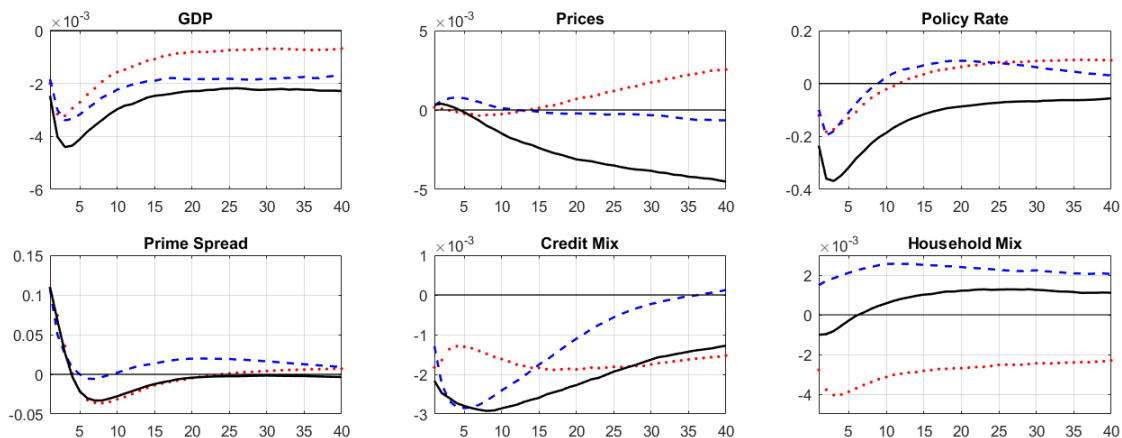
Figure 4: Impulse responses to a one standard deviation adverse household (dotted red), corporate (dashed blue), and bank credit supply shock (solid black) for the extended model. Estimates based on median response.

credit shocks now lead to a persistent price increase instead of decrease. This result is not likely due to the loose monetary response, as the policy rate's path shows little variation following the household and corporate shocks. Mian et al. (2017) find significant evidence of boom-bust cycles for real estate prices following household credit expansions. Although household shocks appear to be non-inflationary in the short-run, this evidence would agree with the price level's long-run response. In addressing the literature's ambiguity regarding credit supply shocks and prices, these results suggest their inflationary effects may be sector-dependent and emphasize the potential limitations of using aggregate credit supply measures.

Transitioning to the financial block, the prime spread rises by about ten basis points for all three shocks, but appears to be least sensitive to corporate credit. This is shown by the spread hovering around steady-state after the first year for the corporate shock while dipping below steady-state for the others. Corporate and bank shocks produce the largest drop in the credit mix reaching -0.28% after six quarters with only -0.15% for household shocks. Consistent with the baseline, the credit mix recovers quickest following corporate shocks and remains around -0.15% after ten years for household and bank credit. The larger declines in GDP and credit growth following bank shocks provide evidence that the shock's source may be critical for identifying the real effects from credit supply disruptions. During the 2008 crisis, financial contagion became an important channel for the recession's size and transmission onto a global scale. While an exogenous disturbance in the banking sector would initially hit bank balances sheets hardest, it would likely spread to other non-bank
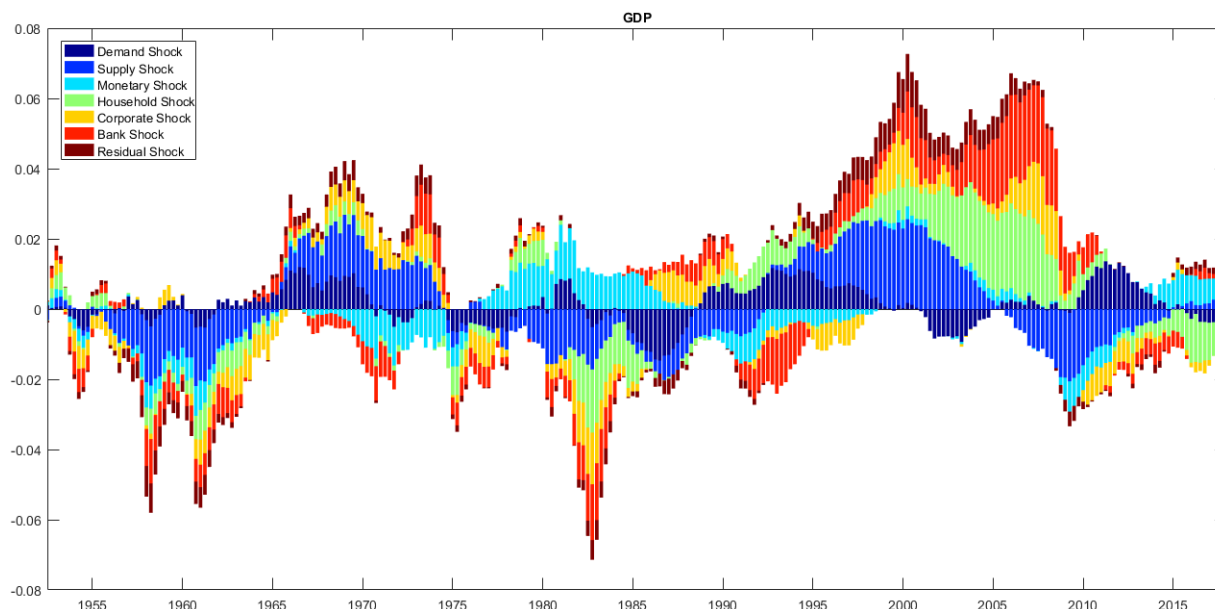
Figure 5: Historical decomposition of GDP forecast errors for the extended model.

lending institutions further suppressing credit and output.

Table 5 in Appendix A displays the extended model's FEVD. Bank shocks are the largest contributer for GDP while household and corporate shocks are significantly less important when compared with the baseline. From explaining close to 30% of GDP errors, they now explain up to 15% along with demand shocks within the first year. At the one-year horizon, bank shocks explain 25% of the error variance while monetary shocks now explain 24% instead of 16% after eight years. For inflation, credit shocks are nearly equivalent contributing to almost 15% of its short-run variation. However, bank shocks matter more for long-run price fluctuations as do the demand and monetary shocks. The policy rate now appears to be most sensitive to demand and bank shocks instead of demand and corporate shocks. This corroborates the corporate shock's limited impact and role for price fluctuations in Figure 4.

5 Historical analysis

This section places the model's results in a historical context to assess their empirical validity and relevance. I draw upon evidence presented by the historical decomposition (HD) for GDP displayed by Figure 5 and the credit shock volatilities in Figure 12 of Appendix A. The HD summarizes the individual contributions for each structural innovation to the total

forecast error of a variable at each point in time. It's computed by transforming the reduced-form residuals into a set of structural innovations and calculating the cumulative impact each innovation makes on that period's forecast error since the beginning of the sample. This allows me to answer questions such as, what share of GDP's forecast errors in 2007 Q4 can be attributed to all current and past household credit supply shocks? As for Figure 12, the volatility for each credit innovation is represented by its quarterly standard deviation from steady-state. Since all restrictions are imposed to identify shocks as contractionary, positive values correspond to negative GDP growth. While the dataset spans 66 years, I focus on periods in which credit shocks make significant contributions to output relative to the non-credit shocks. These periods cover the early 1950s and 1970s; the early 80s and 90s recessions; and the pre-2008 financial crisis years.

5.1   Early 1950s

Beginning with the early 1950s, all three credit shocks contribute to positive GDP growth. This coincides with the introduction of the Diners Club Card that is often regarded as the first modern day credit card. Surrounding the 1953 recession, adverse corporate and bank credit shocks play the largest roles in driving down GDP. During this period, short-term Treasury rates rose while the rates banks could offer on savings and time deposits were bound by Regulation Q. Without the ability to attract customers and funds by raising deposit rates, disintermediation ensued, banks became liquidity constrained, and credit contracted. In addition, new 30-year Treasury bonds were issued offering high coupon rates contributing to a corporate debt sell-off and the adverse corporate credit shocks. Household credit plays a negligible role for this period, however, Figure 12 shows high volatility with adverse shocks rising above two standard deviations in 1953. This pattern is reversed near 1955 with a series of expansionary household and bank shocks. Wojnilower (1980) documents an expansion in bank lending with no-down-payment mortgage advertisements.

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5.2 1970s

The 1970s begin with a pattern of adverse bank and expansionary corporate shocks while household credit plays a negligible role. Credit shocks account for nearly 50% of output fluctuations. Around 1971, bank credit turns expansionary coinciding with the agriculture commodity boom and large dollar depreciation in response to the gold standard abandonment. Credit expansions begin reversing by 1974 with bank shocks reaching two positive standard deviations and household credit becoming the largest contributor. According to Owens and Schreft (1995), rising short-term rates in 1973 led to an increase in the prime rate with banks only lending to the most credit-worthy firms. A housing production slowdown is also documented at this time which may account for the household credit contractions. Later in the decade, all three credit shocks turn expansionary with household credit again as the most critical for GDP. Wojnilower (1980) discusses a bank credit expansion impacting the most credit-sensitive sectors further fueling inflation and house prices in 1976. Kuhn et al. (2017) argues that the period witnessed rising household debt on the intensive margin operating through the credit-supply channel.

5.3 1980-1990 recessions

Significant adverse credit shocks reaching at least two standard deviations begin during the early 1980s recessions. By 1982, credit shocks account for more than 50% of GDP fluctuations. While these recessions are typically attributed to Paul Volcker's disinflation policies, the Carter Administration also imposed a set of credit controls in hopes of slowing inflation. These placed direct restrictions on marginal reserves, unsecured consumer lending, and loans for mergers and acquisitions. While this effectively inhibited credit supply to both household and corporate borrowers, Wojnilower (1985) claims the credit crunch was concentrated in mortgage credit with reduced consumption expenditures accounting for nearly 80% of the GDP drop.

The 1990 recession is associated with a real estate and stock market crash. From Figure 5, bank and corporate credit shocks turn negative while household shocks remain positive from the 1980s mortgage market expansions. According to Bernanke et al. (1991), a New

England real estate crash triggering a bank credit crunch was responsible for the reductions in credit supply. Owens and Schreft (1995) argue in favor of a credit supply shock concentrated in the commercial real estate market: a "sector-specific credit crunch that prevented commercial real estate developers and business borrowers using real estate as collateral from obtaining credit at any price." While these episodes support the adverse corporate and bank shocks, explanations for the household credit expansions remain less clear. However, the recession was followed by regulatory changes in 1992 entailing reduced loan documentation and appraisal requirements for mortgages. This may have counteracted the negative effects from the real estate crash on household credit.

5.4 Pre-financial crisis

Aggregate demand, supply, and corporate credit shocks depress output during the 2001 recession while household credit expands. This is reasonable considering the recession was triggered by the technology stock crash absent a real estate crisis. During the early-mid 2000s, the large and positive GDP fluctuations from bank and household credit supply are consistent with the rapid credit expansions associated with the pre-crisis housing bubble. This period is characterized by historically low policy rates; changes to financial regulation and lending standards; and increased government initiatives to extend homeownership. Prior to 2003, supply and credit shocks are equally responsible for the vast majority of output fluctuations until GDP is driven almost completely by bank and household credit. This supports the extensive empirical literature studying the pivotal role of financial and credit market shocks throughout the period.

With respect to the 2008 financial crisis and Zero Lower Bound (ZLB) period, my results depart from what is typically found in the literature. Many studies find financial market shocks to be among the largest contributers to declining GDP during the crisis, with some FEVD estimates reaching 50% and higher. Mumtaz et al. (2018) suggest the GDP drop in 2009 would have been reduced by 50% in the absence of credit supply shocks. The importance of financial markets for the recession is also well documented throughout the DSGE and theoretical literature. According to Figures 5 and 12, large contractions in household and corporate credit begin at the onset of the crisis, but overall, credit shocks

still held a net positive impact on output. Their impact doesn't turn negative until after 2010. Instead, supply shocks are most responsible for driving down GDP which is consistent with Hamilton (2009) who argues that the early stages of the recession resembled an oil price shock recession due to one of the largest oil price shocks on record. He associates the 2007 rise in oil prices with a combination of increasing demand and stagnating production leading to a collapse in consumer spending, especially on automobiles. Absent the shock, he believes the economy would have been characterized by slow growth, but not a recession. According to Figure 5, the minor contributions from credit shocks during the crisis suggest that the effects from deteriorating credit markets on GDP may have been more predictable than previously thought.

Before concluding this analysis, results from the historical decomposition for inflation during this period are worth discussing. According to Figure 13 in Appendix A, the non-credit shocks explain most price variation for the initial two-thirds of the sample until household and bank credit become significantly more important during the Great Recession. However, bank credit shocks contribute to positive price fluctuations while household shocks elicit a negative impact. From Figure 4, impulse responses suggest a possible long-run procyclical and countercyclical price response to bank and household credit shocks, respectively. Considering the housing bubble and pre-crisis period witnessed expansionary household and bank credit shocks, their counteracting impact on the recession's inflation errors could be their long-run implications from that period. Furlanetto et al. (2017) associates the non-inflationary effects found for financial shocks with the observed "missing disinflation" period surrounding the crisis. In contrast, Abbate et al. (2016) uncover a countercyclical inflation response to credit supply and attribute the missing disinflation to a combination of adverse credit and non-financial shocks. Figure 13 partially reconciles these claims by suggesting household credit shocks were responsible for driving inflation down while aggregate supply and bank credit shocks drove inflation up. These opposing effects would have contributed to a more subdued inflation response during the crisis. Similar to the argument made for the credit-growth relationship's dependency on credit composition, the ambiguity surrounding credit growth and inflation may also hinge on a sector-specific relationship.

6   Conclusion

This paper identifies credit supply shocks based on the sectors in which they arise and analyzes their consequences and relative importance for real economic activity. Within a structural VAR framework, it employs a unique strategy for identifying one monetary policy shock, two macroeconomic shocks, and three credit supply shocks. The credit supply shocks include household credit, corporate credit, and bank credit. While the imposed restrictions are consistent with a large body of theoretical and empirical literature, I remain as agnostic as possible regarding the relationships among the macro and financial variables. Using Bayesian methods and US data spanning the past 66 years, a baseline model is estimated for only household and corporate credit shocks to study the general relationship between private-sector credit supply and activity. I then extend the baseline with the addition of bank credit to investigate the importance of controlling for the underlying shock source.

The model's results suggest that credit supply shocks have not only varied by sector, but their implications for GDP and inflation are also sector-dependent. An adverse credit supply shock may arise in one sector simultaneously with a credit expansion in another rendering an ambiguous net effect on total credit supply and real activity. This re-emphasizes the claim that not all credit cycles are the same and should be studied at the sector-specific level. Results from the model's FEVD suggest that bank credit supply shocks may explain up to 25% of GDP fluctuations which is consistent with the literature on financial sector shocks and business cycles. Household and corporate credit shocks also play a significant role in explaining up to 15% of GDP fluctuations. For inflation, household and bank credit shocks may hold long-run consequences contributing up to 15% of price-level fluctuations. Finally, within a historical context the model captures many credit supply episodes documented in the literature, and provides a possible explanation for the "missing disinflation" observed during the recent financial crisis.

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Appendix A. Additional figures and tables

Table 4
Data and Sources

| Variable	Description	Source
GDP	Log of real GDP	Federal Reserve Bank of St. Louis
GDP deflator	Log of GDP price index	Federal Reserve Bank of St. Louis
Policy rate	Shadow federal funds rate	Board of Governors of the Federal Reserve System, Wu and Xia (2016)
Credit spread	Bank prime loan rate - 3 month Treasury bill	Board of Governors of the Federal Reserve System
Private credit	Loans and debt securities to non-financial private sector	Federal Reserve Bank of St. Louis
Household credit	Loans to households and non-profit institutions serving households	Federal Reserve Bank of St. Louis
Corporate credit	Loans and debt securities to non-financial corporations	Federal Reserve Bank of St. Louis
Bank credit	Loans and debt securities to non-financial private sector provided by domestic banks	Federal Reserve Bank of St. Louis
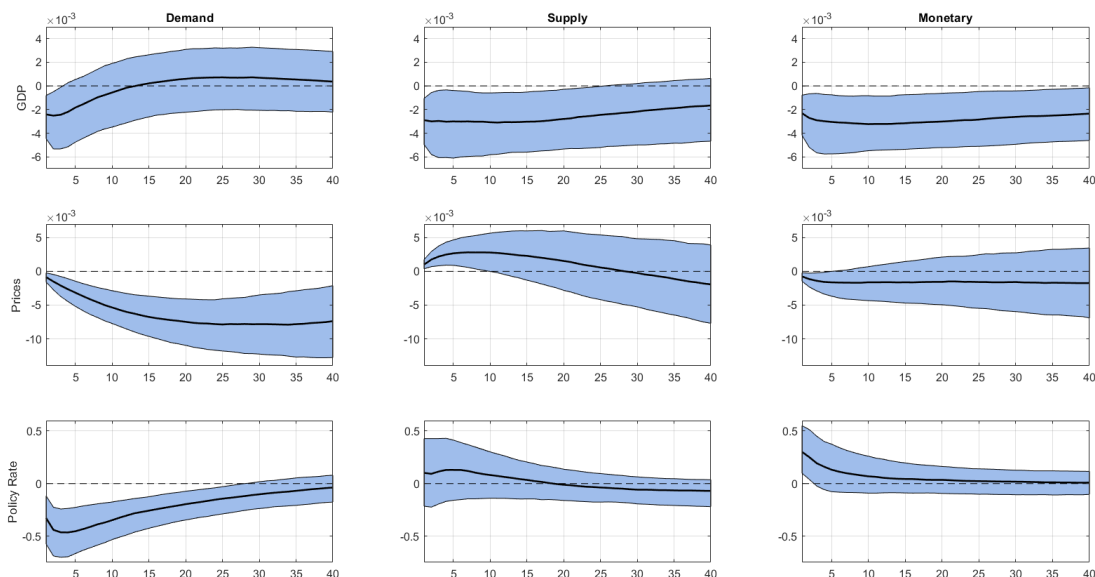
Figure 6: Impulse responses of GDP, prices, and the policy rate to a one standard deviation adverse demand, supply, and monetary policy shock for the baseline model. The solid black line depicts the posterior median response at each horizon while the shaded area indicates the 68% posterior probability region.
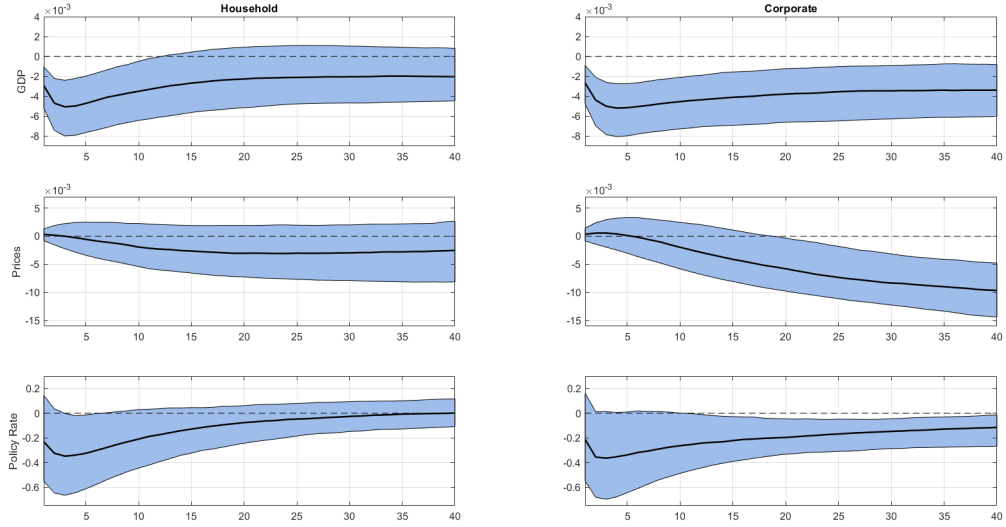
Figure 7: Impulse responses of GDP, prices, and the policy rate to a one standard deviation adverse household and corporate credit supply shock for the baseline model. The solid black line depicts the posterior median response at each horizon while the shaded area indicates the 68% posterior probability region.
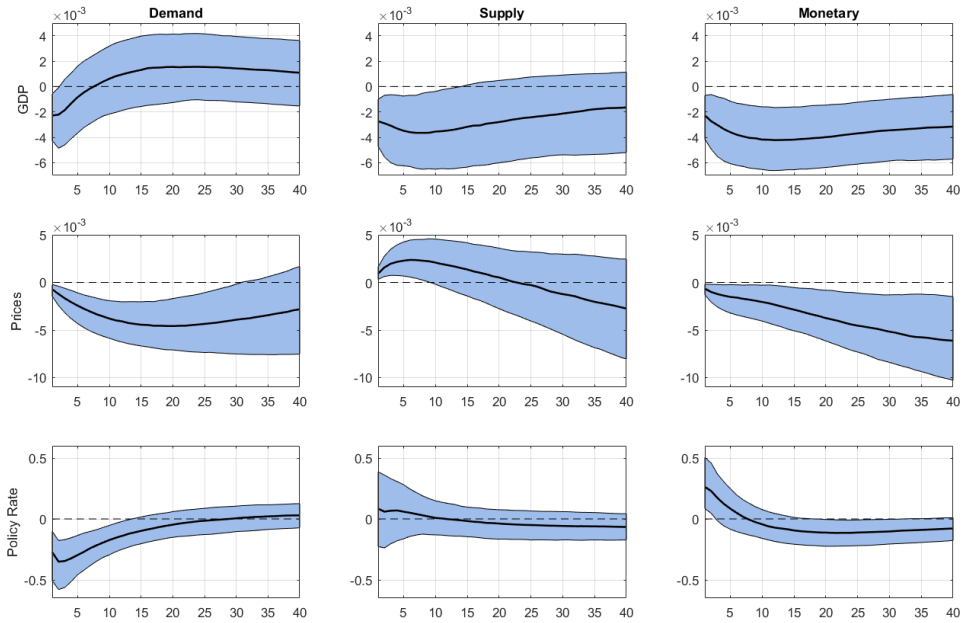

Figure 8: Impulse responses to a one standard deviation adverse demand, supply, and monetary policy shock for the extended model with macro variables only. The solid black line depicts the posterior median response at each horizon while the shaded area indicates the 68% posterior probability region.
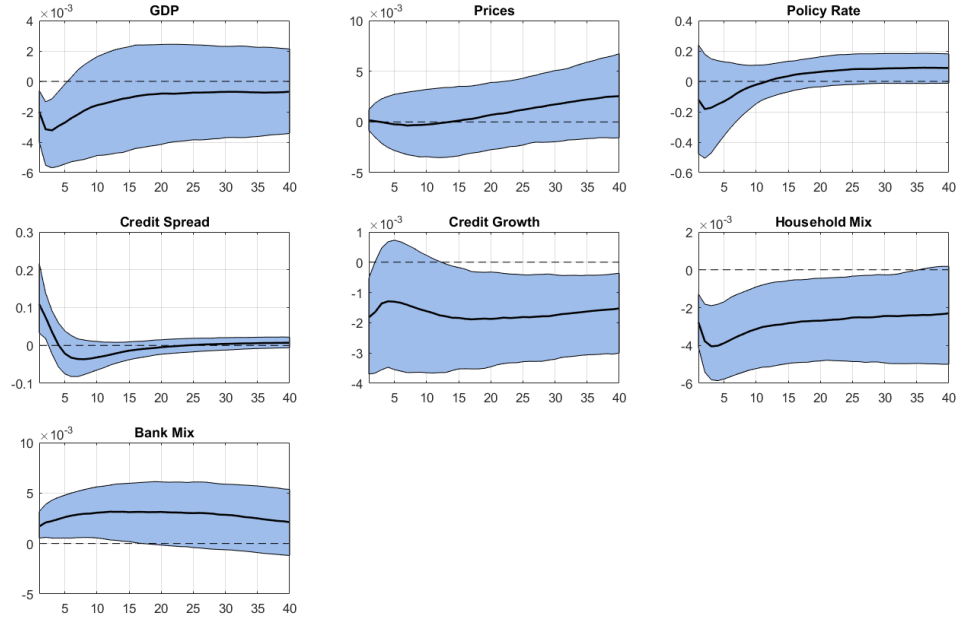
Figure 9: Impulse responses to a one standard deviation adverse household credit supply shock for the extended model. The solid black line depicts the posterior median response at each horizon while the shaded area indicates the 68% posterior probability region.
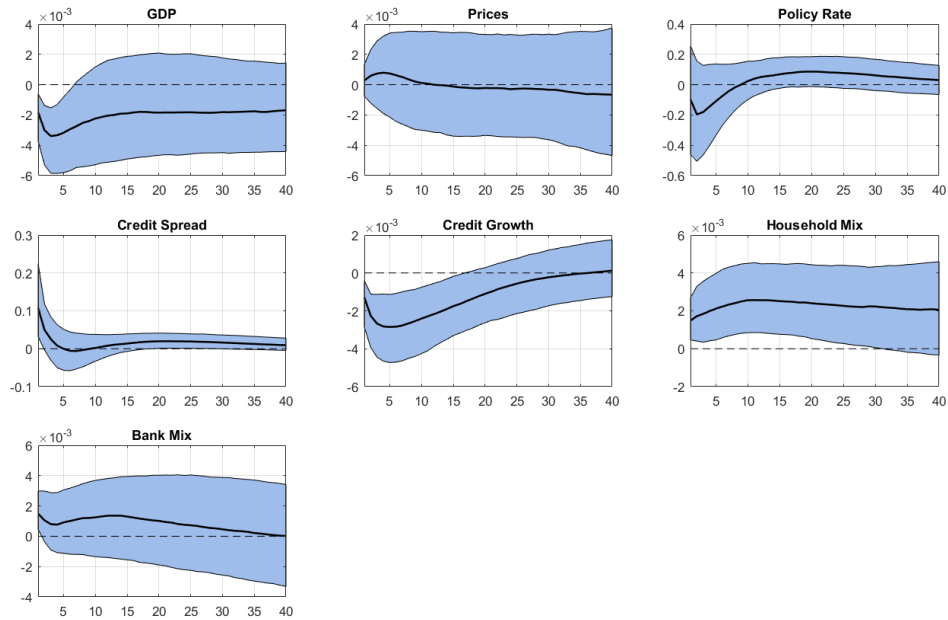

Figure 10: Impulse responses to a one standard deviation adverse corporate credit supply shock for the extended model. The solid black line depicts the posterior median response at each horizon while the shaded area indicates the 68% posterior probability region.
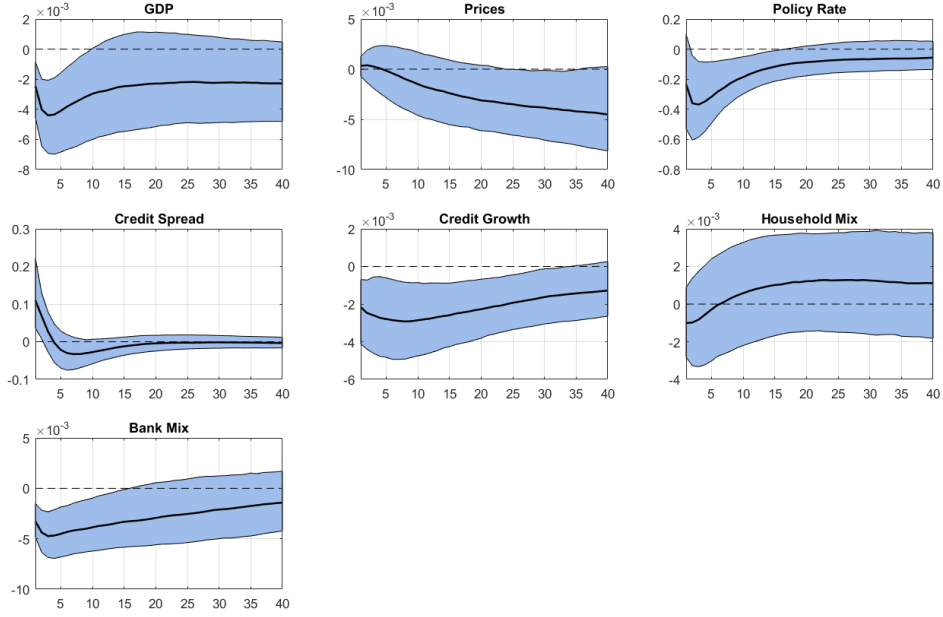
Figure 11: Impulse responses to a one standard deviation adverse bank credit supply shock for the extended model. The solid black line depicts the posterior median response at each horizon while the shaded area indicates the 68% posterior probability region.

Table 5

Median Forecast Error Variance Decomposition for the Extended Model

|	Horizon	Demand	Supply	Monetary	Household	Corporate	Bank	Residual
GDP	1	0.15	0.21	0.14	0.11	0.09	0.17	0.13
	4	0.07	0.15	0.14	0.14	0.15	0.25	0.11
	16	0.07	0.18	0.22	0.11	0.13	0.17	0.12
	32	0.08	0.17	0.23	0.10	0.13	0.16	0.12
Prices	1	0.13	0.22	0.11	0.13	0.15	0.13	0.13
	4	0.16	0.21	0.09	0.13	0.14	0.12	0.14
	16	0.29	0.12	0.11	0.11	0.12	0.13	0.12
	32	0.24	0.12	0.19	0.10	0.09	0.14	0.12
Policy Rate	1	0.16	0.10	0.15	0.15	0.15	0.17	0.13
	4	0.21	0.08	0.09	0.13	0.13	0.24	0.11
	16	0.22	0.09	0.10	0.11	0.12	0.24	0.11
	32	0.19	0.11	0.12	0.11	0.12	0.22	0.12
Prime Spread	1	0.16	0.11	0.22	0.12	0.11	0.12	0.15
	4	0.15	0.14	0.15	0.14	0.13	0.13	0.16
	16	0.20	0.12	0.11	0.15	0.12	0.14	0.15
	32	0.19	0.12	0.13	0.14	0.14	0.13	0.14
Credit Mix	1	0.22	0.21	0.11	0.11	0.05	0.15	0.14
	4	0.24	0.13	0.11	0.07	0.14	0.16	0.14
	16	0.21	0.09	0.11	0.09	0.17	0.21	0.13
	32	0.18	0.10	0.12	0.13	0.13	0.21	0.14
Household Mix	1	0.11	0.10	0.09	0.38	0.11	0.10	0.11
	4	0.12	0.09	0.09	0.41	0.09	0.09	0.10
	16	0.15	0.11	0.09	0.30	0.14	0.10	0.11
	32	0.14	0.15	0.10	0.24	0.14	0.11	0.12
Bank Mix	1	0.10	0.10	0.09	0.10	0.08	0.40	0.12
	4	0.10	0.10	0.11	0.10	0.04	0.41	0.14
	16	0.10	0.11	0.15	0.15	0.06	0.29	0.14
	32	0.12	0.13	0.14	0.17	0.08	0.22	0.14
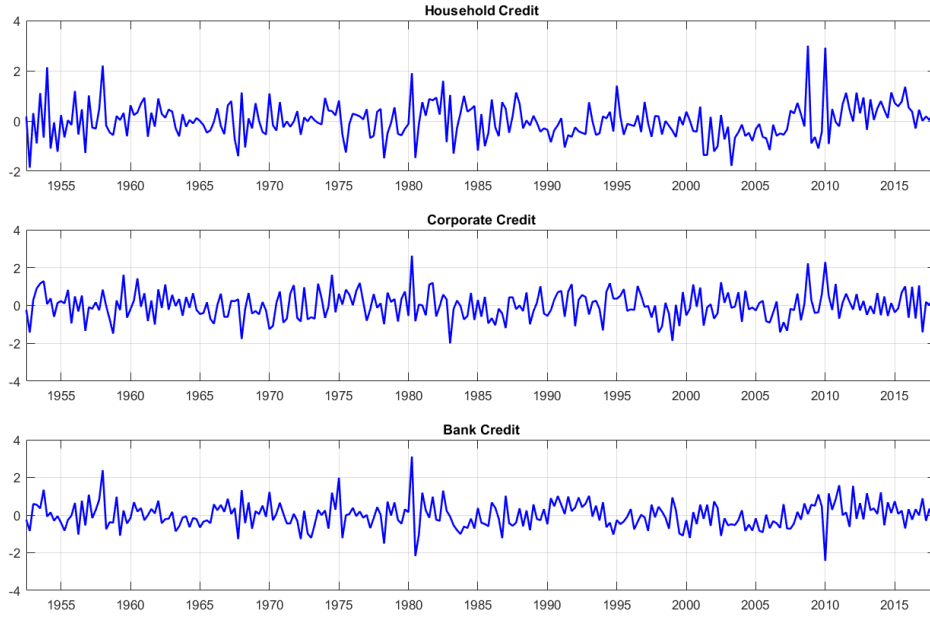
Figure 12: Median credit supply innovations for the extended model. Y-axis units are standard deviations.
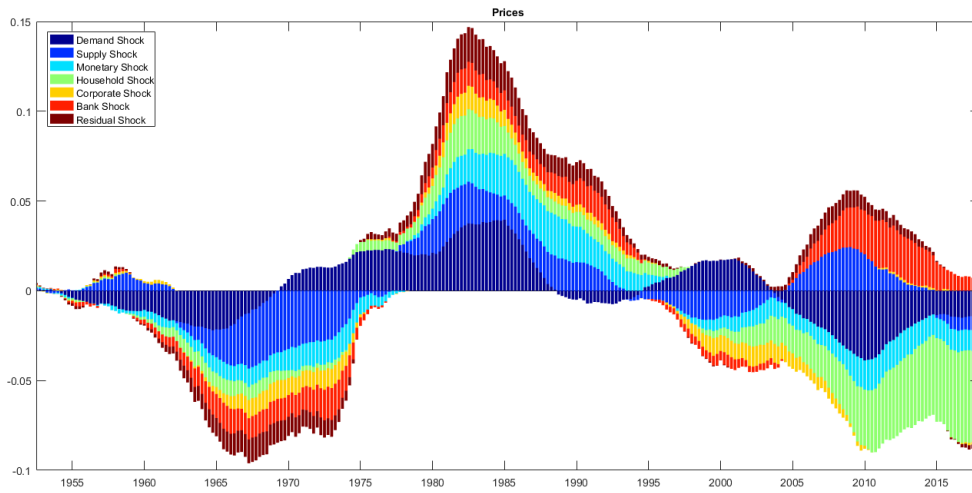

Figure 13: Historical decomposition of price level forecast errors for the extended model.
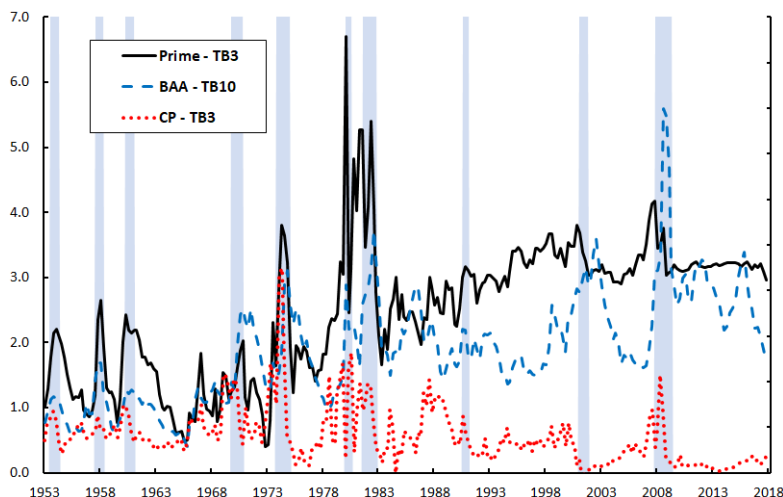
Figure 14: The prime (solid black), BAA corporate bond (dashed blue), and AA commercial paper (dotted red) spreads. Y-axis units are percentage points.

Appendix B. Robustness

In this section, a series of robustness exercises are discussed to further assess the validity of the model's econometric methodology and results. The baseline model's framework is altered in the following four ways to test its robustness: (i) replacing the prime rate spread with a corporate bond and commercial paper spread, (ii) estimating the model under two alternative identification strategies, (iii) extending the lag length out to three, four, and five quarters, and (iv) specifying two alternative priors. Keeping in line with the paper's primary interest, the robustness analysis will focus on the credit shocks and their consequences for GDP and inflation. Since the estimation time for the extended model with two lags exceeds one week, all robustness estimations are performed for the baseline specification with two lags and five shocks identified according to Table 1.

Credit spreads

In the baseline specification, the spread between the prime loan rate and 3-month Treasury rate is used as a proxy for measuring the relative price of credit in the private sector. When analyzing both household and corporate credit shocks within a single VAR, the prime spread is a useful indicator, because it's closely tied to the interest rates bank charge their corporate and non-corporate customers. However, in the VAR literature dealing with credit supply and financial sector shocks, corporate bond yields and spreads are commonly used as the proxy for private sector risk. Figure 14 plots the prime spread, the corporate BAA bond and 10-year Treasury spread, as well
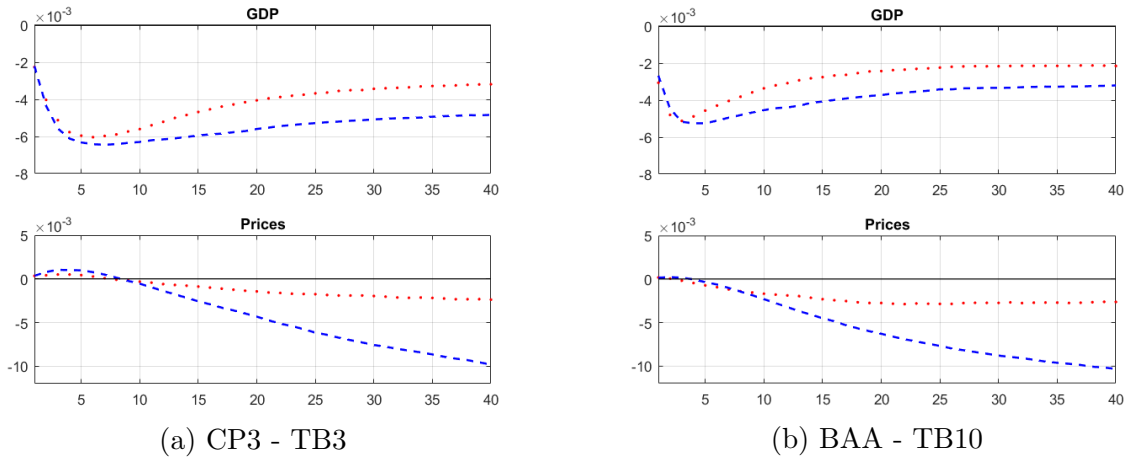
Figure 15: Impulse responses to a one standard deviation adverse household (dotted red) and corporate credit supply shock (dashed blue) with alternative credit spreads. Estimates based on median response.

as the 3-month AA commercial paper and 3-month Treasury spread. While these spreads do rise and fall together on occasion, such as during the recessions in 1973, 1980, and 2008, the magnitude and timing of their movements vary substantially for the majority of the sample. For example, the prime spread was highly active during the early 1950s-1960s while the corporate spreads still fluctuated but with less volatility. In contrast, the bond spread displays higher volatility during the 1969 and 2008 recessions. Overall, the time series of these spreads suggest that they may be responding to different types of risks arising in the private sector.

While many studies only identify a single aggregate credit or financial shock, arguments have been made in defense of using bond spreads to measure the relative risk of lending to households as well. When studying the effects of credit supply shocks to households and firms within two separate VARs, Duchi and Elbourne (2016) use the corporate bond spread in both VARs as a general proxy for the willingness of banks to bear risk and supply credit to the private sector. They argue that since banks play a major role as the market-makers for corporate bonds, bond yields can reflect their overall risk-taking appetite for lending to all customers.

As a robustness check with respect to the credit price proxy, I run two separate estimations of the baseline model: one with the corporate commercial paper spread and one with the corporate bond spread. The impulse responses for GDP and inflation are displayed by Figure 15. For the bond spread, the GDP and inflation responses are nearly identical to those for the baseline. The only subtle difference is that inflation rises marginally on impact for the baseline. However, the GDP response for the commercial paper spread does depart from the baseline in terms of a smaller initial drop, but deeper and more persistent contraction. Both shocks lower GDP to around -0.6%

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before recovery begins after eight quarters. This is compared to a drop of -0.5% and recovery after three quarters for the prime and bond spreads.

Results from the bond spread's FEVD are also similar to the baseline for GDP and inflation and differ by only 1-2 percentage points at all horizons. However, the commerical paper spread's FEVD show that corporate credit shocks explain considerably more GDP variation than the baseline. Compared to 28% and 30% at horizons of one and eight years, respectively, corporate shocks explain 33% and 40% of GDP under the CP spread. At those horizons, household credit also contributes more than the baseline with 29% and 26% compared to 28% and 19%. The FEVD for inflation changes marginally with household credit explaining 3% more after one quarter and corporate credit explaining 6% less after eight years.

Overall, these exercises suggest the median contributions of credit shocks for GDP might be overstated using the CP spread. Looking at Figure 14, the prime spread displays more volatility than the CP spread during some of the non-recessionary periods in the sample. Also, the CP spread appears to follow a relatively flat long-run trend while the prime spread follows an overall upward trend beginning around 1970. More frequent spikes in the prime spread may be associated with more small-scale GDP fluctuations than those for the CP spread. This suggests the prime spread might be more sensitive to minor credit market disruptions and could possibly explain for its lower median contributions.

Identification

As discussed in section 3.3 of the main text, the identification strategy imposes no timing restrictions and remains agnostic to the inflation and policy rate response to credit shocks. Even though more ambiguity surrounds the theoretical literature on credit and timing restrictions, many SVAR studies do impose them to delineate macro and credit shocks. Studies such as Ciccarelli et al. (2010), Peersman (2011), Barnett and Thomas (2014), Peersman and Wagner (2014), and Duchi and Elbourne (2016) assign zero restrictions on the response of GDP and inflation, while Busch et al. (2010) and Halvorsen and Jacobsen (2014) assign them on inflation only. Focusing on the inflation response, theoretical studies have found conflicting procyclical responses (Christiano et al. (2010), Curdia and Woodford (2010), Gertler and Karadi (2011), and Gilchrist and Zakrajšek (2011)) and countercyclical responses (Atta-Mensah and Dib (2008) and Gerali et al. (2010)) to credit supply shocks. From the baseline and extended specifications, the impulse responses for prices

in Figures 2 and 4 do show a near-zero response to credit shocks on impact. Taking these results into account, one alternative identification strategy to test for robustness is assigning zero restrictions on the inflation response. While I argue that leaving inflation unrestricted when confronted with ambiguous theories is the superior approach, imposing zero restrictions on its response is more justified than for GDP or the policy rate.

By setting the price response to zero for the first quarter only, the credit supply shocks are already exclusively identified and no additional sign restrictions are required to separate them from the non-credit shocks. Imposing as few restrictions as possible without compromising accuracy, I remove the restrictions on the credit mix for demand and supply shocks, as well as those on the prime spread for the monetary shock. However, the restrictions on the credit mix and spread for credit supply remain as the price and volume response following credit supply shocks is theoretically sound and consistent. Otherwise, the model may identify shocks completely unrelated to credit supply disturbances.

In addition to zero restrictions, I also check robustness to a second identification strategy that imposes a negative policy rate response to credit shocks on impact. While not fully consistent in theory due to the uncertain inflation response, this restriction assumes the central bank can accommodate the observed GDP contraction following credit shocks within the quarter. The impulse responses for the baseline and extended models displayed by Figures 7-11 also show that while the median policy rate response is negative on impact, the 68% credibility interval still spans positive space. In fact, the 68% credible region never lies below zero for household and corporate credit in the extended model. Studies taking this identification approach include Peersman (2011), Halvorsen and Jacobsen (2014), Gambetti and Musso (2017), and Mumtaz et al. (2018).

While not displayed, the impulse responses under both these identifications show little deviation from the baseline. The only subtle differences are that for household credit, GDP and inflation are marginally higher than the baseline after 40 quarters. For corporate credit, the GDP recovery doesn't begin until closer to the sixth quarter instead of the fifth and the inflation response dips slightly below -1% after 40 quarters.

The FEVD for GDP shows that the two credit shocks contribute less than they do under the baseline specification. For zero restrictions, credit shocks explain between two and six percentage points less than the baseline in the short and long-run, respectively. For the policy rate restriction, credit shocks explain even less ranging from 2% and 7% in the short and long-run. Considering the policy rate falls on impact, the heightened monetary accommodation is likely responsible for credit

shocks playing a more subdued role for GDP fluctuations. However, since the paper's primary results regarding the contributions from credit supply shocks correspond to the one-year horizon, they remain within two percentage points of those for both alternative identifications.

I'll now briefly discuss the FEVD for inflation. As would be expected under zero restrictions, credit shocks explain almost no price variation within the first year. After four years, household credit accounts for only 7% of the variation which is 5% less than in the baseline. Interestingly, corporate credit accounts for 5% less after four years, but 4% more after eight years. For the FFR restriction, both household and corporate credit explain marginally more price variation in the short-run, and corporate credit explains 5% more than the baseline after eight years. Under both alternative strategies, these results for corporate credit reiterate the paper's finding that credit supply shocks may hold long-run implications for inflation. Recalling the IRFs for the extended model, credit shocks from the banking sector accounted for the majority of the long-run price decline that was originally associated with corporate credit in the baseline.

While its understood that price and interest rate movements are important drivers of GDP, the FEVD's sensitivity to both alternative identification strategies is not surprising. However, zero restrictions and recursive orderings can potentially generate significant bias for credit supply shocks as discussed in Gambetti and Musso (2017). Considering identification strategies should have strong theoretical underpinnings, the sign restrictions in this paper's baseline and extended specifications are appealing by assigning more weight to consensus and remaining agnostic where the theory is weak. Also, since the FEVD results at the one-year horizon vary little from the paper's primary conclusions, I argue in favor of leaving inflation and the policy rate unrestricted for credit supply shocks.

Lag length

While the Schwarz Information Criterion (SIC), or Bayesian Information Criterion (BIC), suggests three lags for the baseline model and two lags for the extended model with bank credit, two lags are used in the paper for comparability. However, alternative information criteria including the Akaiki, Final Prediction Error, and Hannan-Quinn suggest up to five lags for the baseline. As robustness checks, the baseline model is estimated with lag lengths of three, four, and five.

For three lags, the impulse responses are nearly identical to those with two lags. The only noticeable differences come from the FEVD for inflation. The corporate credit shock becomes
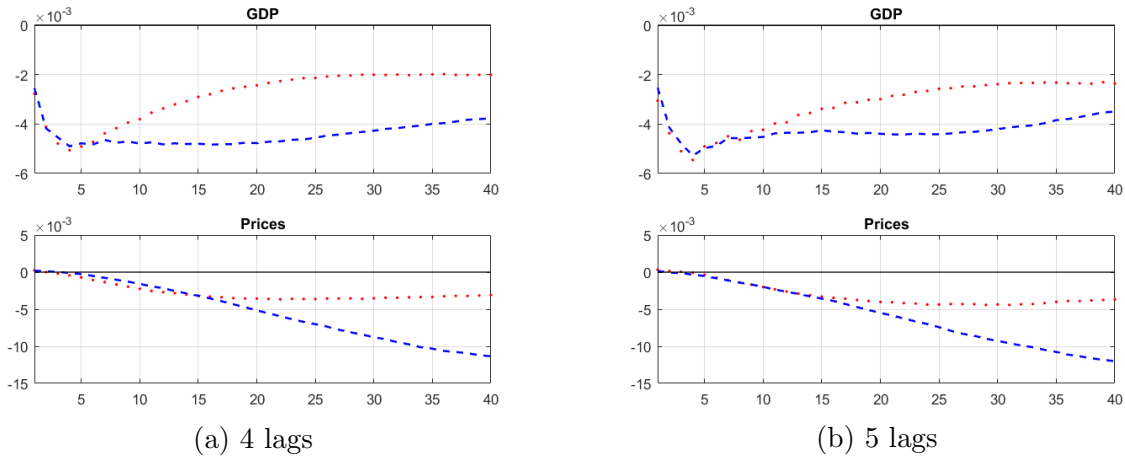
Figure 16: Impulse responses to a one standard deviation adverse household (dotted red) and corporate credit supply shock (dashed blue) with extended lag lengths. Estimates based on median response.

marginally less important by about two percentage points at each horizon. Also, demand shocks explain only 32% of price-level variation instead of 40% after four years, while supply shocks explain 31% instead of 24% after one year. Overall, changes are minimal for the two credit shocks and one additional lag.

The impulse responses for GDP and inflation with four and five lags are displayed by Figure 16. The responses are still similar to the baseline, however, GDP does experience a more delayed recovery following the corporate credit shock. Following the shock, GDP remains below -0.4% up to 15 quarters for the baseline while it takes close to 35 quarters with the extended lag lengths. Both shocks also produce a marginally stronger negative impact on inflation. As for output's variance decomposition, with five lags household credit contributes an additional 3-5% at each horizon while corporate credit explains 1-2% less. Also, the role for monetary policy shocks and output slightly decreases with lag length. The FEVD results for inflation and credit shocks display little variation away from the baseline. The only change is that both shocks explain 1-2% less in the short-run with household shocks explaining 3-4% more after four years and five lags. To summarize, increasing lag length assigns more responsibility to household credit for GDP fluctuations and a slower recovery for corporate credit. However, these changes are marginal and elicit a negligible impact on the paper's primary conclusions.

Prior selection

The baseline and extended models are estimated using the dummy observation prior with 2,000 iterations and burn-in of 1,000. Remaining consistent with the literature, hyperparameters are set

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such that each variable's own first lag coefficient is 0.8, the lag decay is 2, and the overall tightness around the random walk process is 0.1. A tightness value of zero sets the posterior equal to the prior with no information coming from the data while larger values set the posterior closer to OLS estimates. According to Banbura et al. (2010), the estimation and empirical accuracy of VARs with as few as six variables can be improved upon by implementing Bayesian shrinkage techniques and tighter priors. It follows that prior tightness should increase with the number of variables included and is especially critical for macroeconomics time series where collinearity is often present.

Beginning with diffuse priors on β and Σ, the prior introduces dummy, or pseudo, observations for each regression coefficient to match the moments of the popular Minnesota prior. It's a method of indirectly specifying the same distribution via dummies instead of directly imposing restrictions on the variance-covariance matrix Σ. The Minnesota prior asserts the belief that an independent random-walk process is a reasonable center for the time series dynamics of each variable. However, with respect to the baseline model and five shocks, the Minnesota prior requires the inversion of a (72 x 72) matrix while implementing dummy observations reduces this to only a (12 x 12) matrix. This reduces computation time and makes the estimation considerably more tractable for numerical softwares. As opposed to the Minnesota, dummy observations allow for prior covariance between the VAR coefficients in each equation which becomes critical when using interest rates and spreads of similar maturity, as well as when variables enter the model by themselves and inside mix variables. The prior can then be extended by implementing the "initial dummy observation" or "sum-of-coefficients" extensions to better handle unit root and co-integration processes which become problematic for larger VARs and variables that enter in levels. However, since no unit roots are present for the baseline or extended specifications, I do not augment the dummy prior with either extension.

Robustness to prior choice is assessed by estimating the baseline with two alternative priors: the normal-Wishart and normal-diffuse. All hyperparameters remain specified according to the baseline's dummy observation prior, except the normal-diffuse introduces cross-variable variance taking a common value of 0.5. The normal-Wishart prior is a natural conjugate that takes the variance-covariance matrix Σ as unknown in contrast to the Minnesota. It still assumes a multivariate normal distribution for the VAR coefficients, but an inverse-Wishart distribution for Σ. It restricts Σ to be diagonal with its elements parameterized according to the residual variance of individual AR models estimated on each variable. Since the prior imposes a Kronecker structure on the prior for the coefficients, β, it creates dependence between the residual variance and coefficients
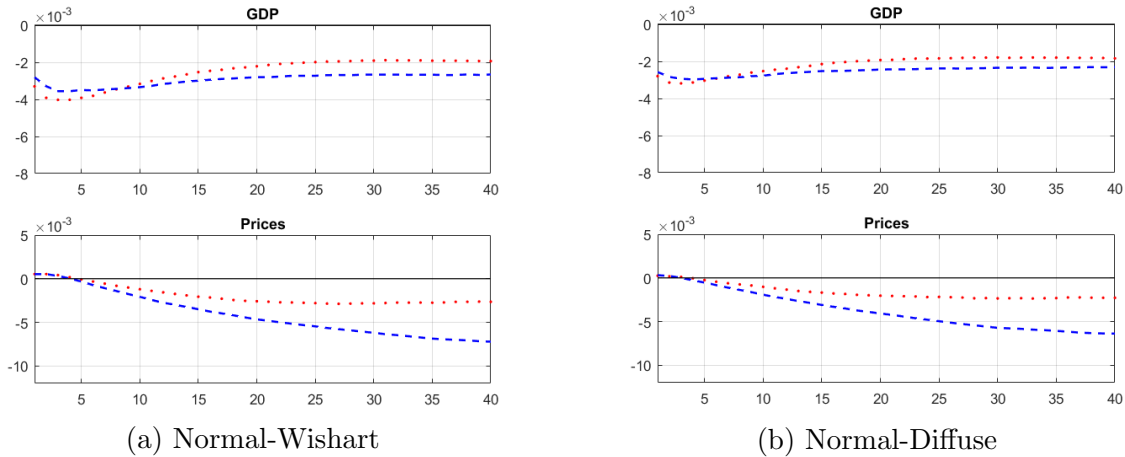
Figure 17: Impulse responses to a one standard deviation adverse household (dotted red) and corporate credit supply shock (dashed blue) with alternative prior specifications. Estimates based on median response.

in each equation.

Alternatively, when the researcher wants to remain even more agnostic with respect to their prior beliefs on Σ, the normal-Diffuse can be used. It combines the multivariate normal prior on the parameters of the Minnesota with a diffuse prior on Σ known as the Jeffrey's prior. This allows Σ to be non-diagonal imposing less prior information than the normal-Wishart. The Jeffrey's prior is improper as it integrates to infinity instead of one leading to an improper or even bimodal posterior. In contrast to the Minnesota and normal-Wishart, draws cannot be made directly from the posterior and numerical methods such as Gibbs sampling must be used instead. Also, the two alternative priors both rely on the Minnesota structure which does not allow for prior covariance among coefficients.

Figure 17 displays the impulse responses to household and corporate credit shocks for each alternative prior. Compared to the baseline, GDP is less sensitive to credit shocks for both, while being the least sensitive under the normal-diffuse. In the baseline, GDP drops to around -0.5%, while here it doesn't dip below -0.4%. In addition, under both alternatives household shocks cause a larger initial drop in GDP before recovering marginally quicker. The general recovery paths are similar across both alternatives. The inflation response is also close to the baseline, except the price level remains less than 0.75% below steady-state under both alternatives compared to 0.1% below steady-state originally.

Transitioning to the FEVD, household credit explains 3% more of the short-run variation in GDP under the normal-Wishart, but explains 5% less under the normal-diffuse. At horizons beyond four years, estimates are mostly unchanged with 1-2% more and 2-3% less for the normal-Wishart

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and diffuse priors, respectively. For corporate credit, the baseline FEVD estimated a contribution of 31% after four years while here it contributes no more than 24% for the normal-Wishart and 21% under the diffuse at any horizon. Estimates within the first quarter remain unchanged. Under the normal-Wishart, credit shocks are still the most important shocks for GDP fluctuations overall. However, supply shocks become dominant for the normal-diffuse prior explaining up to 23% of GDP fluctuations after four years compared to 19% and 21% for the credit shocks. As for inflation, results are nearly unchanged. Corporate credit explains a couple percentage points less under both alternatives while household credit explains marginally more under the normal-Wishart.

While the GDP contributions for corporate credit appear to be more sensitive to prior choice than for household credit, they are still up to six percentage points higher than what is estimated for the extended model. It's also worth commenting on the FEVD for monetary policy shocks. The results under both alternative priors assign a larger role to monetary shocks that are closer in magnitude to the extended model's estimates. Considering this, it's possible the monetary shock's contribution may not be as sensitive to the inclusion of the bank credit shock, as it's already being picked up by the five shock specification under alternative priors. If this were the case, including the bank credit shock with the alternative priors may not significantly alter the FEVD estimates for credit supply contributions and maintain conclusions closer to those made for the extended model.

More generally, the Minnesota, normal-Wishart, and normal-diffuse do not allow prior covariance among the coefficients. Within the context of large BVARs, I argue in favor of the dummy observation prior for not only introducing covariance, as is common for macro-finance analyses, but also for reducing dimensionality and computation time. It's important to consider that the strength of Bayesian estimation comes from the ability to supplement the data with private beliefs for improving estimation and accuracy. The more diffuse priors are, the closer estimates are to OLS and MLE which can become bias in large VARs. As argued in Ni and Sun (2003) and Banbura et al. (2010), using Bayesian estimators with shrinkage priors can dominate MLE and Bayesian estimators with diffuse priors. Therefore, dummy observations are a convenient prior choice for overcoming the Minnesota's limitations while maintaining its advantages in a full Bayesian context.