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THE EXPANSIONARY EFFECTS OF HOUSING CREDIT SUPPLY SHOCKS

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Abstract

This paper studies the macroeconomic effects of exogenous changes in housing credit supply. We identify the credit supply shock with a narrative dataset within a Factor-Augmented VAR. We find that a housing credit supply shock is expansionary in the housing sector, the financial markets as well as on main macroeconomic indicators. A one percent increase in the housing credit supply expands Industrial Production up to 1.4 percent and reduces the unemployment rate by 0.4 percentage points. We show that controlling for missing information and anticipation effects is crucial for evaluating the transmission mechanism of housing credit supply shocks on the macroeconomy.

Keywords: Credit Supply Shocks, Mortgage Markets, Factor Augmented VAR.

JEL codes: E44, E52, G28.

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1 Introduction

The housing mortgage market in the US is one of the largest capital markets in the world. One of its peculiarities is that the US government is directly involved in mortgage market operations via several Government-Sponsored Enterprises (GSEs) and Governmental Agencies, controlling up to 20 percent of the overall mortgage debt in the economy. Moreover, as reported by Fieldhouse et al. (2018), portfolio purchases of the GSEs boost mortgage lending, lower mortgage rates, and, in general, influence prices of various financial assets. However, there is no conclusive answer about the transmission mechanism of portfolio purchases to the real side of the economy. This paper combines those authors' narrative dataset with a Factor-Augmented VAR (FAVAR) and provides empirical evidence of the expansionary effects of housing credit supply shocks. Our baseline model shows that a one percent increase in government portfolio purchases is expansionary on standard credit and financial market indicators, as in Fieldhouse et al. (2018). Additionally, the same shock generates a significant maximal response of industrial production of 1.4 percent and a maximal reduction of the unemployment rate of 0.4 percentage points.

Our results are interesting for two reasons. First, because they provide further empirical evidence of a tight link between the credit volume in the housing market and the real economy, as the theoretical literature typically indicates (e.g. Kiyotaki and Moore, 1997; Iacoviello, 2005; Kaplan et al., 2020). Second, and perhaps more importantly, our results shed light on the expansionary effect of a potentially unconventional policy instrument that can be used to stimulate the economy when fiscal and monetary policy are constrained, for instance when the fiscal space is limited and the interest rate is stuck at the zero lower bound or used for contrasting inflationary pressure.

Measuring the causal effects of a housing credit supply policy change is particularly challenging for, at least, three reasons. First, there is a well-known problem of endogeneity as housing credit supply interventions are rarely the result of random experimentation. Credit supply policies are likely to contemporaneously affect various components of both housing and financial markets. At the same time, many credit supply changes, whether private or from the government, are driven by housing market conditions. Second, there is a problem of anticipation as most government interventions are announced well in advance in the policy arena. Third, there is a problem of information insufficiency, which might arise when policymakers and the private sector have information that is not fully reflected in the empirical model, thus resulting in a contaminated measurement of policy innovations.

In order to effectively solve these issues, we combine the narrative dataset presented in Fieldhouse et al. (2018) of exogenous changes in GSEs purchasing activity with a FAVAR model á la Bernanke et al. (2005) recursively identified, namely a Cholesky identification with the exogenous instrumental variable ordered first. Firstly, as it is common in the literature using narrative dataset (e.g. Ramey and Shapiro, 1998; Romer and Romer, 2010; Cloyne, 2013), we use only the policy changes that are orthogonal to the business cycle or credit market conditions. In so doing, we deal with the endogeneity issue, as the policy interventions can be considered orthogonal to the other observables of interest. Secondly, we use a FAVAR model that controls for a large information set and is robust to measurement error in the variables. In this way, we produce estimates that deal with issues of information insufficiency and measurement errors. Finally, we deal with the anticipation effect by ordering the narrative dataset first in our Cholesky-FAVAR. As shown in Noh (2017) and Plagborg-Møller and Wolf (2021), this "internal instrument" strategy controls for past values of the shocks. This is crucial to obtain valid impulse response estimates when, as in the present study, policy changes are generally announced well before their implementation, thus resulting in the shock of interest being non-invertible in a VAR setting.
We will show that these features of the empirical model are pivotal for a correct understanding of the transmission mechanism of a housing credit supply shock to the real side of the economy.

Literature Review This paper closely relates to the recent macroeconomic literature on the links between credit supply, the housing sector, and the aggregate economy (e.g. Fieldhouse et al., 2018; Justiniano et al., 2019; Mian et al., 2020). In particular, Justiniano et al. (2019) argue that in order to understand the US housing boom that preceded the Great Recession the attention should shift from the frictions on demand side, to rigidities on the supply side of the credit markets. By considering a theoretical model of borrowing and lending they show how focusing on credit supply allows to replicate the empirical stylized facts of the US housing boom in the 2000s: an unprecedented surge in both house prices and household mortgage debt, a fall in mortgage rates and a stable ratio between housing debt and the value of real estate collateral. Our paper contributes to this literature by quantifying, in a data-driven exercise, how credit supply shocks are capable of driving not only housing markets but also real business cycles.

We also relate to the strand of the literature that estimates the effects of credit supply shocks. The closest contribution can be found in Fieldhouse et al. (2018), who identify exogenous shocks to credit supply through a narrative analysis of the lending activity of GSEs in the housing market. They find that non cyclically motivated GSEs' mortgage purchases increase mortgage originations and debt and lead to a very large increase in refinancing activities. Aside from the mortgage market, Fieldhouse et al. (2018) also find that a positive credit supply shock affects the housing market via higher homeownership rates, house prices and housing starts. Along the same line, Mian et al. (2020) construct a proxy for credit supply shocks and analyse their impact at state level and highlight the importance of the mortgage demand channel for the U.S. in the 1980s. We complement these studies by presenting robust evidence on the impact of a credit supply shock to the housing sector and the aggregate level of economic activity. We show that once one controls for information sufficiency and anticipation effects, a credit supply shock of one percent is associated with a peak effect on Industrial Production of 1.23 percent. This result provides further empirical support that interventions in the mortgage market can be used as unconventional economic policy when the use of other instruments is prevented.

The rest of the paper is organized as follows. Section 2 explains the empirical model, Section 3 describes the core results of the paper. Finally, Section 4 concludes.

2 The Empirical Specification

Empirical model In the empirical application we adopt a non-stationary factor model VAR, as proposed by Barigozzi et al. (2021).[1] This econometric approach can be briefly summarised as follows. Consider a panel of M possibly non-stationary time-series X_t. The factor model is defined as:

$$X_t = c + b\tau + \Lambda F_t + \xi_t \tag{1}$$

where c is an intercept, τ denotes a time-trend, F_t are the R non-stationary factors, Λ is a $M \times R$ matrix of factor loadings and ξ_t are idiosyncratic components that are allowed to

[1] There are two main advantages of using this approach compared to its stationary counterpart. First, the non-stationary model accounts for cointegration in the common factors, a feature that both economic and econometric theory suggest to be extremely likely, thus it offers a more realistic representation of the data. Second, in the stationary factor models the IRFs are cumulated and have the undesirable property that all shocks have long-run effects on the levels of the variables, a property that is at odds with macroeconomic theory. In contrast, with the non-stationary approach we estimate a VAR in levels for the estimated factors, thus the IRFs are not cumulated.

be $I(1)$ or $I(0)$. Following Barigozzi et al. (2021), the factors can be consistently estimated using a principal components (PC) estimator. In particular, the factor loadings are estimated via PC analysis of the first differenced data ΔX_t. With these in hand, the factors are estimated as $\hat{F}_t = \hat{\Lambda}' \left(X_t - \hat{c} - \hat{b}\tau \right)$. Adopting the Bai and Ng (2002) criteria, it suggests the presence of 12 factors.[2] The dynamics are given by the VAR model as follows:

$$Y_t = c + \sum_{j=1}^{P} \beta_j Y_{t-j} + u_t \tag{2}$$

$$u_t \sim \mathcal{N}(0, \sigma^2) \tag{3}$$

where $Y_t = \left(M_t; Z_t; \hat{F}_t\right)'$ denotes the matrix $N \times 1$ matrix of endogenous variables, that are regressed on the $N \times (NP+1) \times 1$ regressors and β denotes the $N \times (NP+1)$ matrix of coefficients $\beta = [\beta_{1,\ldots,}\beta_P, c]$.

As in Fieldhouse et al. (2018), M_t denotes the non-cyclical narrative policy indicator expressed in constant dollars, while Z_t is the annualized cumulative sum of agency mortgage commitments made over the eight months period.[3] Both M_t and Z_t are expressed as ratios of a deterministic trend in real personal income obtained by fitting a third-degree polynomial of time to the log of personal income and deflated by the core PCE price index.

We adopt a Bayesian approach to estimation. We assume a non-informative prior for σ. The posterior distribution of the parameters of the VAR models in equation 2 is approximated using a Gibbs algorithm to draw from known conditional posteriors. The algorithm uses 20,000 iterations, with a burn-in of 10,000.

The reduced form residuals are related to the underlying structural shocks through the matrix A_0 as follows:

$$u_t = A_0 \varepsilon_t. \tag{4}$$

In order to retrieve the A_0 impact matrix, we follow Plagborg-Møller and Wolf (2021) and Noh (2017) and use a Choleski decomposition of the variance-covariance matrix with the instrumental variable ordered first. We prefer the recursive identification over the standard proxy VAR approach since on top of being much simpler and faster, it also produces reliable impulse responses when shocks are anticipated.[4]

[2] The framework of Barigozzi et al. (2021) allows for F_t to be reduced rank with their space spanned by $Q \leq R$ dynamic factors. We follow Alessi and Kerssenfischer (2019) and set $R = Q$.

[3] The Z_t variable is included in the model for scaling purposes.

[4] The shocks we identify are anticipated credit supply shocks which fail invertibility and compromise the estimation of impulse responses in a Proxy-VAR model, as discussed in Stock and Watson (2018).

Data. We briefly present the data here and refer the reader to Appendix A for a comprehensive description of the dataset. The dataset for the FAVAR model contains 135 macroeconomic and financial series. We use all the variables in the FRED-MD dataset that are available from January 1967 for a total of 126 variables. FRED data variables are used as follows: all the variables that in the original FRED-MD dataset are not transformed, first differenced or second differenced prior to factor extraction are left unchanged and all the remaining variables are expressed in logarithm. Then, we complement this dataset with nine additional variables taken from Fieldhouse et al. (2018) and are described briefly in Table 1 and more thoroughly in Appendix A. The sample runs at a monthly frequency from January 1967 to December 2006.

Table 1 – Data series used in the model estimation

Variable name	Transformation	Source
126 variables	log and none	FRED-MD
Agency Net Portfolio Purchases (NPURC)	log	Fieldhouse et al. (2018)
Real mortgage originations (ORIG)	log and deflated by core PCE index	Fieldhouse et al. (2018)
Nominal House Price Index (HPRICE)	log and deflated by core PCE index	Fieldhouse et al. (2018)
BAA-AAA corporate bond spread (SBAA)	none	Fieldhouse et al. (2018)
Total Mortgage Debt (MDEBT)	log and deflated by core PCE index	Fieldhouse et al. (2018)
Conventional Mortgage Interest Rate (CONV)	none	Fieldhouse et al. (2018)
Conventional Mortgage Spread over 10 Y rate (SCONV)	none	Fieldhouse et al. (2018)
Non-cyclical narrative policy indicator (M_t)	deflated by core PCE index	Fieldhouse et al. (2018)
Sum of Agency mortgage commitments (Z_t)	deflated by core PCE index	Fieldhouse et al. (2018)

Notes. The table lists the variables included in the baseline model. The sample is January 1967 to December 2006. Both M_t and Z_t are expressed as ratios of a deterministic trend in real personal income obtained by fitting a third-degree polynomial of time to the log of personal income

3 Empirical Results

In this section we asses how the economy responds to an increase in agency asset purchases by analysing the impulse response functions generated by a credit supply shock. We study an anticipated shock and we report the response of economic variables to an innovation that increases the agency flow market share by one percentage point and that becomes anticipated eight periods before. Recall that expected agency purchases are proxied by agency commitments made over the following eight months. This is because at this horizon the robust F-statistic associated with the narrative instrument in the first-stage regression is the largest, see Fieldhouse et al. (2018).

Figure 1 displays how the housing sector and the mortgage market respond to the policy shock under consideration. Each of the panels in the figure shows the point estimates and 68 percent credibility set for the first 20 months after the increase. Overall our findings are consistent with those presented in Fieldhouse et al. (2018). Led by the increase in agency purchases, the mortgage market expands with mortgage rates as well as other interest rates falling. As will see below, this has a soaring effects on house prices.

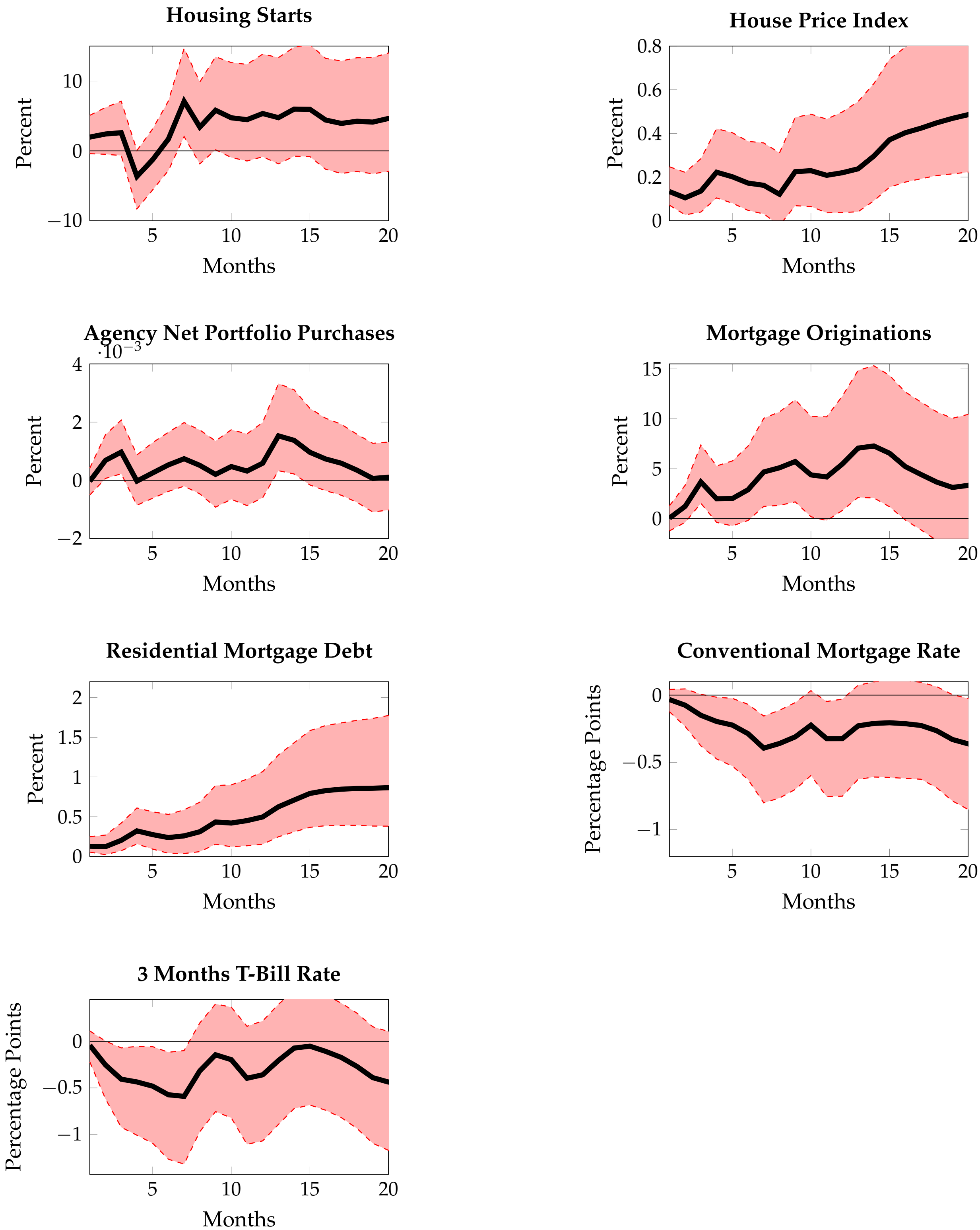
In particular, the first two panels illustrate the response of the housing sector. Residential investment, i.e., monthly housing starts, increases by 7%, seven months after the shock while The real house price index rises immediately on impact and keep on rising steadily, with the increase being statistically significant throughout the whole time horizon.

The next three panels illustrate how volumes respond in the mortgage market. The increase in agency net portfolio purchases leads to a big expansion in mortgage originations. They start raising immediately after the shock, reaching the peak 14 months after the shock, at around 7%. Furthermore, mortgage credit increases significantly and persistently following the credit supply shock. More precisely, the stock of residential mortgage debt steadily rises to levels that are about 0.32% higher after 4 quarters and reaching 1% by the end of the horizon.

The remaining panels of Figure 1 illustrate the effects of the credit supply shock on interest rates.[5] Specifically, the fixed interest rate on 30-year mortgages in the primary market, known as the conventional mortgage rate, responds negatively and peaks at approximately -40 basis points six months after the shock. This decrease in mortgage

[5] In the appendix (figure B.1) we present additional evidence of the impact of the credit supply shock on interest rate and credit spreads.

Figure 1 – IRFs to a 1% Credit Supply Shock, Housing and Credit Variables.



Notes: FAVAR with Cholesky structural identification. Solid black lines: median. Shaded areas: 68% credibility sets.

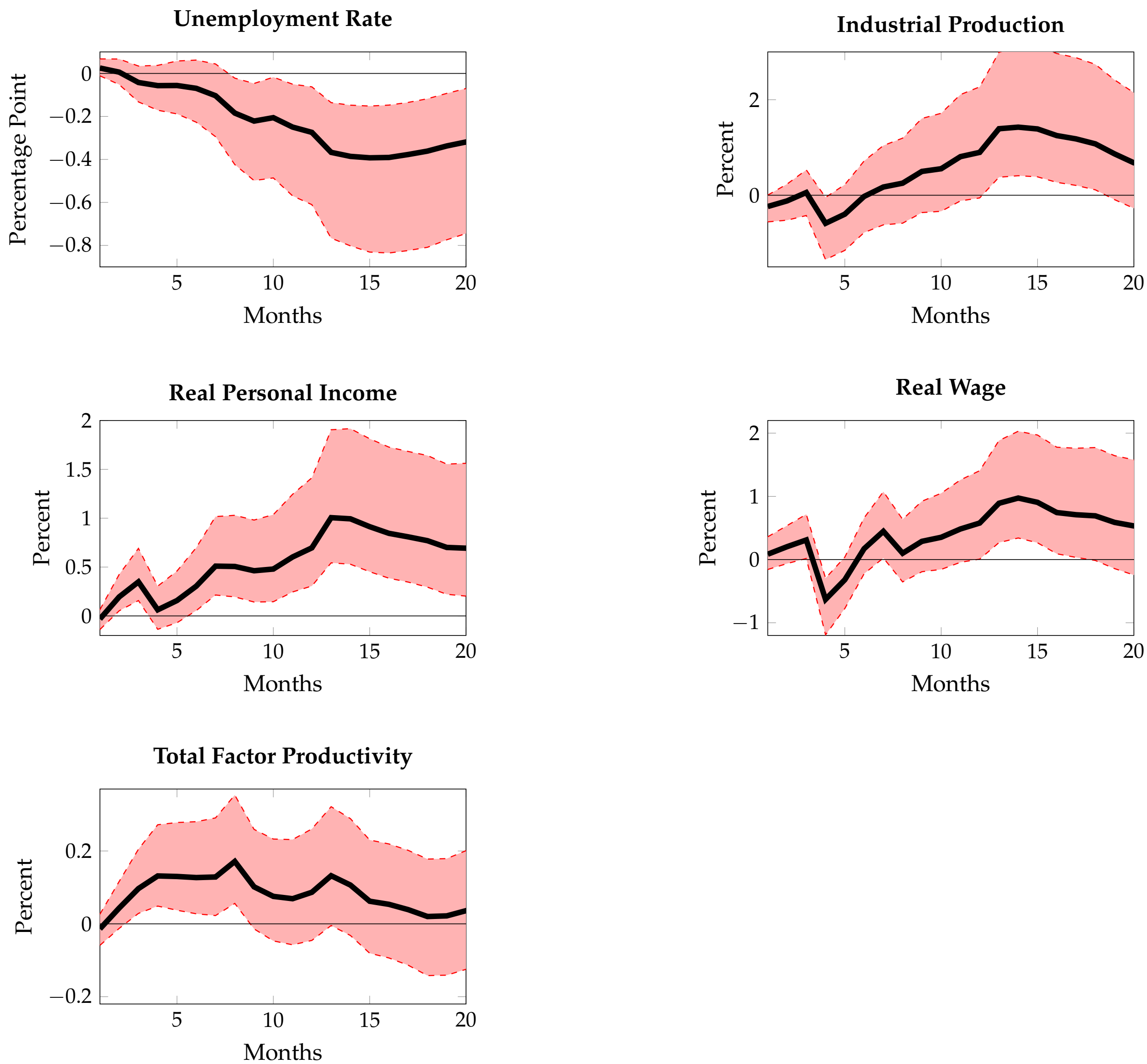
rates is statistically significant and persistent throughout the entire period examined. The spillover effects of this increase in mortgage credit supply extend to the 3-month T-Bill rate which experiences even a more significant decline. With only a couple of months delay, the T-Bill rate persistently drops by 0.35 and reaches a minimum of -0.6 percentage points after six months.

Figure 2 contains the main result of the paper: standard economic indicators such as industrial production, personal income and unemployment respond positively to a housing credit supply shock. Real personal income increases by 35 basis points after 3 months and reaches its peak at 1% after 13 months. Apart from a brief spell between the second and third month, the expansionary effect of the credit supply shock on real personal income is statistically significant throughout the entire horizon. Industrial production exhibits a 0.6% fall after 4 months and from there it increases reaching a peak of 1.42% after 14 months. The expansion is statistically significant between the 13th and the 18th month. Unemployment decreases with significant effects starting after 8 months and reaching a peak of -0.39% after 15 months. We also observe an increase of the total factor productivity with peak of 0.17% after 8 months. The effects of a credit supply shock on real wages is somewhat less clear, as real wages fall by 0.63% after 4 months and then increase by 0.97% after 14 months.

Two points are worth making. The first observation is purely methodological. While we use the same narrative dataset of Fieldhouse et al. (2018), we also exploit the richer information content of a bigger dataset (via the factor model). As such, our results indicate that controlling for a large information set is pivotal for obtaining an expansionary effect of a house credit supply shock on the economy. Section 3.1 further digs into this aspect.

The second observation hinges upon the everlasting dilemma in macroeconomics: is it a matter of supply, a matter of demand, or they both matter? Our empirical results suggest that credit supply side factors play an important role in understanding the dynamics of the housing market and the business cycle. The idea behind our transmission mechanism goes as follow. An expansion in a sector of the economy has positive repercussions on the aggregate economy productive capacity. GSEs portfolio purchases initiate an overall expansion of credit in the mortgage market. The increase in mortgage availability leads to an expansion in the housing sector. We observe an increase in both housing starts and mortgage originations, and the house price index as in a standard demand-driven boom. However, this expansionary effect is not confined to the housing sector. What we highlight here is that the overall productive capacity of the aggregate economy is boosted.

Figure 2 – IRFs to a 1% Credit Supply Shock, Macroeconomic Indicators



Notes: FAVAR with Cholesky structural identification. Solid black lines: median. Shaded areas: 68 % credibility sets.

Following the GSEs portfolio purchases, we observe an increase in productive capacity, together with an increase in real personal income and a fall in the unemployment rate. In this sense, housing credit supply shock has expansionary effects on the real aggregate economy.

3.1 The Importance of Factors

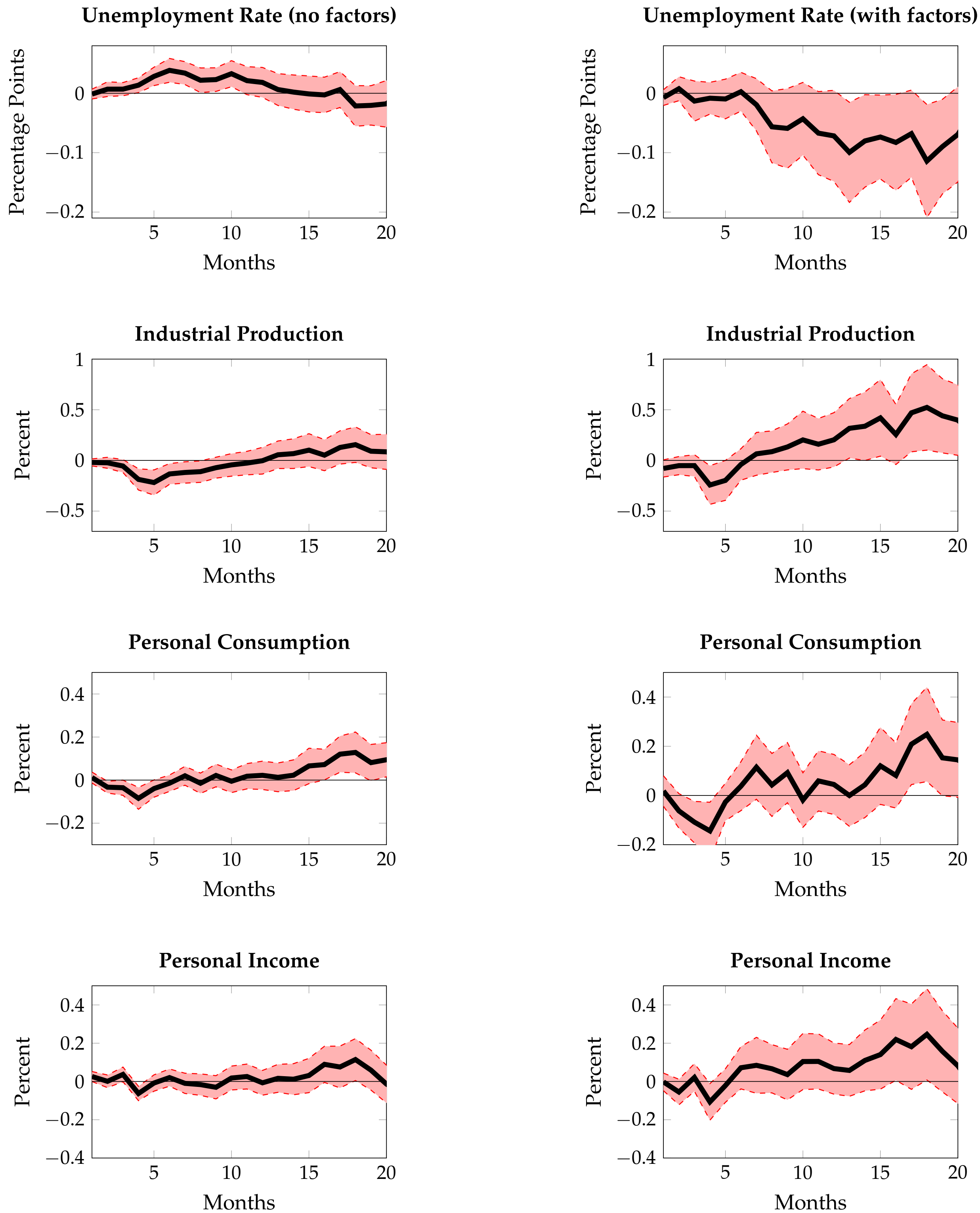
While our FAVAR model indicates a clear expansionary role for credit supply shocks, one can rightly wonder whether our results depend on the specific methodology adopted or whether instead there is a more fundamental issue of missing information. In order to better understand this, we replicate the same instrumental-variable local projection (IV-LP) empirical model of Fieldhouse et al. (2018) and then we enrich that same model with factors. Figure 3 presents two sets of IRFs of a 1% credit supply shocks on standard macroeconomic indicators, first without factors and then with 9 factors and their lags.[6]

The main take-home form this experiment is that controlling for missing information via a factor model is important for the correct evaluation of housing credit policy. For example, Figure 3 shows that without controlling for information insufficiency, the unemployment rate exhibits a statistical significant increase after 5 months. However, including factors in the estimation recollects the main result of the paper in which positive credit supply shocks are expansionary and, as such, reduce significantly the unemployment rate. Similarly, Industrial Production starts falling after 3 months in the scenario without factors, while the same variable shows a significant increase after five quarters in the model with. This same logic can be applied to personal consumption and personal income: including factors imply a much amplified response of these variables, which turn significant one year and a half after the shock.

In figure 4 we repeat the same exercise, but we consider credit and financial variables. In this case, while adding factors does to not change the qualitative response of these variables, it nevertheless amplifies their responses to a positive housing credit supply shock. All in all, whether we consider standard macroeconomic indicators or credit market variables, empirical specifications with factors magnify the response to the credit supply policy interventions.

[6] For consistency, we use the same number of factors as inn our benchmark model.

Figure 3 – IRFs to a 1% Credit Supply Shock, Role of Factors, Macroeconomic Variables.



Notes: LP-IV identification without factors (left column) and with factors (right column). Solid black line: median. Shaded area: 68 % credible set.

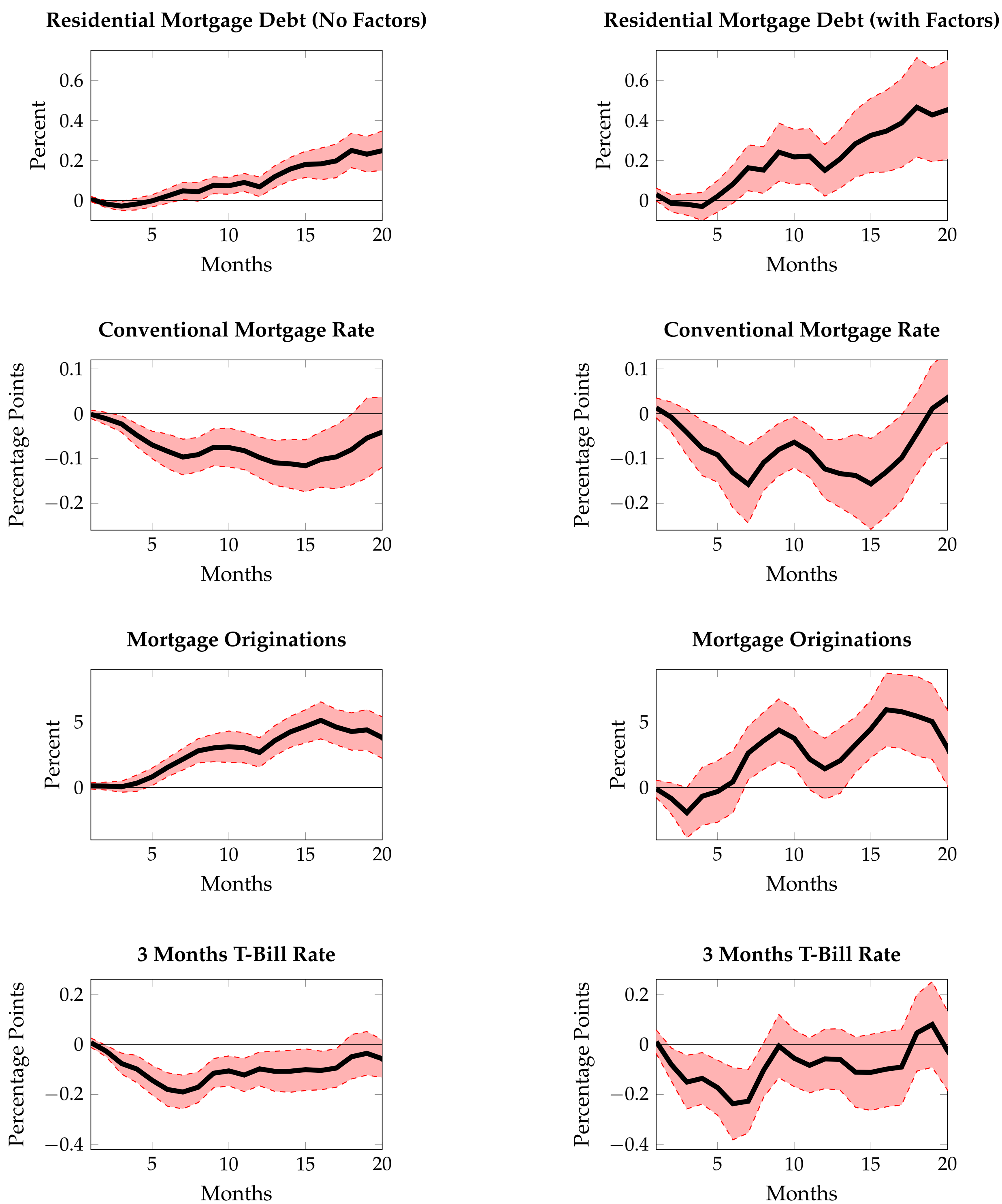
4 Conclusion

In this paper we provide empirical evidence of the effects of a housing credit supply shock. Adopting a Factor Augmented SVAR, we show that increases in government portfolio purchases are expansionary on housing and credit market variables, such as housing starts and residential mortgage debt, as well as on standard macroeconomic indicators, such as the unemployment rate and industrial production. While carrying out the main message of the paper, we also stress various important aspects for the correct evaluation of credit supply shocks, in particular the pivotal role of controlling for missing information.

As we discussed above, we believe our study is interesting for at least two reasons. First, because it provides further empirical evidence of a tight link between the credit volume in the housing market and the macroeconomy, as the theoretical literature typically indicates (see Kiyotaki and Moore, 1997; Iacoviello, 2005; Kaplan et al., 2020). Second, and perhaps more importantly, because our results shed light on the expansionary effects of a (potentially) unconventional policy instrument that can be used to stimulate the economy and the financial markets when fiscal and monetary policy are constrained, for instance when the fiscal space is limited and the interest rate is used for stabilizing inflation.

There are several potential avenue for future research. First of all, one can look at the distributional effects of housing credit supply shocks. For example it could be interesting to explore the heterogeneous effects of our policy shocks based on differences of household portfolio composition, along the line of Pidkuyko (2022). Second, one could study the international spillovers of housing policy shocks. As it is well known, US policy shocks have strong effects on global markets, e.g., Miranda-Agrippino and Rey (2020). As such, it is likely that government interventions in the mortgage sector cause business and credit cycle fluctuations around the world. Finally, it would be interesting to analyse the uncertainty in the housing credit supply. As a large body of empirical evidence shows, e.g., Bloom (2009), second-order shocks impacting uncertainty have first order importance at business cycle frequency. So ex-ante it is plausible that uncertainty in the housing market credit supply could have comparable effects on macroeconomic indicators such as industrial production and unemployment.

Figure 4 – IRFs to a 1% Credit Supply Shock, Role of Factors, Housing and Credit Variables.



Notes: LP-IV identification without factors (left column) and with factors (right column). Solid black line: median. Shaded area: 68 % credible set.

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A Description of the data

FRED-MD and FRED-QD are large macroeconomic databases designed for the empirical analysis of 'big data.' These datasets consist of monthly (MD) and quarterly (QD) observations, mirroring the coverage of datasets commonly used in the existing literature. They are continuously updated in real-time through the FRED database and are publicly accessible, making it easier to replicate empirical research. In particular, FRED-MD contains 135 variables spanning from January 1959 to the present day, categorized into eight groups as follows: Output and income (17 variables), Labor market (32 variables), Housing (10 variables), Consumption, orders, and inventories (14 variables), Money and credit (14 variables), Interest and exchange rates (22 variables), Prices (21 variables), and Stock market (5 variables). On top of the 126 variables from the FRED datasets, we also include the housing variables as in Fieldhouse et al. (2018) which they extensively describe in their appendix[7] as below:

Agency Net Portfolio Purchases (NPURC) is the sum of net portfolios purchases of both whole loans as well as mortgage pools, and of issues of mortgage pools respectively, by Fannie Mae, Freddie Mac, Ginnie Mae, the FHLBanks, the Treasury Department, the Federal Reserve, and a number of other government agencies.

Real mortgage originations (ORIG) are total originations of long-term mortgage loans for 1-to-4 nonfarm homes and multifamily residential properties. The monthly series is interpolated after 1997 using quarterly data on originations (series USMORTORA in Datastream) and weekly data on mortgage applications (series MBAVBASC on Bloomberg), both from the Mortgage Bankers' Asso ciation (MBA).

Nominal House Price Index (HPRICE): House prices post-1975 are measured by the Freddie Mac house price index (FMHPI)[8]. The data are extended before 1975 by splicing with the home purchase component of the BLS Consumer Price Index (PHCPI from FRED), obtained from Shiller (2015), and seasonally adjusted using the X-13 program from the Census Bureau. The series is deflated by the nominal price level, measured by the core PCE price index to obtain a real house price index (series PCEPILFE from FRED).

BAA-AAA corporate bond spread (SBAA): The BAA and AAA corporate bond rates are the Moody's seasoned BAA and AAA yields (series BAA and AAA from FRED).

[7] The full detailed description can be found in the Online Appendix III of the Fieldhouse et al. (2018) paper: file:qje.oxfordjournals.org

[8] available at http://www.freddiemac.com/finance/house_price_index.html

Total Mortgage Debt (MDEBT) is a monthly series based on interpolation of the quarterly mortgage debt series from the Financial Accounts of the United States (see Figure I) using the series on monthly originations. The series is constructed by linear interpolation of the implied quarterly repayment rates. The final series is seasonally adjusted using the X-13 program from the Census Bureau.

Conventional Mortgage Interest Rate (CONV) is the 30-year fixed-rate conventional conforming mortgage rate. From 1971 onwards, the conventional rate is the monthly average commitment rate from the Freddie Mac primary mortgage market survey. Pre-1971 data is from the Federal Housing Administration (FHA)/Department of Housing and Urban Development (HUD) series for the primary conventional market rate, available from the Federal Reserve Bulletin (various issues). The FHA mortgage rate is the 30-year fixed-rate FHA-guaranteed mortgage rate. Rate data for FHA-mortgages offered in the secondary market from 1963 is provided by FHA/HUD and is available from various issues of the Federal Reserve Bulletin.

Conventional Mortgage Spread over 10 Y rate (SCONV) This spread is computed as the ratio between the conventional mortgage rate which is the 30-year fixed-rate conventional conforming mortgage rate (FHA/HUD as well as the Freddie Mac series) and the 10-year Treasury rate.

Non-cyclical narrative policy indicator (M_t) is the instrumental variable constructed by Fieldhouse et al. (2018) through a narrative analysis to identify those historical policy changes clasified as unrelated to short-run cyclical or credit market shocks, leading to expansions or contractions in agency mortgage holdings.

Sum of Agency mortgage commitments (Z_t) are the sum of the Fannie Mae, Freddie Mac and Federal reserve series:

> Fannie Mae: Monthly data on the stock of total outstanding unfulfilled commitments from 1953 to 1990 is available from various issues of the Federal Reserve Bulletin. To obtain net purchase commitments made during the month, we add net purchases to the net change in commitments outstanding. From 1990 onwards we use net commitments (issued less to sell) from the Federal Reserve Bulletin (up to 2003) and Fannie's monthly volume summaries (2003 onwards).
>
> Freddie Mac: Monthly data on Freddie's net portfolio commitments (issued less to sell) is from Fred die's monthly volume summaries from 1998 onwards. For observations before 1998, we use Freddie net portfolio purchases.

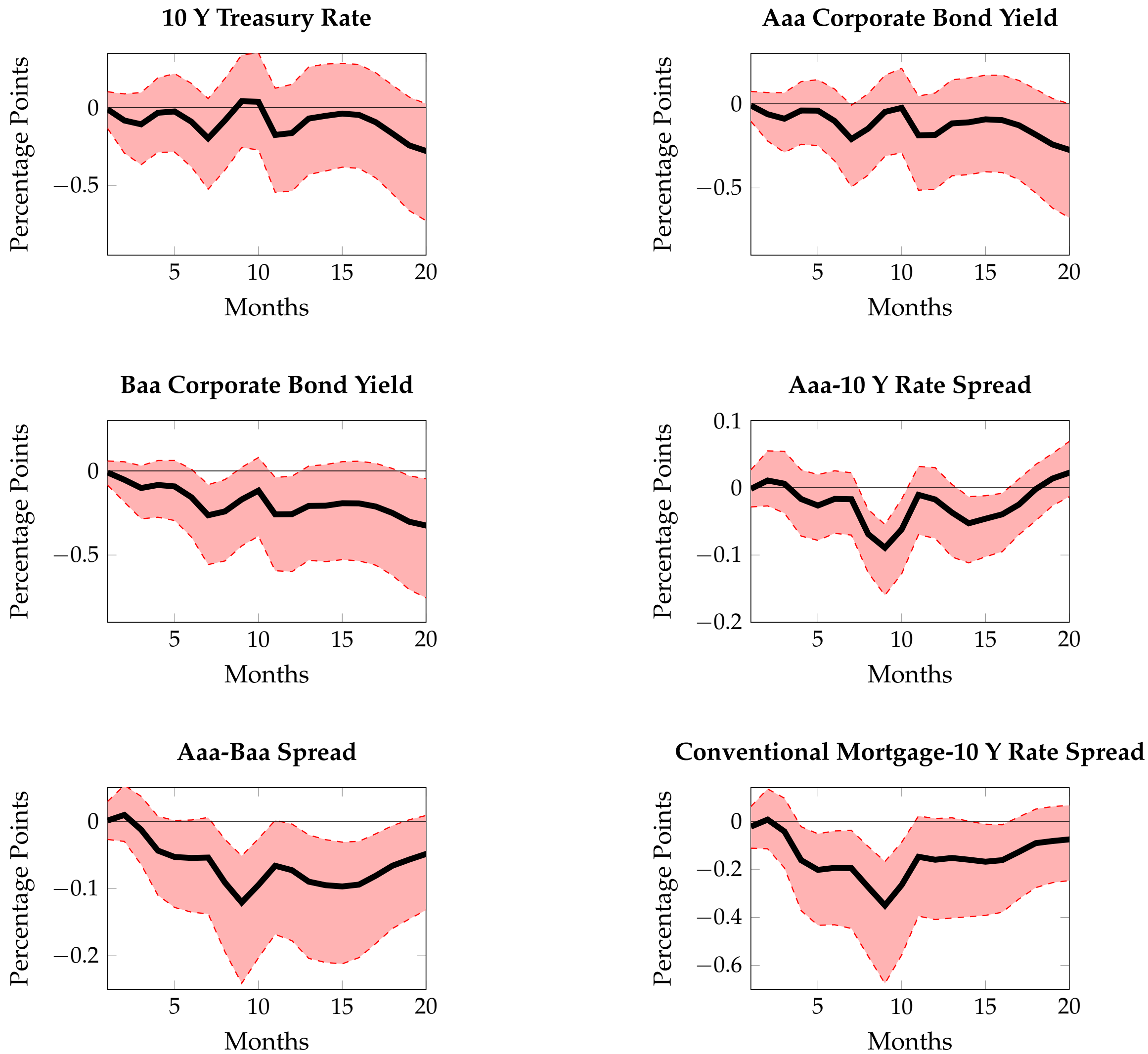
Federal Reserve: Data on MBS purchases using the trade date is available from the Board of Governors[9] and the Federal Reserve Bank of New York.

B Response of Other Financial Variables

Figure B.1 provides additional evidence on the impact of the credit supply shock on interest rates and credit spreads. The 10-year treasury rate remains relatively unchanged in the initial months, but as the full extent of agency mortgage purchases come into effect, it gradually begins to decrease, reaching statistical significance toward the end of the horizon at -0.4 percentage points after 19 months. We find that both AAA-rated and BAA-rated corporate bond yields exhibit a similar response to the mortgage rate. Initially, we observe almost no effect, followed by a gradual decline that becomes statistically significant after 6 and 7 months, respectively, at around negative 20 basis points. In the remaining three panels of the figure, we examine the spread between AAA-rated corporate bond rates and the 10-year Treasury rate, the spread between AAA-rated and BAA-rated corporate bond rates, and the spread between the conventional mortgage rate and the 10-year Treasury rate. All of these spreads respond negatively to the shock, with the peak effect occurring after 8 months. This is consistent with the positive spillover effect of agency purchases on the demand for longer-term bonds.

[9] https://www.federalreserve.gov/newsevents/reform_mbs.html

Figure B.1 – IRFs to a 1% Credit Supply Shock, Financial Variables.



Notes: FAVAR with Cholesky identification. Solid black lines: median. Shaded areas: 68 % credibility sets.