The Impact of Borrower-Based Macroprudential Tools: A Mesoeconometric Approach

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Abstract

This paper introduces a novel econometric framework, referred to as a mesoeconometric approach, which integrates a micro-level identification into a macroeconometric framework. The model is designed to assess the effects of borrower-based measures (BBMs) on the housing market, household credit and the broader economy. In the first step, we identify lending standards shocks using a structural vector autoregressive (SVAR) model, assuming they capture the contribution of BBMs following their implementation. We then leverage the heterogeneous effects of these measures across different segments of the lending standards distribution to isolate the portion of the shocks attributable to BBMs. We apply our framework to French data, evaluating the effects of the 2019 implementation of caps on the debt-service-to-income (DSTI) ratios and maturity of new housing loans. Overall, our framework serves as a valuable tool for conducting *ex post* impact assessments of BBMs, even in data-constrained environments, and is readily adaptable to evaluate similar macroprudential policies in other settings.

Keywords: macroprudential policy, lending standards shocks, housing market, borrower-based measures

JEL Classifications: E44, G21, G28

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1. Introduction

The global financial crisis propelled household indebtedness to the forefront of policy debates. Governments and central banks around the world have begun implementing *borrower-based measures* (BBMs) to contain excessive credit growth and safeguard financial stability, using tools such as caps to debt-service-to-income (DSTI) ratios, loan-to-value (LTV) or loan maturity. Yet, little is known about the macroeconomic effects of these measures in practice. Are BBMs successful in restraining housing loan volumes and tempering house price growth? How do they affect borrowing rates, and do they impose unintended constraints on the real economy or credit access?

Contribution. To address these questions, we propose a novel two-step empirical framework that quantifies the aggregate effects of BBMs by exploiting their heterogeneous impact across the distribution of new housing loans. We refer to this methodology as a *mesoeconometric strategy*, which lies at the intersection of macroeconometric and microeconometric analysis. In December 2019, amid growing vulnerabilities in the French housing loan market, the High Council for Financial Stability (HCSF)—France's macroprudential authority—gradually introduced recommendations to limit DSTI ratios and loan maturities at origination, eventually making these guidelines legally binding, with further adjustments implemented in the years following their adoption. This phased implementation strategy creates a unique setting in which the evolving measure can be interpreted as a continuous lending standards shock affecting some segments of the new housing loan distribution while leaving others largely unaltered.

In the first stage of our strategy, we construct an instrumental variable for lending standards shocks using responses from French banks to a quarterly euro area survey on housing loan lending standards. This instrument is then incorporated into a macroeconomic vector autoregression (VAR) model to capture exogenous shifts in lending conditions. In the second stage, we exploit heterogeneity in the evolution of the borrower distribution, more specifically, the differential impact on loans with high DSTI or long maturities that were targeted by the measure, in order to isolate the component of the lending standards shock directly attributable to BBMs. Drawing on our two-step strategy, we estimate the dynamic causal effects of BBM shocks on housing loan volumes, borrowing rates, and house prices.

Results. Our empirical analysis yields several key findings regarding the effects of lending standards shocks on the French housing market. First, our impulse response analysis indicates that a contractionary lending standards shock is associated with an immediate and statistically significant increase in housing loan borrowing costs, along with a gradual decline in outstanding housing loan amounts. These patterns observed in household credit translate into lower house price growth. The effects of lending standards shocks on the broader economy are somewhat less precisely estimated, but our results tend to indicate a moderate impact on residential investment growth and household real income growth. Using forecast variance ratio analysis, we confirm that lending standards shocks account for a significant share of the total variation in housing price and loan dynamics.

To ensure the robustness of these results, we compare impulse responses obtained from our benchmark external instrument approach, where we use the recoverability-based instrument (Plagborg-Møller and Wolf, 2022), with those derived from an alternative internal instrument approach that relaxes the invertibility and recoverability assumptions. The impulse responses from both approaches are very similar, although the confidence intervals in the recoverability-based specification are notably narrower. This consistency reinforces our identification strategy, suggesting that even if the lending standards shock is not strictly invertible, it remains recoverable and can be reliably measured.

Turning to the effects of the BBM-induced lending standards shocks, historical decompositions indicate that they contributed to mitigating housing loan growth in France, although their contribution appears relatively small compared to other drivers of housing loan dynamics. Similarly, we observe limited effects on house prices, which tend to fade towards the end of the sample period. Interestingly, the estimated impacts on residential investment growth and real income growth are also limited, suggesting that the macroeconomic costs associated with the measure are marginal. These results confirm that such tools can enhance the safety of credit markets by tightening lending standards without adversely affecting credit access and overall demand. Our robustness exercises, however, indicate that further work could strengthen the precision in determining the magnitude of BBM effects.

Related Literature. Our paper contributes to the extensive literature evaluating the effects of policy responses to financial crises, particularly those aimed at mitigating household indebtedness growth, by examining the macroeconomic implications of BBMs. In doing so, we bridge the gap between micro-level evidence from individual-level data and the aggregate outcomes captured by macroeconomic models. Prior studies have highlighted the role of household leverage in fueling asset price bubbles before the Global Financial Crisis (Eggertsson and Krugman, 2012; Mian and Sufi, 2011a; Mian et al., 2013) and its impact on consumer spending in the aftermath (Mian and Sufi, 2014). The post-crisis policy response in the United States, which has included both ex post mortgage restructuring programs (Agarwal et al., 2017; Mayer et al., 2014) and ex ante leverage caps (Bianchi and Mendoza, 2010; Farhi and Werning, 2013; Korinek and Simsek, 2016), serves as a backdrop to our investigation. Similar measures have been adopted in Europe and elsewhere. Recent contributions using administrative data (van Bekkum et al., 2024) have evaluated the real effects of borrower-based macroprudential policies at the household level. Our objective is to focus on their aggregate consequences, namely their transmission through the credit market to affect aggregate demand, house prices, and overall economic activity.

Recent structural macroeconomic models have attempted to better incorporate the heterogeneous nature of borrower constraints. For example, a DSGE model with heterogeneous agents and LTV as well as payment-to-income (PTI) constraints (Greenwald, 2018) underscores the importance of the mortgage credit channel in macroeconomic transmission. However, these models often rely on strong simplifying assumptions that limit their data-driven policy assessments. Collectively, these studies underscore the need for a comprehensive approach that captures the interplay between micro-level borrower restrictions and macro-level outcomes.

Our methodology builds on recent advances in macroeconometric modeling that identify structural shocks and quantify their effects even under noninvertibility (Plagborg-Møller and Wolf, 2022). To identify our lending standards shocks, we extend the approach developed by Bassett et al. (2014) and Altavilla et al. (2019), leveraging qualitative "soft" information from banks' survey responses on lending standards to isolate exogenous variations in lending standards.

Roadmap. The paper proceeds as follows. In Section 2., we describe the institutional background underlying the implementation of the French housing loan BBM. Section 3. outlines the construction of the proxy for lending standards that serves as our instrumental variable in the VAR model detailed in Section 4.. Section 5. presents our empirical results on the aggregate effects of lending standards shocks and BBMs. Section 6. concludes.

2. Institutional Background of the French Borrower-Based Measure

Pre-2019 Motivations for the HCSF's Measure. Excessive credit growth, particularly in the housing sector, has been shown to heighten systemic risks by making households more vulnerable to economic shocks, such as income fluctuations or housing price declines (Mian and Sufi (2011b); Jorda et al. (2015)). Research emphasizes the procyclical nature of housing credit and its role in amplifying economic cycles, leading to more pronounced financial instability during downturns (see Schularick and Taylor (2012)). At the same time, the importance of macroprudential policies, such as limiting LTV and DSTI ratios, in curbing housing market imbalances and improving financial resilience has been well-documented. In 2019, the HCSF, the French macroprudential authority, published a diagnostic report on the risks associated with residential real estate, revealing that the housing market had been characterized for several years by a progressive loosening of lending conditions. This loosening was notably seen in the rising DSTI ratios and the growing maturity of loans. The proportion of new housing loans with a DSTI exceeding 35% maturities longer than 25 years at origination increased significantly after 2015. Such practices increased the vulnerability of households, making their ability to repay more sensitive to adverse income shocks, thus raising the risk of default. The easing of lending standards also contributed to the significant growth in household indebtedness, increasing the economy's sensitivity to macroeconomic shocks.

Description, Scope and Timeline of the Measure. In response, the HCSF sought to limit the build-up of systemic risks by implementing a set of macroprudential measures to tighten the conditions for housing loan origination. Initially introduced as a recommendation in December 2019, the HCSF then adopted a legally binding norm in January 2022 (see Figure 1). This norm is in its most recent form based on two key criteria: (i) the DSTI ratio of borrowers should not exceed 35%, and (ii) the maturity of housing loans should not exceed 25 years. These measures, referred to as income borrower-based measures (I-BBMs), were designed to improve the sustainability of household debt by ensuring that borrowers are not overly burdened by excessive debt servicing obligations.

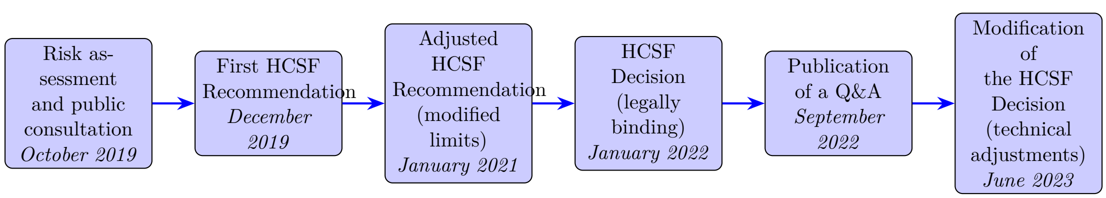


Figure 1: Timeline of the HCSF measure related to credit standards for housing loans

The HCSF's decision to target the DSTI ratio, rather than using an alternative tool like the LTV ratio, was based on several considerations. First, the DSTI ratio was already widely used by French banks to assess the borrower's ability to repay, making it a natural choice for regulatory action. Furthermore, the LTV ratio is inherently procyclical: when house prices rise, borrowing capacity increases, potentially leading to excessive debt accumulation during boom periods. The DSTI ratio, on the other hand, is more stable and directly reflects the borrower's income, providing a more effective tool to control lending in all market conditions. The DSTI ratio is calculated using (i) the maximum annual debt servicing over the duration of the loan and (ii) the borrower's income at the time the loan is originated, without any assumptions about future income increases. This ensures that the measure remains robust, even in the face of changes in household income over time.

Implementation and adjustments. The implementation of the measure was gradual, with the HCSF opting for a step-by-step approach to allow time for stakeholder feedback and adjustment. Given that this was the first macroprudential measure directly impacting households in France, the HCSF initially introduced it as a non-binding recommendation in December 2019. This recommendation tested the adequacy of a 33% DSTI limit, a 25-year maturity limit, and a 15% flexibility margin. After assessing the initial impact, the HCSF revised the recommendation in January 2021, slightly raising the DSTI limit to 35% and increasing the flexibility margin to 20%. The recommendation became legally binding in January 2022. In 2023, the HCSF introduced technical adjustments to address implementation challenges faced by banks, without altering the measure's main thresholds.

3. A Proxy for Housing Loan Lending Standards Shocks

The first step in our empirical strategy is to construct a proxy variable that aims at capturing exogenous variations in lending standards for housing loans. Properly identifying the macroeconomic consequences of lending standards conditions requires disentangling supply-driven variations from fluctuations induced by borrower demand and wider macro-financial factors. To this end, we draw on the euro area Bank Lending Survey (BLS), which provides timely, bank-level information on changes in credit standards (see Ciccarelli et al., 2013, 2015; Altavilla et al., 2019; Bassett et al., 2014).

3.1. The Bank Lending Survey

A central question in the BLS asks to a representative sample of euro area banks:

> *"Over the past three months, how have your bank's credit standards as applied to the approval of loans to households changed?"*
> *(Possible answers: tightened considerably, tightened somewhat, remained basically unchanged, eased somewhat, eased considerably.)*

Responses to this question offer rich, soft information that can capture changes in banks' lending behavior. In particular, and following Lown and Morgan (2006) and Bassett et al. (2014), we derive from these qualitative responses a raw net diffusion index (NDI), often interpreted as an indicator of lending standards conditions. Specifically, the NDI is computed as

$$\mathrm{NDI}_t \;=\; \Big(\%\text{ of banks reporting tightening at }t\Big) \;-\; \Big(\%\text{ of banks reporting easing at }t\Big). \tag{1}$$

Endogenity concerns. A simple NDI can conflate supply- and demand-driven factors. A high positive value of the NDI may, for example, reflect a deterioration in borrower quality and a consequent drop in demand rather than an exogenous contraction in the willingness of banks to lend. This limitation underscores the importance of carefully purging from the responses those influences stemming from banks' internal conditions, macroeconomic fluctuations or borrower demand. Controlling for demand factors is essential, given that the NDI for banks' perceived credit loosening or tightening exhibits a significantly negative correlation (–0.36) with the NDI for housing loan demand, as shown in Figure 2.

3.2. Exogenous Changes in Lending Standards

Following the methodology of Bassett et al. (2014), Altavilla et al. (2019), and related work (e.g., Ciccarelli et al., 2013; Lown and Morgan, 2006), we address this concern by estimating a linear model that relates the bank-level BLS responses to demand factors as reported in other questions of the BLS as well as a wide range of bank-specific and macroeconomic variables. In principle, the BLS's question yields five categories, ranging from *"tightened considerably"* to *"eased considerably"*. However, in practice, we follow Altavilla et al. (2019) by collapsing these five responses into three broader bins: *"tightening," "neutral,"* and *"easing."* Specifically, we group *"tightened considerably"* and *"tightened somewhat"* together as *"tightening," "eased somewhat"* and *"eased considerably"* as *"easing,"* and retain *"basically unchanged"* as *"neutral."* This simplification is motivated by the empirical distribution of BLS's individuals replies, which are largely concentrated in three main outcome categories as shown in Figures 3 .

Accordingly, we define for each bank i in our sample and for quarter t a variable

$$D_{i,t}^{CS} \in \{-1, 0, +1\},$$

where -1 indicates easing, 0 is neutral, and $+1$ represents tightening. By collapsing the

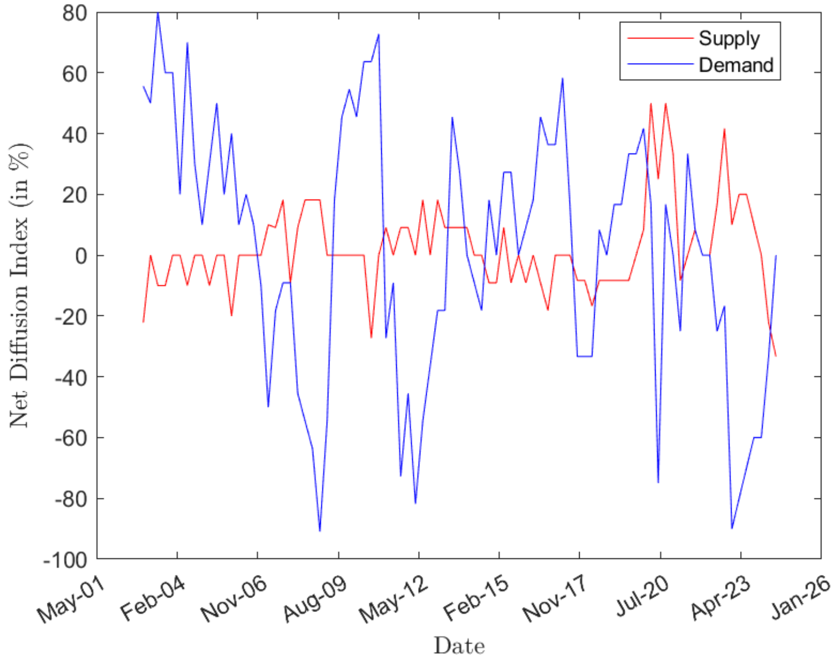


Figure 2: Evolution of the net diffusion index regarding credit standards on the supply side and demand factors.
Note: The figure reports the results on lending standards and demand contained in the bank lending survey for France. The red line depicts the change in overall bank lending standards (net tightening); the blue line depicts the diffusion index for overall loan demand. A positive value of the diffusion index indicates a net tightening/increase in credit standards/demand, while a negative value indicates a net easing/decrease in credit standards/demand. The sample period extends from Q4 2002 to Q2 2024.

detailed responses into three categories, we retain key information on whether conditions have tightened, loosened, or remained unchanged. We compute the moving average over four quarters of this indicator to smooth out short-term fluctuations.

We then estimate the following model:

$$D_{i,t}^{CS,ma} = \beta_i + \boldsymbol{\beta}_1 \mathbf{W}_t + \beta_2 D_{i,t}^{Demand,ma} + \nu_{i,t}, \tag{2}$$

where $D_{i,t}^{CS,ma}$ is the four-quarter moving average of banks' behavior regarding lending standards. Similar to Altavilla et al. (2019), $\mathbf{W}_t$ is a vector of macro-financial controls containing real GDP growth, yearly change in unemployment rate, quarterly change in short-term interest rate, and change in the VSTOXX. These controls are chosen to capture the state or the changes in the macroeconomic and financial environment. In the spirit of Bassett et al. (2014), we include the four-quarter moving average of the BLS-based measures of credit demand perceived by bank i at quarter t ($D_{i,t}^{Demand,ma}$). The model also includes bank fixed

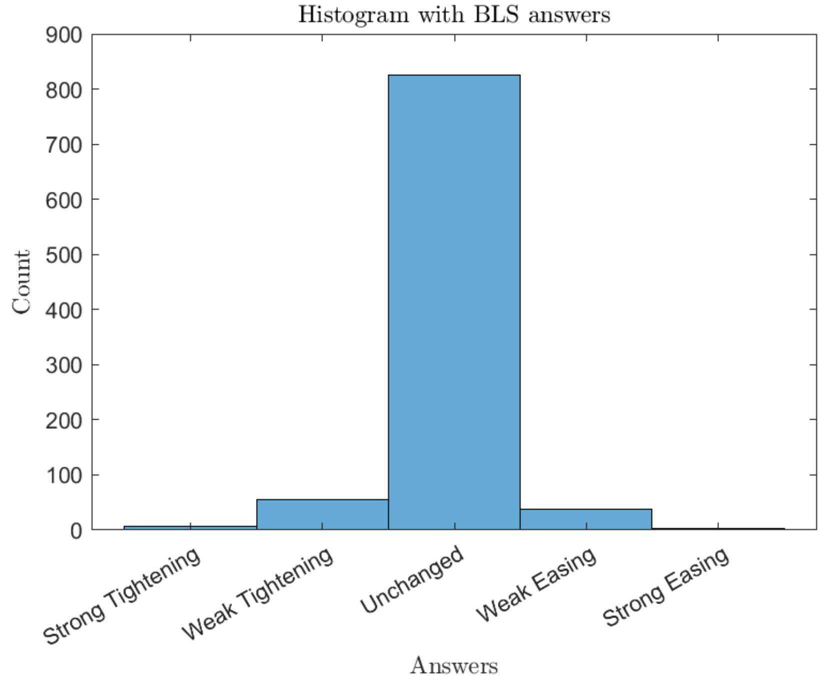


Figure 3: Histogram of the Bank Lending Survey's answers from French banks regarding the evolution of perceived credit standards.
Note: The figure shows the distribution of responses on perceived housing loan credit standards provided by all French banks participating in the euro area Bank Lending Survey, covering the period from Q4 2002 to Q2 2024.

effects.

By controlling for macroeconomic fundamentals and indicators of borrower demand, we isolate the portion of banks' reported credit standards that is not attributable to these confounding factors and allow us to be confident in our claim that we are only capture some metrics related to lending standards shocks. This residual can be viewed as an *exogenous* lending standards shock, akin to a quasi-random "treatment" when holding observable factors constant (Imbens, 2004). Altavilla et al. (2019) adopt an inverse propensity score re-weighting technique for the same purpose, while others (Ciccarelli et al., 2013; Bassett et al., 2014) match bank-level BLS answers with individual bank balance sheet data to net out structural heterogeneity. Once the model is estimated, the gap between each individual bank's actual answer and the fitted probability from the observed covariates provides a natural candidate for capturing orthogonal movements in lending standards. We then aggregate these bank-level residuals to obtain a single measure at the country level.

3.3. Estimation and construction of the housing lending standards proxy

Table 1 presents the estimation results for our OLS specification, where the dependent variable is the four-quarter moving average of banks' answers regarding credit standards. All regressions absorb bank fixed effects to account for time-invariant differences in banks' lending standards perceptions or practices and cluster standard errors at the bank level.

Table 1: OLS Regression on the Four-Quarter Moving Average of Credit Standards

	(1)
Demand (4q movav)	0.1219***
	(0.0151)
Real GDP Growth	–0.9157***
	(0.2760)
Change in Unemployment Rate	0.0239**
	(0.0104)
Short-term Rate Change	0.0308***
	(0.0095)
VSTOXX Change	0.0006
	(0.0008)
Constant	0.0415***
	(0.0073)
Bank Fixed Effects	Yes
Observations	916
F(5, 899)	19.82
Prob > F	0.0000
R-squared	0.1754
Adj. R-squared	0.1608
Root MSE	0.1980

Notes: Sample period: Q4 2002–Q2 2024. Number of banks = 12. The dependent variable is the four-quarter moving average of the credit standards, Demand (4q movav). All estimations are ordinary least squares (OLS) regressions with standard errors clustered by bank (in parentheses). Coefficients appear on the first row, with robust (clustered) standard errors on the second row. Asterisks denote significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Bank fixed effects are included but not reported in the table.

A higher value of the demand index ("Demand (4q movav)") is associated with tighter credit standards, as indicated by the positive and significant coefficient. Conversely, stronger real activity (proxied by "Real GDP Growth") reduces net tightening. The impact of labor market conditions ("Change in Unemployment Rate") and short-term rate changes is also statistically significant and consistent with the notion that higher rates or weaker labor market conditions coincide with somewhat tighter credit standards. The coefficient on the "VSTOXX Change" is small and not statistically significant, suggesting that once other macroeconomic and demand factors are controlled for, volatility plays a limited role in explaining changes in credit standards on housing loans.

Our instrumental variable, Z_t, that will serve as the instrumental variable in our VAR model, is constructed by aggregating the individual bank-level shocks according to:

$$Z_t = \sum_{i=1}^{I} \omega_{i,t} \times \hat{\nu}_{i,t}, \tag{3}$$

where I is the number of banks in our sample ($I = 12$), $\hat{\nu}_{i,t}$ correspond to the estimated residuals in Equation 2 and $\omega_{i,t}$'s are the weights assigned to each bank in the sample. For simplicity, we assumed an equally-weighted sum of the residuals.

Figure 4 shows our estimates of exogenous lending standards changes as estimated and aggregated from equations 2 and 3. A positive value of this proxy means a tightening of lending standards. The estimates show that lending standards have tightened remarkably alongside the introduction of the BBM measure in 2020Q1. It also shows that lending standards somewhat tightened around the 2008 financial crisis period.

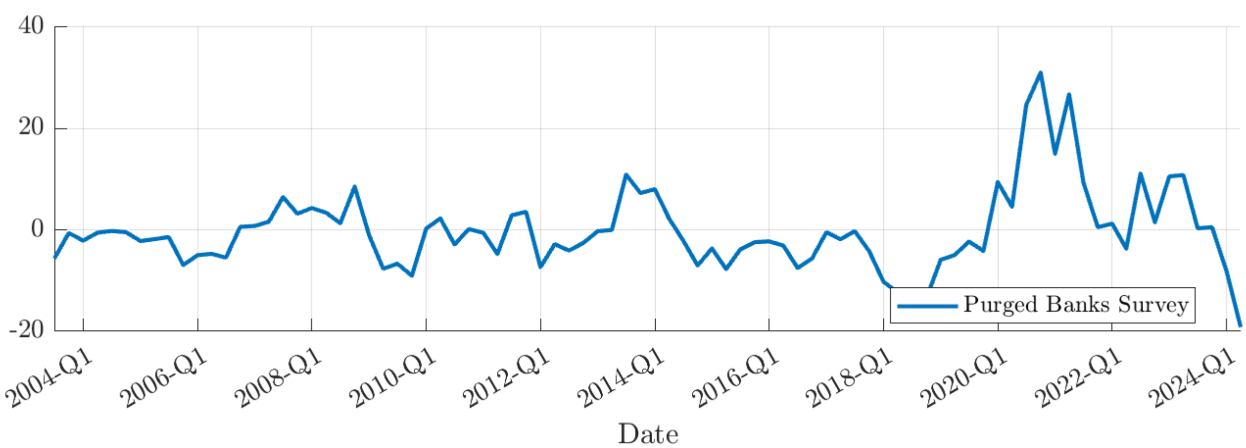


Figure 4: An Estimated Proxy for lending standards Shocks

4. Baseline Econometric Framework

We begin by specifying our econometric framework, which is based on a vector autoregression (VAR) model incorporating French macroeconomic financial variables specific to the housing and housing loan markets. The choice of a VAR model is primarily motivated by the relatively short sample period, which precludes the use of alternative approaches such as Jordà (2005)'s local projection method (Jorda et al. (2015), Ramey and Zubairy (2018)), as these require estimating separate instrumental variable regressions for each impulse horizon.

Our empirical strategy unfolds in two steps to identify lending standards shocks that can be attributed to borrower-based measures. First, we isolate lending standards shocks, regardless of whether they stem from borrower-based policies. To this end, we employ a proxy variable derived from French banks' responses to the Bank Lending Survey (BLS), as previously discussed. While the BLS is a useful proxy, it may contain measurement error and should not be interpreted as a direct measure of lending standards shocks (see Stock and Watson (2018)). Consequently, we use it as an instrument in our VAR model rather than a direct shock.

In the second step, we leverage a parsimonious econometric model to extract the component of lending standards shocks specifically attributable to the borrower-based measure. This is achieved by examining differential dynamics across segments of new housing loan issuance - comparing those directly targeted by the policy intervention with those left unaffected.

4.1. Specification of our VAR Model

We consider the following VAR model to capture the dynamic relationships between French housing market variables:

$$\mathbf{y}_t \;=\; \mathbf{b} \;+\; \sum_{k=1}^{p} \mathbf{A}_k \, \mathbf{y}_{t-k} \;+\; \sum_{l=0}^{q} \mathbf{B}_l \, \mathbf{x}_{t-l} \;+\; \mathbf{u}_t, \tag{4}$$

where p is the lag order, $\mathbf{y}_t$ is a $n_y \times 1$ vector of endogenous variables, $\mathbf{x}_t$ is a $n_x \times 1$ vector of exogenous variables, $\mathbf{u}_t$ is a $n_y \times 1$ vector of reduced-form innovations with covariance matrix $Var(u_t) = \Sigma$, b is a $n_y \times 1$ vector of constants, $\mathbf{A}_1, \cdots, \mathbf{A}_p$ are $n_y \times n_y$ autoregressive matrices and $\mathbf{B}_0, \cdots, \mathbf{B}_q$ are $n_y \times n_x$ matrices.

The endogenous vector $\mathbf{y}_t$ comprises six variables that capture both supply- and demand-side dynamics in the housing and housing loan markets: real residential investment, real house prices, real outstanding housing credit, nominal housing loan lending rates, real household disposable income, and real GDP. Together, these variables reflect bank lending behavior, households' financing costs and purchasing power, and overall housing market conditions. The model includes one exogenous variable, $\mathbf{x}_t$: the 10-year government bond yield, which serves as a proxy for banks' long-term funding costs.

All variables are expressed in first differences of logarithms, except for the housing loan lending rate and the 10-year government bond yield, which are included in levels. In all estimations, we employ four lags for both the endogenous and exogenous variables in Equation (4).

Invertibility. Conventional SVAR models implicitly assume invertibility. The system is said to be invertible with respect to the endogenous vector $\mathbf{y}_t$ if the number, n_ε, of underlying structural shocks, $\boldsymbol{\varepsilon}_t$, is the same as the number of endogenous variables, n_y, and if the shocks are spanned by current and past values of the endogenous variables (see Plagborg-Møller and Wolf (2022) for further details). In such a setting, and under the reasonable assumption that the chosen lag order is correctly specified, the reduced-form innovations $\mathbf{u}_t$ can be expressed as linear combinations of the underlying structural shocks:

$$\mathbf{u}_t = \mathbf{S}\,\boldsymbol{\varepsilon}_t, \tag{5}$$

where $\boldsymbol{\varepsilon}_t$ is an $n_y \times 1$ vector of mutually uncorrelated *structural* shocks, i.e. $\mathrm{E}[\boldsymbol{\varepsilon}_t] = 0$ and $\mathrm{Var}(\boldsymbol{\varepsilon}_t) = \boldsymbol{\Omega}$ where $\boldsymbol{\Omega}$ is diagonal, and $\mathbf{S}$ is the *impact matrix* that maps each structural shock into the reduced-form innovations $\mathbf{u}_t$. From $\boldsymbol{\Sigma} = \boldsymbol{S}\,\boldsymbol{\Omega}\,\boldsymbol{S}'$, each column of $\mathbf{S}$ can be interpreted as the immediate effect of each structural shock on the endogenous variables in $\mathbf{y}_t$.

Among these structural shocks, we focus on the *lending standards shock*. Without loss of generality, let $\boldsymbol{\varepsilon}_{1,t}$ denote this shock, and let $\mathbf{s}_1$ be the first column of $\mathbf{S}$. Identifying $\mathbf{s}_1$ allows us to trace the impact of an exogenous change in lending standards on the endogenous variables in $\mathbf{y}_t$.

4.2. Identification of Housing Loan Lending Standards Shocks

We now turn to the identification of the structural shock related to housing loan lending standards.

External Instrument Approach. A widely used identification strategy in empirical macroeconomics is the *external instrument* approach. This method relies on the availability of a proxy variable that is correlated with the structural shock of interest. However, the approach is only valid under the condition that the shock is invertible.We assume we have access to a proxy variable for the structural shock, as defined in Equation (3).

Let us define $\tilde{Z}_t$ the residual obtained from regressing Z_t on its own lags, on the lags of the endogenous macroeconomic observables $\{\mathbf{y}_\tau\}_{-\infty<\tau<t}$ and on the lags of and the current values of the exogenous variables $\{\mathbf{x}_\tau\}_{-\infty<\tau\leq t}$. Formally, we define:

$$\tilde{Z}_t \equiv Z_t - \mathbb{E}\Big(Z_t \mid \{Z_\tau, y_\tau, x_\tau\}_{-\infty<\tau<t}, x_t\Big)$$

Here, we use $\tilde{Z}_t$ as an instrument for identification. For this variable to be a valid instrument, two key conditions must hold:

- **Relevance:** Our instrument, $\tilde{Z}_t$, must be correlated with the structural lending standards shock, i.e.,
$$\mathbb{E}[\tilde{Z}_t\, \varepsilon_{1,t}] = \alpha \neq 0. \tag{6}$$

- **Exogeneity:** Our instrument, $\tilde{Z}_t$, must be orthogonal to all the other structural shocks of our model, i.e.,
$$\mathbb{E}[\tilde{Z}_t\, \varepsilon_{j,t}] = 0, \quad \forall j \neq 1. \tag{7}$$

Together with the invertibility assumption in (5), these conditions imply that our instrument can be expressed as a linear combination of the structural shock of interest and a measurement error:

$$\tilde{Z}_t = a\, \varepsilon_{1,t} + j_\chi\, \chi_t, \quad \forall t, \tag{8}$$

where a is a scale parameter, j_χ is a non-negative scalar capturing the loading of the proxy variable on the measurement error, χ_t.

In practice, we estimate the relationship between the reduced-form residuals $\mathbf{u}_t$ and the structural shock $\varepsilon_{1,t}$ - that is, the first column of the impact matrix, $\mathbf{s}_1$- using a two-stage least squares (2SLS) procedure (see Mertens and Ravn, 2013). Specifically, we regress the estimated reduced-form residuals, $\hat{\mathbf{u}}_t$ on $\hat{u}_{1,t}$ using $\tilde{Z}_t$ as an instrument. The procedure involves two stages: the first stage regresses the reduced-form residual of the first variable, $\hat{u}_{1,t}$, in the VAR on the external instrument; the second stage regresses the residuals of the remaining endogenous variables on the fitted values from the first stage. This yields an estimate of the structural impact vector, $\mathbf{s}_1$, which is proportional to the following moment ratio:

$$\mathbf{s}_1 \propto \frac{\mathbb{E}[\tilde{Z}_t \mathbf{u}_t]}{\mathbb{E}[\tilde{Z}_t u_{1,t}]} \tag{9}$$

This approach is only valid provided that $\mathbf{E}[\tilde{Z}_t u_{1,t}] \neq 0$ - in other words, that $\tilde{Z}_t$ is not a weak instrument for $u_{1,t}$. The instrument identifies the structural lending standards shock up to sign and scale. For interpretability, it is common to normalize the structural impact vector $\mathbf{s}_1$ such that a one-unit structural shock increases the first endogenous variable (e.g., a measure of credit volume) by exactly one unit. This normalization anchors the scale of the shock and aids in interpreting the dynamic responses of the system.

Although the external instrument approach can be highly efficient, it is susceptible bias if the system is non-invertible or if the instrument $\tilde{Z}_t$ is imperfectly measured and fails to fully capture lending standards fluctuations (see Stock and Watson, 2018; Mertens and Ravn, 2013). To ensure valid inference, we employ a residual-based moving block bootstrap as proposed by Jentsch and Lunsford (2019).

Internal Instrument Approach. An alternative identification strategy is the *internal instrument* approach, which relaxes the invertibility assumption in (5). In addition to satisfying the relevance and exogeneity conditions in (6) and (7), an internal instrument, Z_t, must also be orthogonal to all the leads and lags of all the structural shocks:

$$\mathbb{E}[Z_t \, \boldsymbol{\varepsilon}_{t+j}] = \mathbf{0}, \quad \forall j \neq 0.$$

Rather than treating Z_t as an external instrument, we incorporate it directly into the system of endogenous variables by augmenting the VAR and placing Z_t as the first variable in the ordering. Specifically, we define the augmented vector, $\bar{\boldsymbol{y}}_t$, as follows:

$$\bar{\boldsymbol{y}}_t = \begin{pmatrix} Z_t \\ \boldsymbol{y}_t \end{pmatrix}.$$

We perform a Cholesky decomposition on the covariance matrix $\boldsymbol{\Sigma}_{\bar{\boldsymbol{y}}}$ of $\bar{\boldsymbol{y}}_t$, denoted $\boldsymbol{\Sigma}^*$. To obtain the impulse responses functions regarding our structural shock of interest, we extract the first column of this decomposition, normalized by its first element:

$$\bar{\mathbf{s}}_1 = \frac{\boldsymbol{\Sigma}^*_{:,1}}{\boldsymbol{\Sigma}^*_{1,1}}.$$

This approach does not require us to assume invertibility of the original VAR in Equation (4). It remains valid even in the presence of measurement error in the instrument or if the shock is non-invertible (Ramey, 2011; Plagborg-Møller and Wolf, 2021).

Point Identification of the lending standards Shock. The external instrument strategy, while it assumes the invertibility of lending standards shocks, provides a point-identified series for the lending standards shock $\varepsilon_{1,t}$. Relaxing invertibility typically results in the loss of point identification for the structural shocks, to account for the potential measurement error of the instrument. In addition, the internal instrument approach—while robust to non-invertibility—only permits the estimation of relative impulse responses, and doesn't provide a point-identified series of the structural shock.

In this context, Plagborg-Møller and Wolf (2022) propose an identified set for the structural shock when the invertibility assumption is relaxed. An alternative way to achieve point identification is to impose the recoverability assumption—that is, the shock is not only spanned by current and past but also future values of the observed macroeconomic variables. Under recoverability, the shock can be identified as the projection of the instrument on the space spanned by these variables. Formally, we define by $\tilde{Z}_t^{\dagger}$ the cross-projection of $\tilde{Z}_t$ (our instrument residual) onto all leads and lags of the endogenous and exogenous variables, i.e. $\mathbf{y}_t$ and $\mathbf{x}_t$ as

$$\tilde{Z}_t^{\dagger} = E\Big(\tilde{Z}_t \mid \{y_\tau, x_\tau\}_{-\infty<\tau<\infty}\Big). \tag{10}$$

Then, if the shock is recoverable (i.e., if $E\Big(\varepsilon_{1,t} \mid \{y_\tau, x_\tau\}_{-\infty<\tau<\infty}\Big) = \varepsilon_{1,t}$), we can identify the shock up to scale as

$$\varepsilon_{1,t} = \frac{1}{a}\,\tilde{Z}_t^{\dagger}.$$

Benchmark Strategy. In order to choose a benchmark for our model, we test for the invertibility and recoverability of the lending standards shock using the procedure proposed by Plagborg-Møller and Wolf (2022) (see Appendix A1.). Although our test results reject the invertibility assumption at the 90% confidence level, they indicate that our lending standards shock is recoverable. In this regard, we adopt the recoverable model and use $\tilde{Z}_t^{\dagger}$ as our benchmark instrument for the lending standards shock. This instrument eliminates any measurement error in $\tilde{Z}_t$ as it corresponds to the projection of $\tilde{Z}_t$ onto current, lagged, and future values of the macroeconomic observables (as specified in Equation (10)). As a robustness check, we also present results using the internal instrument approach after relaxing both the invertibility and recoverability assumptions. Our main findings remain robust both qualitatively and quantitatively.

4.3. Identification of Macroprudential Policy Effects

In the second step of our framework, we decompose the lending standards shock series $\varepsilon_{1,t}$ into two distinct components in the period following the implementation of the measure: a regular bank-induced component and a BBM-induced component. To identify and recover these components, we impose three key identification assumptions.

Assumption 1 *Following the implementation of the borrower-based measure (BBM), the lending standards shock is assumed to consist of two additive components: one attributable to the BBM itself ("BBM-induced lending standards shock"), and the other reflecting regular bank-driven factors ("bank-induced lending standards shock").*

For periods prior to the implementation of the borrower-based measure (BBM), denoted by T^* (in our case, $T^* = 2020$:Q1), the observed shock is driven solely by the regular lending standards component, denoted $\widetilde{\varepsilon}_{1,t}$. For $t \geq T^*$, the observed shock is modeled as the sum of the regular component and an additional BBM-induced component, such that:

$$\varepsilon_{1,t} = \begin{cases} \widetilde{\varepsilon}_{1,t}, & t < T^*, \\ \widetilde{\varepsilon}_{1,t} + \varepsilon_{1,t}^{\mathrm{BBM}}, & t \geq T^*, \end{cases} \tag{11}$$

Assumption 2 *The BBM-induced component, $\varepsilon_{1,t}^{BBM}$, is assumed to affect only selected segments of the lending standards distribution.*

To isolate the BBM-induced component from the regular bank-induced component, we rely on the assumption that the macroprudential measure primarily affects credit volumes around the targeted regulatory thresholds. In particular, its influence is assumed to manifest in loans issued just above the thresholds, which are directly subject to the measure, as well as in loans just below the thresholds, due to a communicating-vessel effect. By contrast, credit volumes well below the thresholds are assumed to remain largely unaffected. This heterogeneous impact underpins a treatment-versus-control group identification strategy.

In the case of France, where the borrower-based measure targets both the debt service-to-income (DSTI) ratio and loan maturity, we identify two candidate *treatment groups*: i) the share of total loan volumes with a DSTI above 35%, and ii) the share with maturities exceeding 25 years. These segments are expected to be directly affected by the implementation of the BBM and to exhibit an immediate response. As control groups, we consider loans with a DSTI below 20% and those with maturities between 10 and 15 years—segments that are sufficiently distant from the regulatory thresholds and therefore likely to remain largely unaffected by the policy.

Figure 5 presents four aggregate series derived from our loan-level dataset. The top two panels show the share of newly issued loans exceeding the BBM's regulatory thresholds—specifically, loans with a DSTI above 35% and maturities beyond 25 years. These segments correspond to borrower groups most directly targeted by the policy. As illustrated, both series exhibit a sharp and immediate decline following the BBM announcement, reflecting a rapid adjustment in borrower lending capacity. This pattern suggests that borrowers close to the thresholds are compelled to respond swiftly by modifying loan terms to remain compliant. In contrast, the bottom two panels plot the shares of new loans with DSTI ratios below 20% and maturities between 10 and 15 years—groups located well below the policy thresholds. These series display relatively stable trends over time, supporting the assumption that borrower segments distant from the targeted thresholds were largely unaffected by the BBM.

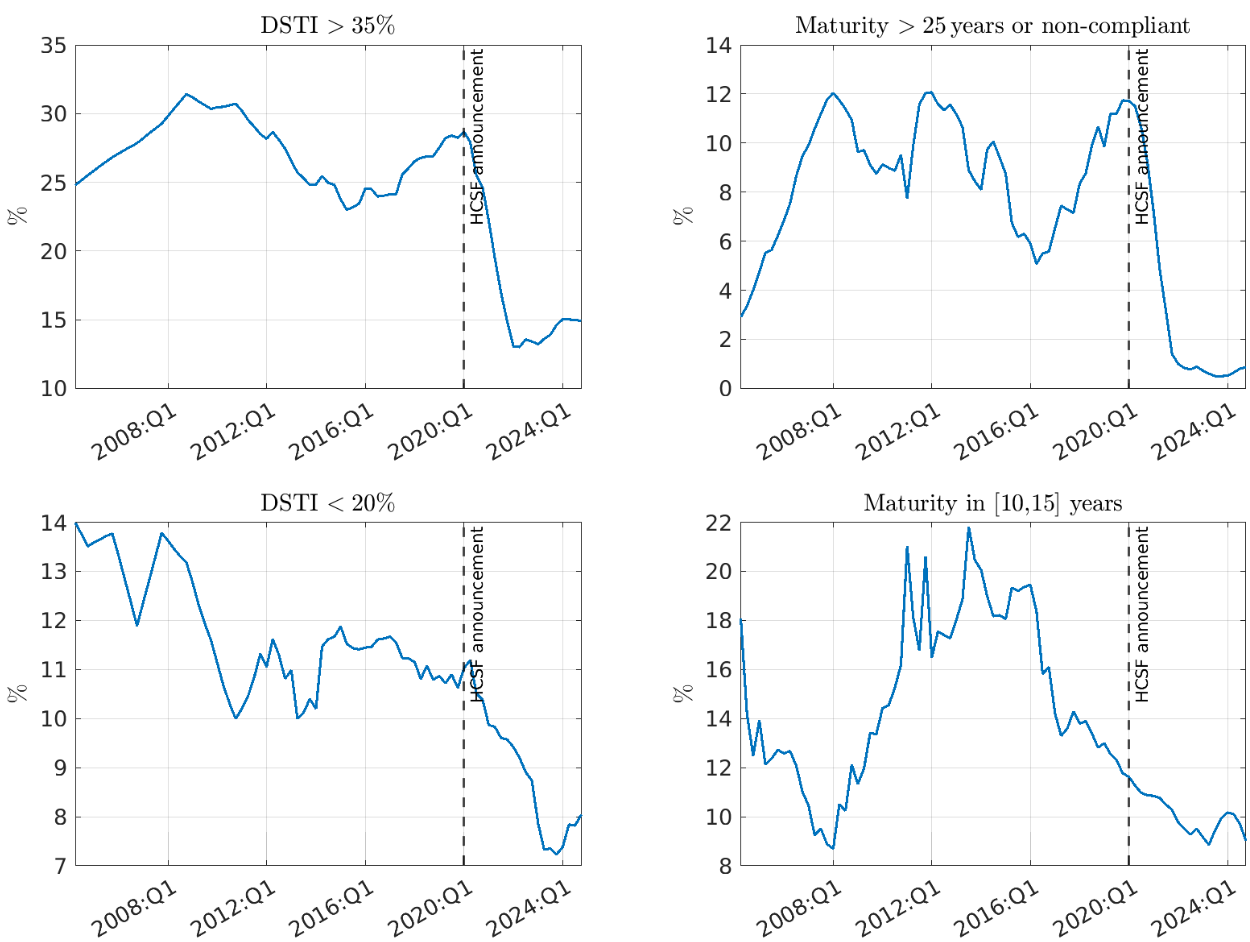


Figure 5: Distribution of lending standards.

For each borrower characteristic of interest, we denote the share of new loans in a given category by $f^j_{i,t}$, where i indexes the lending standard (DSTI ratio or maturity) and j identifies the group, either control (C) or treatment (T). We begin by modeling each series $f^j_{i,t}$ as the sum of its predictable component and an innovation:

$$f^j_{i,t} = E\left(f^j_{i,t} \,\middle|\, \{y_\tau, x_\tau, f^j_{i,\tau}\}_{\tau<t}\right) + \tilde{f}^j_{i,t}. \tag{12}$$

Here, $E\left(f^j_{i,t} \,\middle|\, \{y_\tau, x_\tau, f^j_{i,\tau}\}_{\tau<t}\right)$ is the component predicted from lagged macroeconomic variables (y_t and x_t) and past values of $f^j_{i,t}$. The innovation $\tilde{f}^j_{i,t}$ captures all unpredicted variations, including unforeseen macroeconomic shocks and structural lending standards shocks.

Next, we decompose the innovation $\tilde{f}^j_{i,t}$ into three components: one driven by the regular lending standards component, another attributable to the BBM-induced component, and a residual term capturing other macroeconomic disturbances. Formally, we posit that each purged series can be expressed as

$$\tilde{f}^j_{i,t} = \alpha^j_{i,1}\, \tilde{\epsilon}_{1,t} + \alpha^j_{i,2}\, \epsilon^{\text{BBM}}_{1,t} + \zeta^j_{i,t}, \tag{13}$$

where $\zeta^j_{i,t}$ represents the residual macroeconomic disturbances.

A key identifying assumption is that the control series are unaffected by the BBM-induced component after the policy implementation, such that:

$$E\left[\tilde{f}^C_{i,t}\, \epsilon^{\text{BBM}}_{1,t}\right] = 0 \tag{14}$$

whereas for the treatment series we allow:

$$E\left[\tilde{f}^T_{i,t}\, \epsilon^{\text{BBM}}_{1,t}\right] \neq 0 \tag{15}$$

Accordingly, the treatment series load on both $\tilde{\epsilon}_{1,t}$ and $\epsilon^{\text{BBM}}_{1,t}$, while the control series load solely on $\tilde{\epsilon}_{1,t}$.

Assumption 3 *The regular and BBM-induced components are constant multiples of the lending standards shocks*

We posit that the BBM component ($\epsilon^{\text{BBM}}_{1,t}$) corresponds to a constant multiple k of the lending standards shocks after the introduction of the measure, and zero beforhand:

$$\epsilon^{\text{BBM}}_{1,t} = \begin{cases} 0, & t < T^*, \\ k\, \epsilon_{1,t}, & t \geq T^*. \end{cases} \tag{16}$$

In combination with Equation (11), this implies that the regular lending standard component ($\widetilde{\epsilon}_{1,t}$) is also a scaled value of the lending standards shocks, with a constant factor $(1-k)$. As a robustness exercise, we provide an alternative estimation strategy in which we do not impose this final identifying assumption, in order to assess its influence on the results (see Appendix).

Closed-form solution This strategy relies on the identifying assumptions defined by equations (11), (14), (15) and (16). According to these assumptions, we can define two systems. In the pre-BBM period ($t < T^*$), we have the following equations:

$$\begin{cases} \tilde{f}^{C}_{\mathrm{i},t} = \alpha^{C}_{\mathrm{i},1}\, \epsilon_{1,t} + \zeta^{C}_{\mathrm{i},t}, \\ \tilde{f}^{T}_{\mathrm{i},t} = \alpha^{T}_{\mathrm{i},1}\, \epsilon_{1,t} + \zeta^{T}_{\mathrm{i},t}. \end{cases} \tag{17}$$

In the post-BBM period ($t \geq T^*$), the relationships are the following:

$$\begin{cases} \tilde{f}^{C}_{\mathrm{i},t} = \alpha^{C}_{\mathrm{i},1}\,(1-k)\, \epsilon_{1,t} + \zeta^{C}_{\mathrm{i},t}, \\ \tilde{f}^{T}_{\mathrm{i},t} = \left[\alpha^{T}_{\mathrm{i},1}\,(1-k) + \alpha^{T}_{\mathrm{i},2}\, k\right] \epsilon_{1,t} + \zeta^{T}_{\mathrm{i},t}. \end{cases} \tag{18}$$

By regressing $\tilde{f}^{C}_{\mathrm{i},t}$ and $\tilde{f}^{T}_{\mathrm{i},t}$ series on the lending standards shocks $\epsilon_{1,t}$ for the two sub-periods pre- and post-BBM, denoted *pre* and *post*, we obtain estimates of the parameters defined in equations (17) and (18). In particular, focusing on the control group, we can obtain the OLS estimates $\beta^{C}_{i,t}$, related to the paramaters of equations (17) and (18) as follows:

$$\begin{cases} \beta^{C}_{i,\mathrm{pre}} = \alpha^{C}_{i,1} \\ \beta^{C}_{i,\mathrm{post}} = \alpha^{C}_{i,1}\,(1-k) \end{cases}$$

Which gives us:

$$k \;=\; 1 \;-\; \frac{\beta^{C}_{i,\mathrm{post}}}{\beta^{C}_{i,\mathrm{pre}}}. \tag{19}$$

Equation (19) allows us to recover k and, eventually, the two components of the lending standards shocks $\epsilon^{\mathrm{BBM}}_{1,t}$ and $\widetilde{\epsilon}_{1,t}$, both directly related to k.

4.4. Estimation

Our sample covers the period from 2000Q1 to 2024Q4, with the instrumental variable (IV) period spanning from 2003Q3 to 2024Q2. Accordingly, our two-stage least squares (2SLS) regressions are performed over the period in which both the reduced-form residuals from

Equation (4) and the instrument are available (Miranda-Agrippino and Ricco, 2021; Känzig, 2021). For the internal instrument approach, missing values of the istrument are filled with zeros (McKay and Wolf, 2023). We use data about the distribution of lending standards from 2004Q1 to 2024Q4, in estimating the purged fraction series from the expected component (as specified in Equation (12)). We include four lags of the macroeconomic observables (i.e. vectors y_t and x_t) and past values of the fraction series $f_{i,t}$ to compute the innovation $\tilde{f}_{i,t}$.

5. Baseline Results

In this section, we present the main empirical findings of our study. We first report impulse response functions (IRFs) of the endogenous variables to a negative lending standards shock, followed by results on forecast variance ratios (FVRs). Finally, we discuss the historical importance of lending standards shocks and the specific macroeconomic effects of borrower-based macroprudential measures. We highlight the robustness of our benchmark strategy—which relies on an external instrument (using $\tilde{Z}_t^{\dagger}$) that assumes recoverability of the lending standards shock—by comparing it with results obtained from an internal instrument approach.

5.1. Impulse Responses to the Lending Standards Shock

Figure 6 displays the IRFs of the six endogenous variables to a one standard error contractionary lending standards shock. These impulse responses are estimated using our benchmark external instrument approach, which employs $\tilde{Z}_t^{\dagger}$ as an instrument. This instrument is derived by projecting $\tilde{Z}_t$ on current, past, and future values of the macroeconomic observables, thus assuming recoverability of the lending standards shock while relaxing the invertibility assumption. The figure indicates that a contractionary shock leads to a peak increase in the housing interest rate of approximately 0.10pp in the very first quarters. Higher borrowing costs are associated with a decline in housing loan growth (approximately 1.5pp at peak) that remains persistent, while residential investment growth declines by around 1pp after four quarters. The shock also exerts a notable impact on housing price growth. Household real income falls slightly on impact, reflecting a modest dampening of household purchasing power.

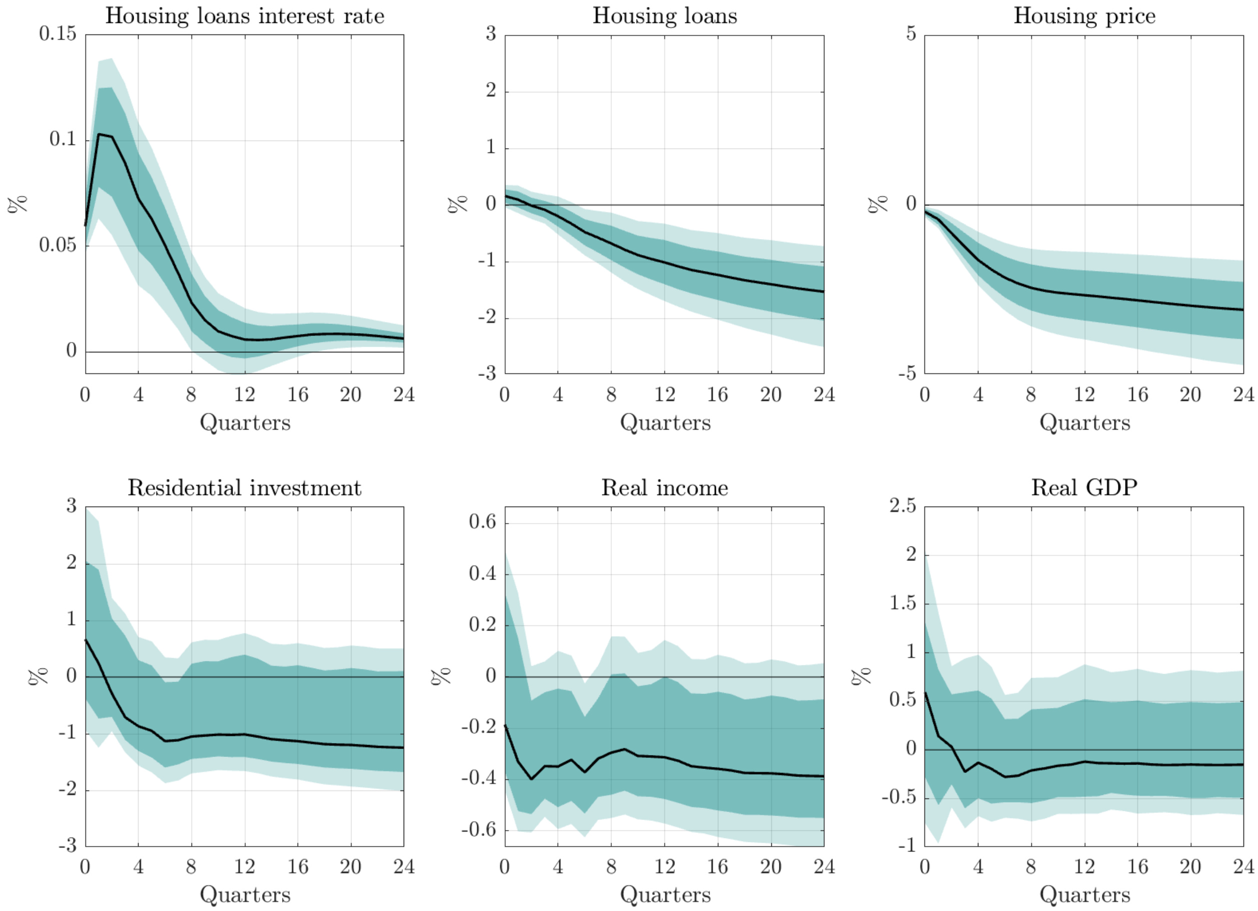


Figure 6: Impulse response functions to a one standard error contractionary lending standards shock. Black solid lines denote the point estimate; the shaded blue areas indicate the 16th–84th and 5th–95th percentile bands. The responses are estimated using an external instrument approach with $\tilde{Z}_t^{\dagger}$ as the instrument, which assumes recoverability of the lending standards shock.

Next, Figure 7 compares the IRFs of our benchmark external instrument approach with those obtained using an internal instrument approach. Although the internal instrument approach—relaxing both invertibility and recoverability—only yields relative impulse responses, the estimated responses are very similar to those from our benchmark strategy. This comparison confirms the robustness of our results.

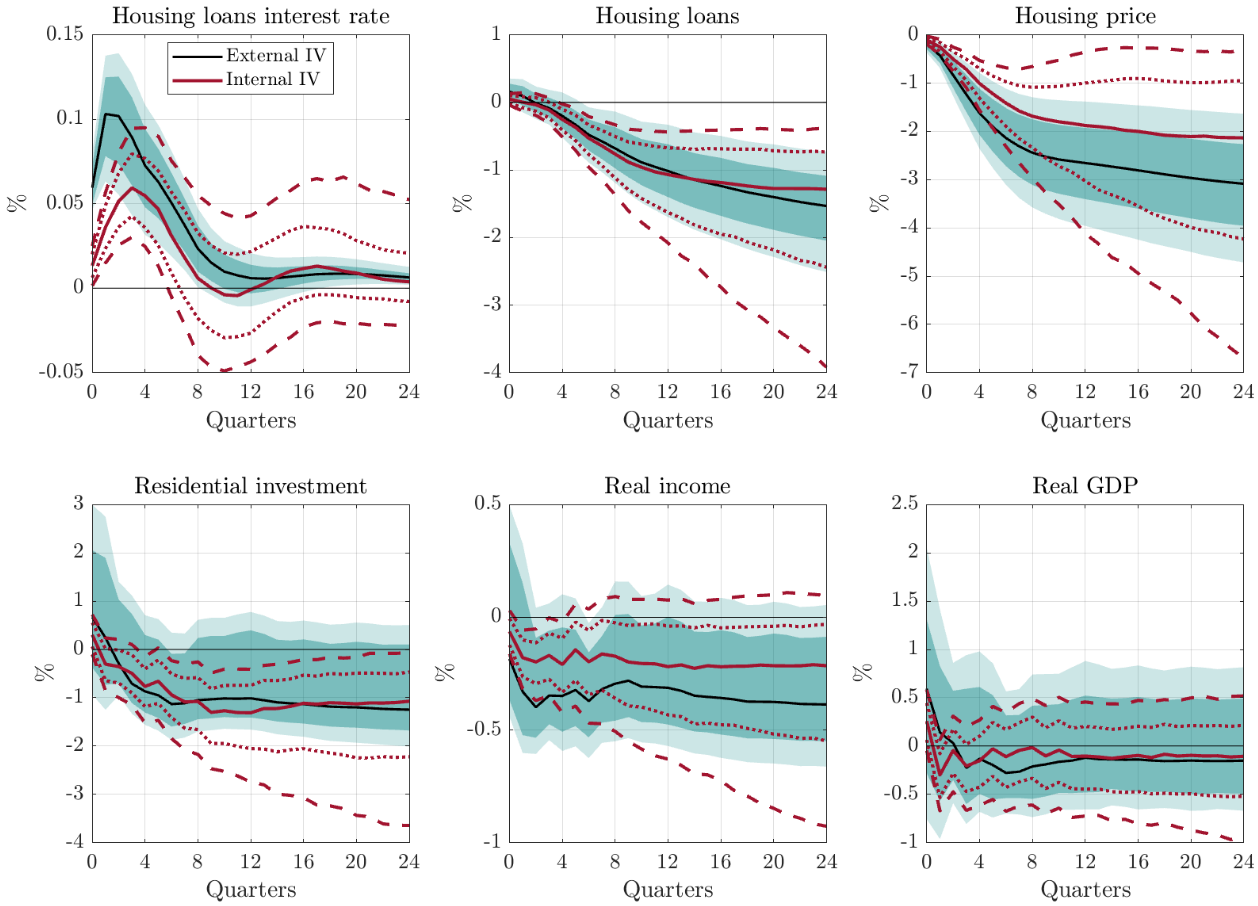


Figure 7: Impulse response functions to a contractionary lending standards shock: Black lines (with blue shaded bands) show the posterior median and confidence intervals from the benchmark external instrument approach using $\tilde{Z}_t^{\dagger}$, whereas red lines (with dashed and dotted red bands) represent results from the internal instrument approach.

5.2. Forecast Variance Ratio (FVR) Results

We estimate the forecast variance ratio using our benchmark structural vector autoregression with instrumental variable (SVAR-IV) approach. The FVR for variable i at horizon h is defined as

$$\mathrm{FVR}_{i,h} = 1 - \frac{\mathrm{Var}\Big(y_{i,t+h} \,\Big|\, \{y_\tau\}_{-\infty<\tau\leq t},\ \{\epsilon_{1,\tau}\}_{t<\tau<\infty}\Big)}{\mathrm{Var}\Big(y_{i,t+h} \,\Big|\, \{y_\tau\}_{-\infty<\tau\leq t}\Big)}. \tag{20}$$

This ratio measures the reduction in forecast uncertainty about $y_{i,t+h}$ when the entire future path of the lending standards shock $\epsilon_{1,\tau}$ is known.

Figure 8 presents the FVR estimates from our benchmark model. The results indicate that lending standards shocks account for a substantial share of the variation in housing price growth, while their explanatory power for the other macroeconomic variables is more modest. Additional results using a structural vector moving average with instrumental variable (SVMA-IV) specification (which relaxes the assumptions of invertibility and recoverability) are reported in Appendix C2..

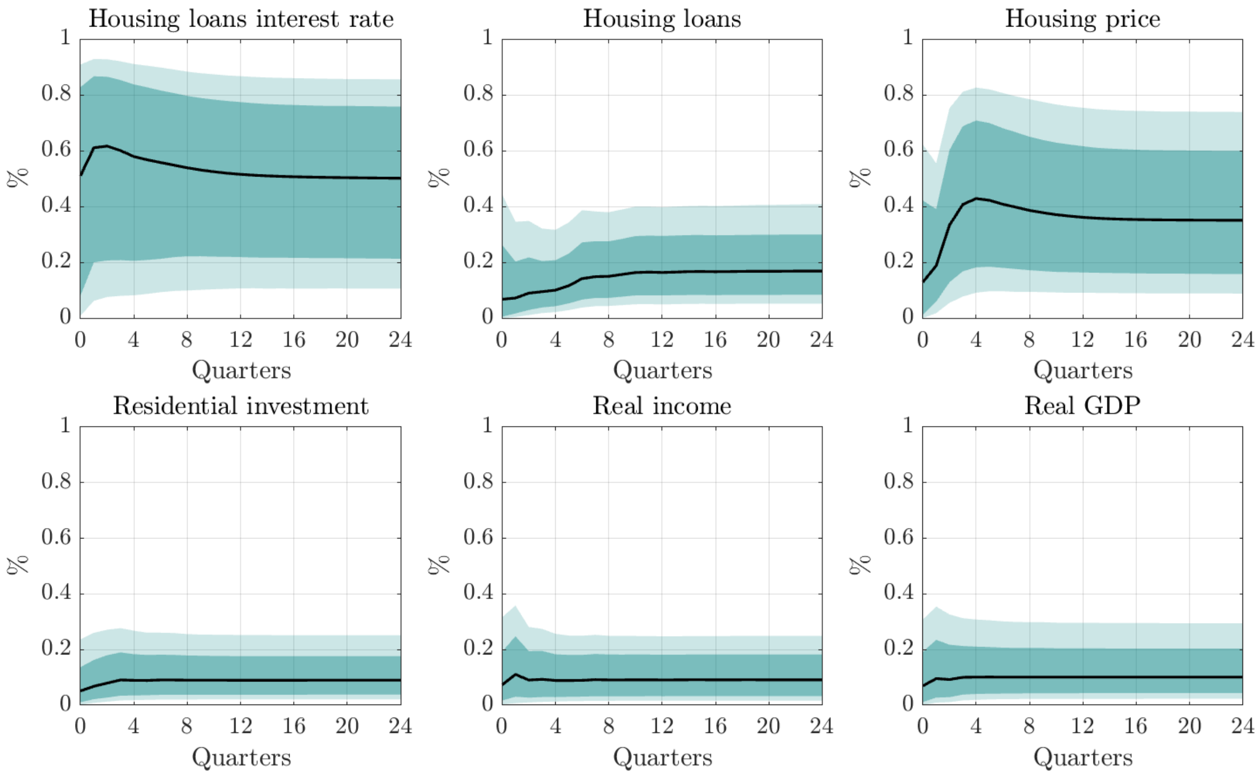
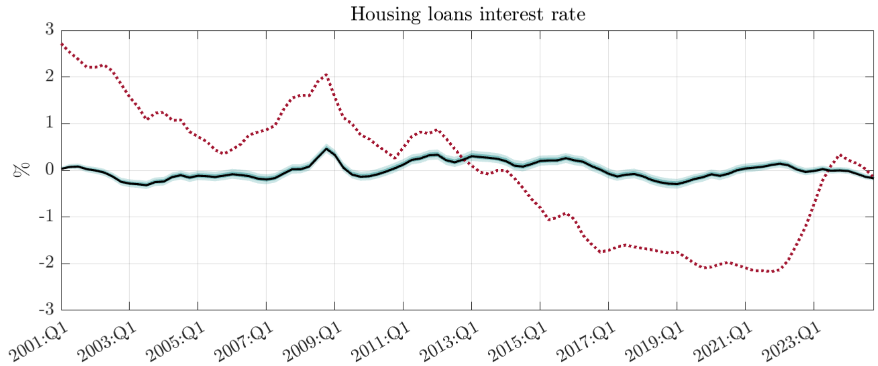


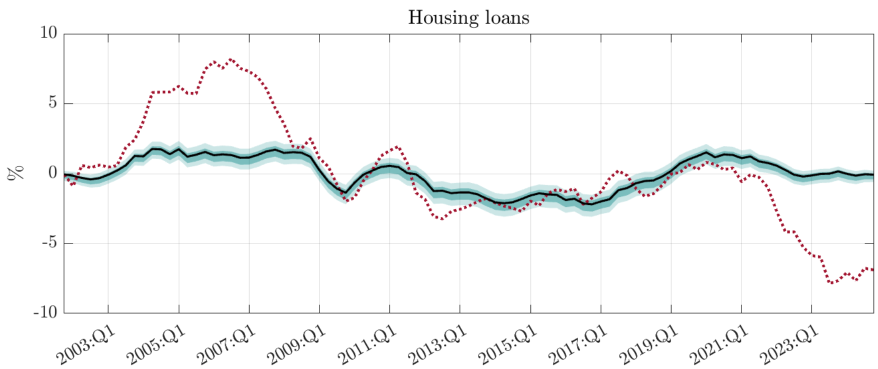
Figure 8: Forecast Variance Ratio (FVR) Estimates using our benchmark external instrument approach. The graph displays the point estimate and the 16th, 84th, 5th, and 95th percentile Bootstrap bands for each variable.

5.3. Historical Importance of Lending Standards Shocks

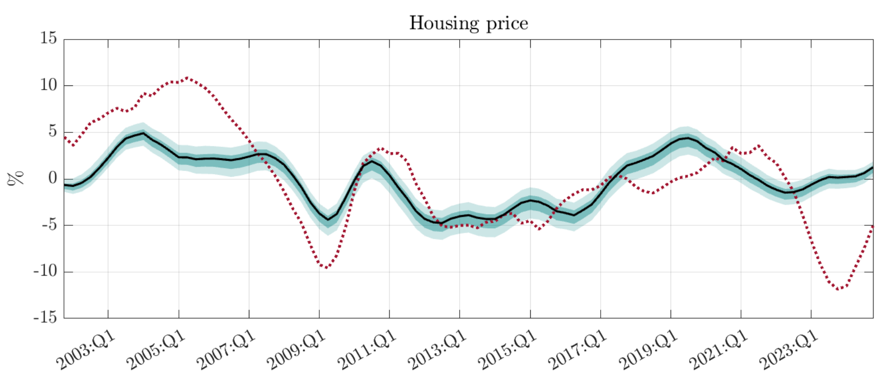
Figure 9 illustrates the cumulative historical contribution of lending standards shocks to three key housing market variables: housing loan interest rate, real housing loans year-on-year growth, and real housing price year-on-year growth. The results show that lending standards shocks account for substantial variations in both housing loans and housing prices following the global financial crisis and during the euro debt crisis. In the post-2015 period until the Covid crisis, easing lending standards constraints contributed to increasing housing loan volumes in France. The recent trough in the housing market after Covid appears to be driven primarily by factors other than lending standards shocks, such as aggregate demand, aggregate supply shocks, and monetary policy tightening. Finally, lending standards shocks have relatively less historical importance to explain the movements in housing lending rates, which are largely determined by other macroeconomic factors. Additional results for other variables are reported in the Appendix B1.



(a) Historical decomposition for housing loan interest rate



(b) Historical decomposition for real outstanding amounts of housing loans year-on-year growth



(c) Historical decomposition for real house price year-on-year growth

Figure 9: Historical decomposition estimates for housing loan interest rate, real housing loans growth, and real housing price growth. The graphs display the cumulative contribution of lending standards shocks along with 68% and 90% confidence bands (in percent deviations from the mean); red dotted lines indicate the observed series demeaned.

5.4. Effects of BBM-induced changes in lending standards

Finally, we present our main results on the effects of the borrower-based measures implemented in France. Our identified series of the regular lending standards component and the BBM component are derived as described in section 4.3. (see Appendix B2. for the series of both components). In the estimation relying on constant proportionality of the BBM component, the estimated value of the k parameter defined in (19) is 1.04, indicating that the BBM components tend to offset the regular lending standards components. Figure 10 shows the historical decompositions for three key housing market variables: housing loan interest rate, real housing loans year-on-year growth, and real housing price year-on-year growth. The results indicate that the BBM had a contractionary effect on the housing loan interest rate, with a peak impact of approximately 0.17 percentage points in 2022Q1, and contributed to a net yearly accumulated decline in housing prices of about 1.3 percentage points in 2021. Following this trough, the measure begins to exert a cumulative positive effect on housing prices. For housing loans, the net cumulative yearly effect of the BBM is approximately 0.67 percentage points in 2022. These findings suggest that macroprudential policy has had a significant but moderate impact on the housing market and household credit over the recent years. Finally, the results indicate that the contribution of the BBM-induced component to real residential investment, real income, and real GDP is limited.

The second estimation strategy yields similar patterns but more pronounced effects (see appendix **??**). This calls for further robustness checks to determine which identifying assumptions should ultimately be selected and to improve the precision in estimating the magnitude of BBM effects.

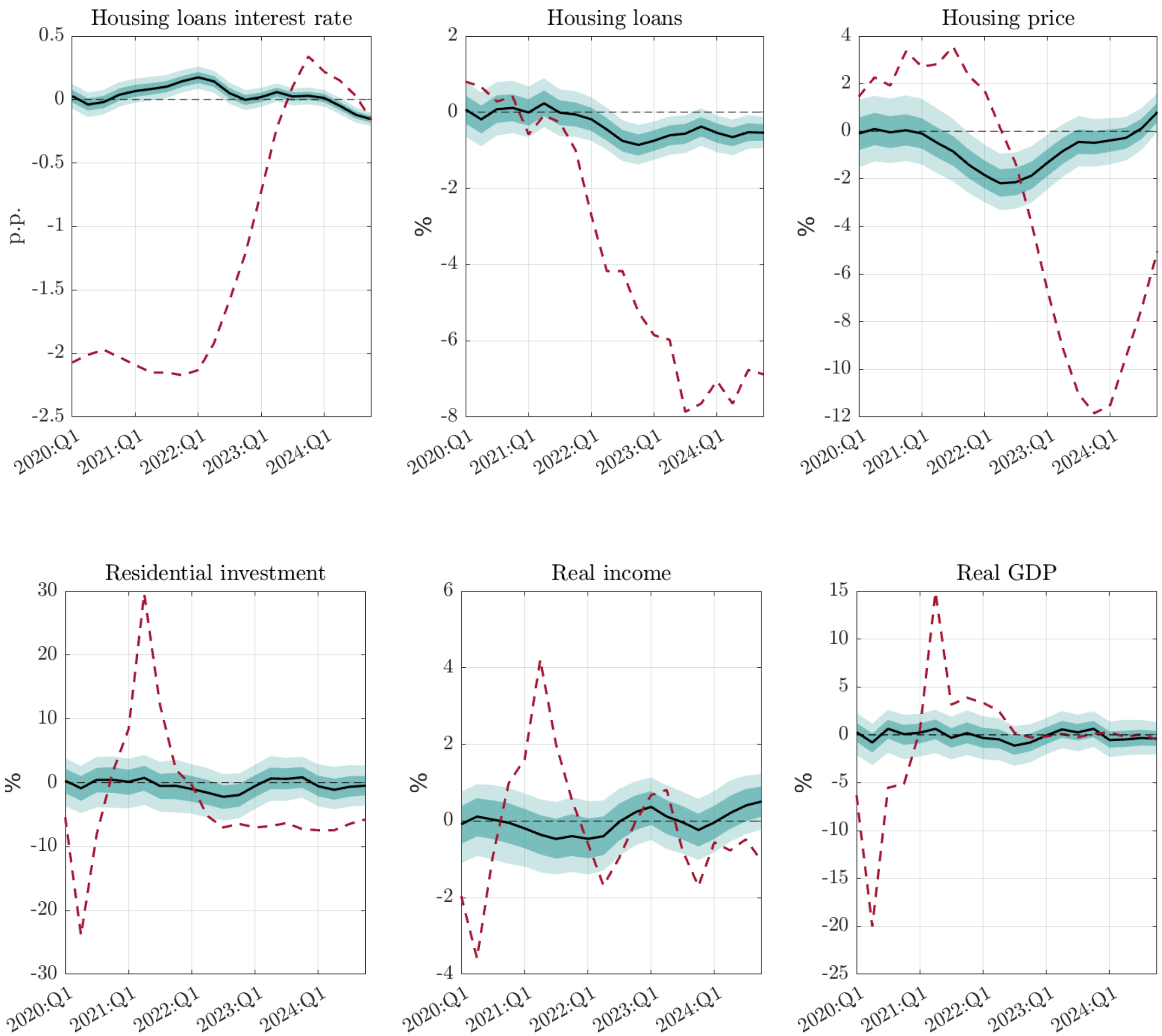


Figure 10: Cumulative historical contributions of BBM component along with 68% and 90% confidence bands (in percent deviations from the mean). Red dotted lines indicate the observed series demeaned.

6. Conclusion

Our study demonstrates that lending standards shocks exert robust and persistent effects on the French housing market, household credit, and the broader economy. We develop a novel two-step macroeconometric framework that leverages heterogeneous responses across borrower segments to extract from these shocks the effects of borrower-based measures. Our empirical results reveal that tightening BBMs leads to a statistically significant but limited contraction in outstanding housing loan growth, a slight increase in borrowing costs, and a slowdown in house price growth. The effects on real residential investment growth, real household income growth, and real GDP growth appear limited. These findings support the view that BBMs can play a crucial role in mitigating systemic risks with limited macroeconomic costs. Exploiting the evolution of housing loan distribution along several dimensions (DSTI and maturity) and aggregate macroeconomic outcomes, our mesoeconometric approach bridges an important gap in the literature to assess the aggregate effects of these macroprudential policies. Overall, our framework provides a valuable tool for ex post evaluation of macroprudential policies in data-constrained environments. Future research could extend this analysis to different institutional settings and explore potential complementarities with other regulatory measures.

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A Instrument and Test for Invertibility

A1. Pretest for Invertibility and Recoverability

Next, we report the results of our pretest for invertibility and recoverability following the procedure of Plagborg-Møller and Wolf (2022). Although the test rejects the invertibility assumption at the 90% confidence level—since the estimated R_0^2 bounds do not include 1—the bounds for the degree of recoverability, R_∞^2, along with their 90% confidence intervals, both include 1. This indicates that while the shock is not invertible, it is largely recoverable. These findings justify our use of the recoverable instrument $\tilde{Z}_t^\dagger$ (see Equation (10)) as our benchmark for identifying the lending standards shock.

Table 2: Bounds on the Degree of Invertibility (R_0^2) and the Degree of Recoverability (R_∞^2)

	R_0^2	R_∞^2
Bound estimates	[0.17, 0.61]	[0.27, 1.00]
90% Confidence Interval	[0.0, 0.85]	[0.16, 1.00]

A2. The recoverable Instrument

Figure 11 shows the recoverable instrument $\tilde{Z}_t^\dagger$ used after purging out the measurement error following equation (10).

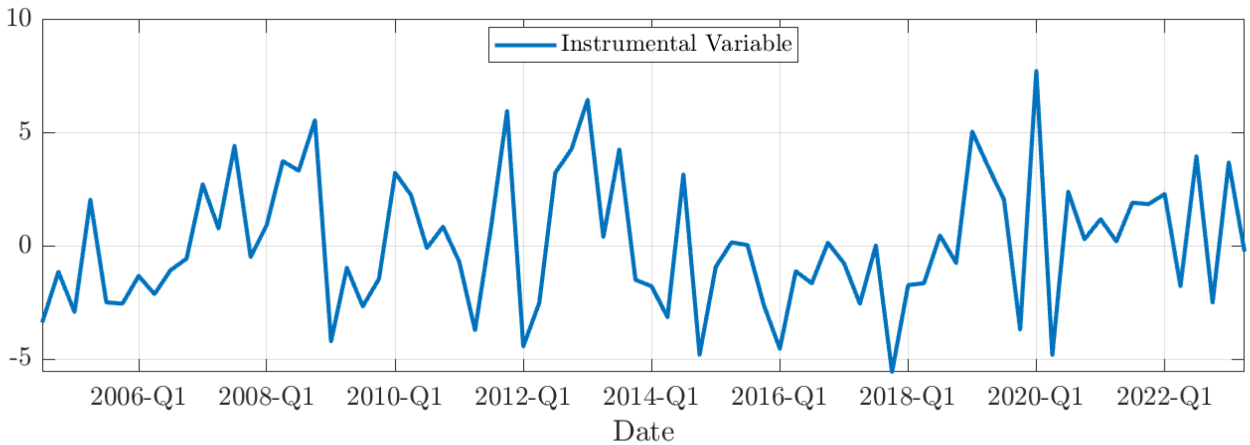


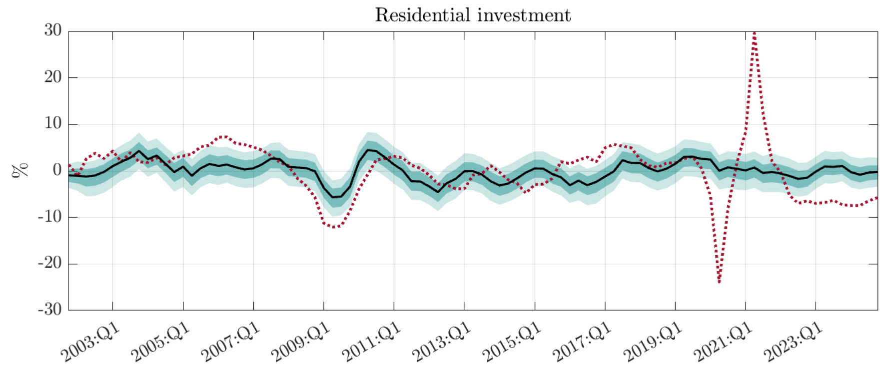
Figure 11

B Complementary Results

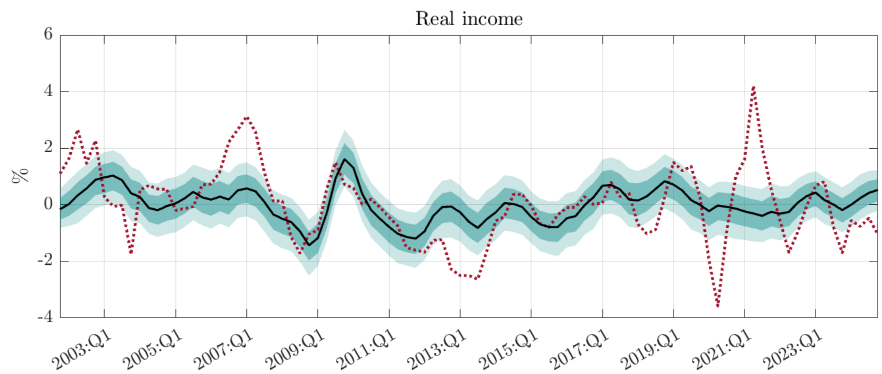
In this section, we present additional empirical evidence that complements our main findings by focusing on the historical role of lending standards shocks. Specifically, we document: (i) the cumulative historical contribution of lending standards shocks to key macroeconomic variables, (ii) the separate identification of the overall lending standards shock into its regular component and the BBM-induced component, and (iii) the historical importance of the BBM component obtained from the second methodology in section B3..

B1. Historical Decompositions of Macro Variables

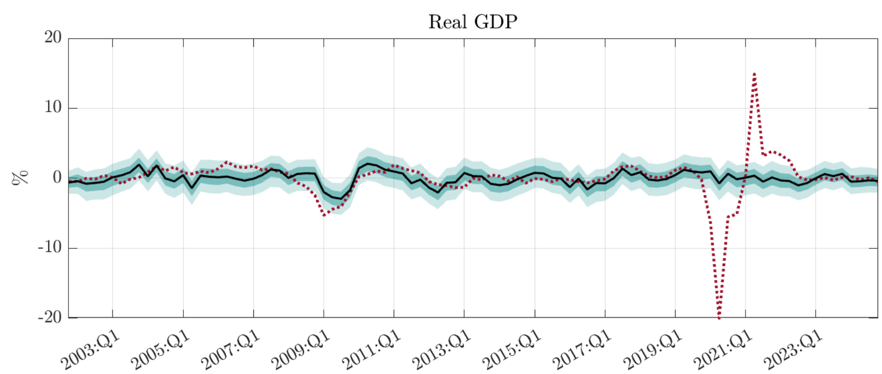
Figure 12 displays the historical decomposition estimates for real residential investment, real income, and real GDP. These graphs show the cumulative impact of lending standards shocks on these variables, along with 68% and 90% confidence bands (expressed as percent deviations from the mean). The results indicate that lending standards shocks have historically explained a substantial fraction of the variation in macro variables during the 2008 financial crisis, while their contribution during the COVID period was very limited.



(a) Real residential investment yoy growth



(b) Real income yoy growth



(c) Real GDP yoy growth

Figure 12: Historical decomposition estimates for real residential investment, real income, and GDP. The figures display the cumulative impact of lending standards shocks along with 68% and 90% confidence bands (in percent deviations from the mean). Red dotted lines indicate the observed series demeaned.

B2. Identification of Shock Components

Next, we present the identified series resulting from our second-step decomposition, which separates the overall lending standards shock into its regular component and the BBM-induced component. Figure 13 shows the regular component (depicted in red) and the BBM-induced component (depicted in dashed blue).

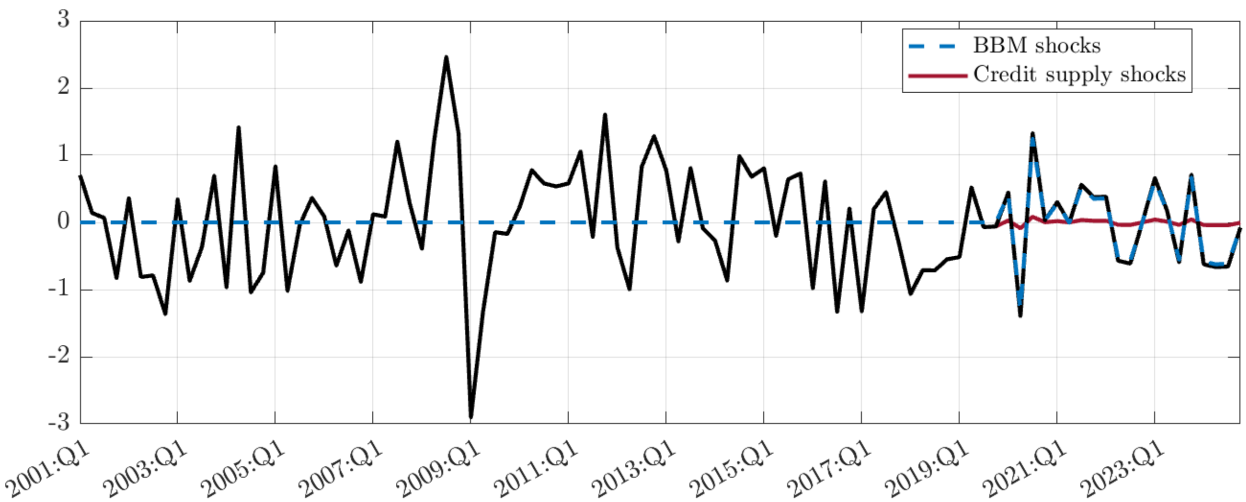


Figure 13: Identified series of lending standards shocks. Red: regular component ($\tilde{\epsilon}_{1,t}$); Blue: BBM-induced component ($\epsilon_{1,t}^{\text{BBM}}$).

B3. Estimation of the BBM component, without enforcing the constant proportionality assumption

This estimation strategy does not impose the restriction that the two components of the lending standards shock defined in equation 11 are constant multiples of the overall shock. Accordingly, equation 16 is not imposed.

Step 1 For the treatment series, which are expected to be directly affected by the BBM-induced component, we estimate the regression:

$$\tilde{f}_{i,t}^{T} = \alpha_{i,2}^{T}\Big(\epsilon_{1,t} \times \mathbf{1}\{t \geq T^{*}\}\Big) + \eta_{i,t}^{T}, \tag{21}$$

The residuals $\eta_{i,t}^{T}$ obtained from this regression are purged of any correlation with $\tilde{\epsilon}_{1,t}$ in the post-BBM period.

Step 2 For $t < T^*$, we construct a new dependent variable $v^j_{i,t}$ that combines the outcomes from both series types:

$$v_{i,t} = \begin{cases} \eta^T_{i,t} \\ \tilde{f}^C_{i,t}. \end{cases}$$

We then estimate the regression

$$v^j_{i,t} = \alpha^j_{i,1}\Big(\epsilon_{1,t} \times \mathbf{1}\{t < T^*\}\Big) + \xi^j_{i,t}. \tag{22}$$

This yields estimates of $\alpha^j_{i,1}$ for all four series, with the residuals $\xi^j_{i,t}$ representing the innovations from the Step 2 regressions.

Combining the results from Steps 1 and 2, we can write:

$$\boldsymbol{\xi}_t = \begin{pmatrix} \xi^T_{\text{dsti},t} \\ \xi^T_{\text{matu},t} \\ \xi^C_{\text{dsti},t} \\ \xi^C_{\text{matu},t} \end{pmatrix} = \begin{pmatrix} \alpha^T_{\text{dsti},1} - \alpha^T_{\text{dsti},2} \\ \alpha^T_{\text{matu},1} - \alpha^T_{\text{matu},2} \\ \alpha^C_{\text{dsti},1} \\ \alpha^C_{\text{matu},1} \end{pmatrix} \widetilde{\epsilon}_{1,t} \times \mathbf{1}\{t \geq T^*\} + \mathbf{e}_t, \tag{23}$$

where the coefficients $\alpha^j_{i,1}$ and $\alpha^j_{i,2}$ have been estimated via our two-step strategy (with $\xi^j_{i,t}$ denoting the residuals from the pre-BBM regressions). In this equation, $\widetilde{\epsilon}_{1,t}$ represents the regular, off-BBM component of the lending standards shock. Note that at this stage we have not yet estimated the series $\widetilde{\epsilon}_{1,t}$; its estimation is addressed in the subsequent step.

Step 3 To ensure that any changes in the observed covariance structure are not spuriously attributed to the BBM-induced component, we impose that the variance–covariance matrix of the noise $\mathbf{e}_t$ remains stable across the two periods, before and after T^*. Because $\widetilde{\epsilon}_{1,t}$ is by definition orthogonal to $\mathbf{e}_t$ and $\boldsymbol{\xi}_t$, it follows that the conditional variance of $\boldsymbol{\xi}_t$ given $\widetilde{\epsilon}_{1,t}$ is equivalent to the unconditional variance of $\mathbf{e}_t$, such that

$$\text{Var}\Big(\boldsymbol{\xi}_t \mid \widetilde{\epsilon}_{1,t}\Big) = \text{Var}\Big(\mathbf{e}_t\Big).$$

We define the variance–covariance matrices of $\boldsymbol{\xi}_t$ as $\Omega^{\text{pre}} = \text{Var}(\boldsymbol{\xi}_t)$ for $t < T^*$ and $\Omega^{\text{post}} = \text{Var}(\boldsymbol{\xi}_t)$ for $t \geq T^*$. Hence, we choose the post-BBM path of the regular lending standards shock $\widetilde{\epsilon}_{1,t}$ by solving the following minimization problem:

$$\min_{\{\widetilde{\epsilon}_{1,t}\}} \Big\| \Omega^{\text{post}} - \Omega^{\text{pre}} \Big\|_F,$$

where $\|\cdot\|_F$ denotes the Frobenius norm. This criterion guarantees that the variance–covariance matrix of the consolidated residuals in the post-BBM period closely matches that in the pre-BBM period, ensuring that any change in volatility is not misattributed to the BBM-induced component $\epsilon_{1,t}^{\mathrm{BBM}}$.

Recovering the BBM-Induced Component. Finally, to recover the series of the BBM-induced component, we subtract the estimated off-BBM component from the overall observed lending standards shock $\epsilon_{1,t}$. That is,

$$\epsilon_{1,t}^{\mathrm{BBM}} = \epsilon_{1,t} \times \mathbf{1}\{t \geq T^*\} - \widetilde{\epsilon}_{1,t} \times \mathbf{1}\{t \geq T^*\}.$$

This subtraction isolates the portion of the overall lending standards shock that is attributable to the BBM, completing our estimation strategy.

Estimation Figure 14 shows the historical cumulative importance of the BBM component estimated from the second estimation strategy outlined in section B3. The results show a pronounced effect of the BBM measure.

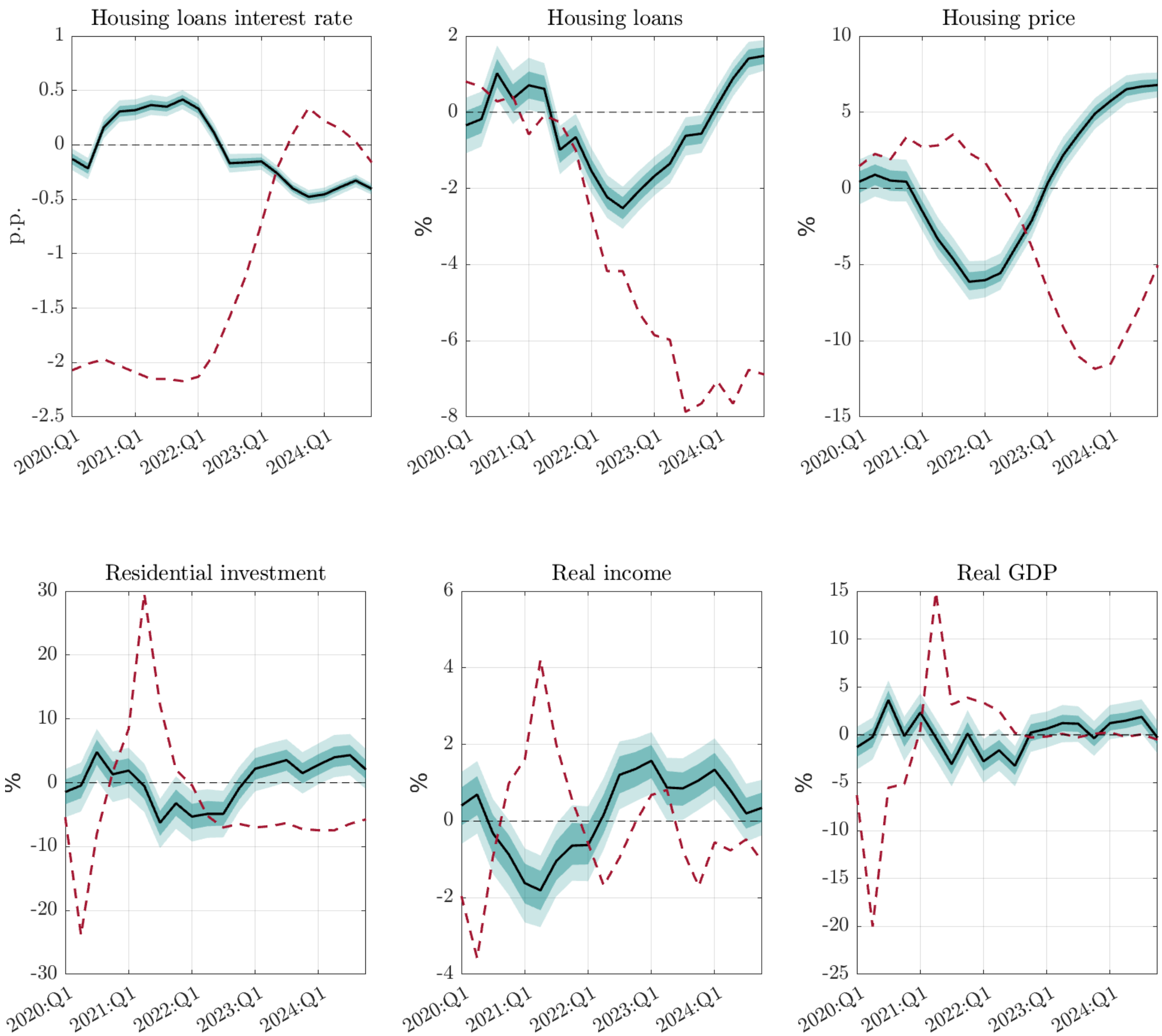


Figure 14: Cumulative historical contributions of BBM component along with 68% and 90% confidence bands (in percent deviations from the mean). Red dotted lines indicate the observed series demeaned. Results from the second methodology outlined in section B3.

C Robustness

To verify the stability of our main findings, we present additional analyses that explore alternative model specifications and identification strategies. In particular, we examine impulse responses estimated in log levels and compare forecast variance ratio (FVR) estimates obtained via two complementary approaches.

C1. Log-Level Impulse Responses

Figure 15 displays the impulse response functions (IRFs) to a negative lending standards shock estimated in log levels. In this specification, the blue solid line represents the posterior median, and the shaded blue area shows the 16th, 84th, 5th, and 95th percentile bands. The dynamics observed in these level-based IRFs closely resemble those obtained using log-differences in the main text, thereby confirming the robustness of our results across different data transformations.

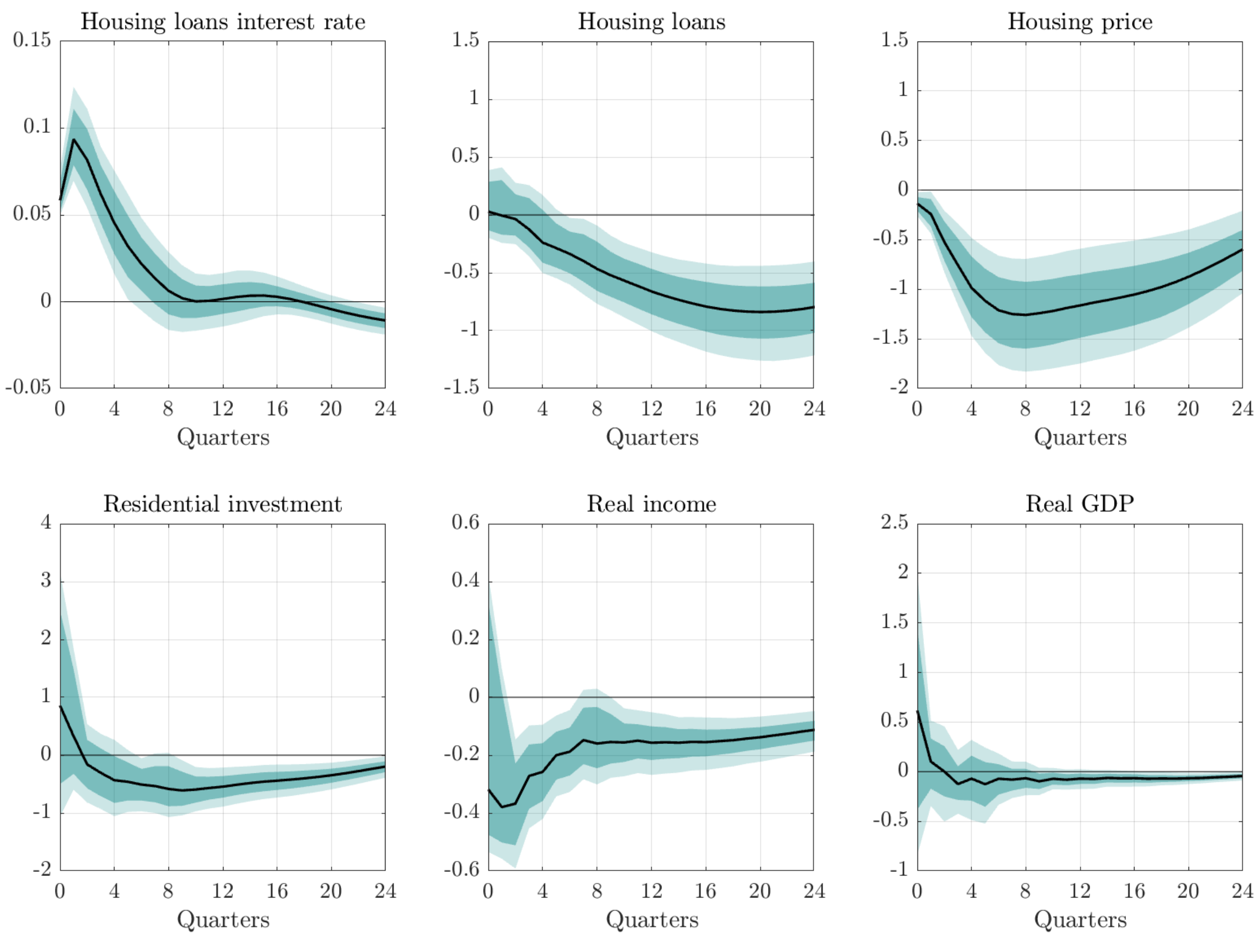


Figure 15: Impulse response functions to a negative lending standards shock estimated in log levels. Black: posterior median (solid) and 16th, 84th, 5th, and 95th percentile bands (shaded).

C2. Forecast Variance Ratio (FVR) Results

We estimate the forecast variance ratio (FVR) using two complementary strategies. First, our benchmark strategy employs an SVAR-IV model using the recoverable instrument $\tilde{Z}_t^{\dagger}$, which assumes recoverability and provides a point-identified series for $\epsilon_{1,t}$. The resulting FVR estimates are displayed as orange lines with associated 68 and 90% confidence bands. Second, we apply an invertibility-robust SVMA-IV method following the procedures of Plagborg-Møller and Wolf (2022), which yields an identified set for the FVR, shown as a shaded area with dashed 90% confidence intervals. Figure 16 compares these two sets of FVR estimates for each of the six endogenous variables. Notably, the SVAR-IV approach tends to underestimate the role of lending standards shocks in explaining the variance of the housing loans relative to our SVMA-IV results. Otherwise, the results of the two approaches look identical.

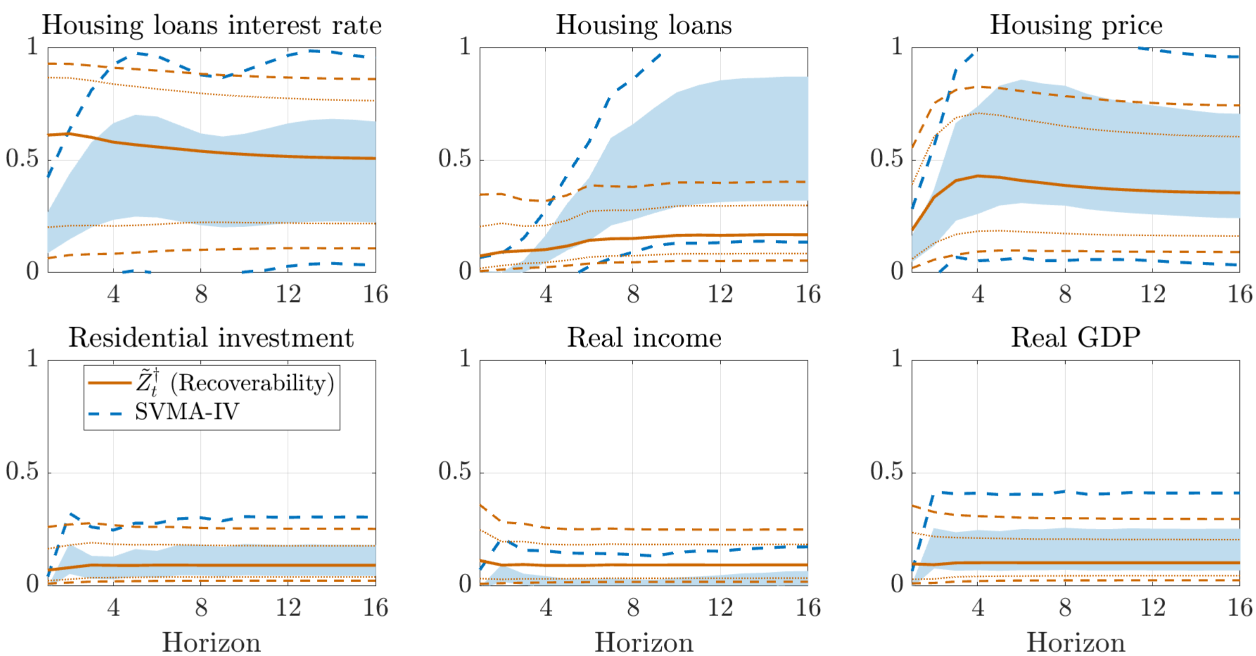


Figure 16: Forecast Variance Ratio (FVR) Estimates. The graph displays the FVR estimated from two strategies: (i) the benchmark SVAR-IV model using the recoverable instrument $\tilde{Z}_t^{\dagger}$, shown with orange lines and associated 68 and 90% confidence bands; and (ii) the invertibility-robust SVMA-IV approach following Plagborg-Møller and Wolf (2022), which yields an identified set (shaded area) with lower and upper bound estimates and dashed 90% confidence intervals.