WORKING paper

BANQUE DE FRANCE
EUROSYSTÈME

The Macroeconomic Effects of Regulating Household Leverage: A Mesoeconometric Approach[1]

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July 2026, WP #1051

ABSTRACT

We develop a mesoeconometric framework to quantify the macroeconomic effects of policies that target household leverage. We focus on borrower-based macroprudential measures (BBMs), which regulate lending standards at loan origination. The approach first identifies lending standards shocks in a structural VAR-IV framework and then exploits heterogeneous borrower responses to BBMs to isolate the policy-induced component of those shocks. We apply this framework to France, where caps on debt-service-to-income (DSTI) ratios and loan maturities were introduced in 2019. We show that lending standards shocks have persistent and economically meaningful effects on housing and credit dynamics. By contrast, the BBM-induced component has statistically significant but economically moderate effects. In credit markets, the measure raises borrowing interest rates by around 0.15 to 0.20 percentage points and slows the growth of real outstanding housing credit by up to 0.8 percentage points between 2022 and 2023, a period during which outstanding credit fell by as much as 8%, mainly as a result of higher interest rates. The measure also reduces house price growth by 2 to 3 percentage points at its trough. We find no significant impact on real residential investment, household income, or real GDP. These results indicate that BBMs primarily affect the riskiest component of the housing credit market without generating broad macroeconomic spillovers, highlighting their role as targeted tools for enhancing financial resilience.

Keywords: Macroprudential Policy, Lending Standards Shocks, Housing Market, Borrower-Based Measures

JEL classification: E44, G21, G28

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[1] We are grateful for comments from Borağan Aruoba, Ryan Banerjee, Thorsten Beck, Adrien Bilal, Diana Bonfim, Thibaut Duprey, Anne Epaulard, Christian Hellwig, Paul Hubert, Diego Känzig, Anil Kashyap, Magali Marx, Nour Meddahi (as a discussant), Sarah Mouabbi, John Muellbauer, Steven Ongena, Marco Pagano, José-Luis Peydro (as a discussant), Eugen Tereanu, and Gauthier Vermandel.

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NON-TECHNICAL SUMMARY

Since the Global Financial Crisis, policymakers have paid increasing attention to household leverage as a potential source of financial instability. When housing credit expands too rapidly and lending conditions become too loose, households can become more vulnerable to adverse shocks, while the broader economy becomes more exposed to housing-market downturns. In France, these concerns led to the introduction of macroprudential measures in the form of a regulation on housing loan lending standards, also referred to as borrower-based measures (BBMs). First introduced as a recommendation in December 2019 and later made legally binding in 2022, these measures limit the debt-service-to-income (DSTI) ratio and the maturity of new housing loans (distinct from other types of BBMs such as loan-to-value caps), while allowing banks a flexibility margin.

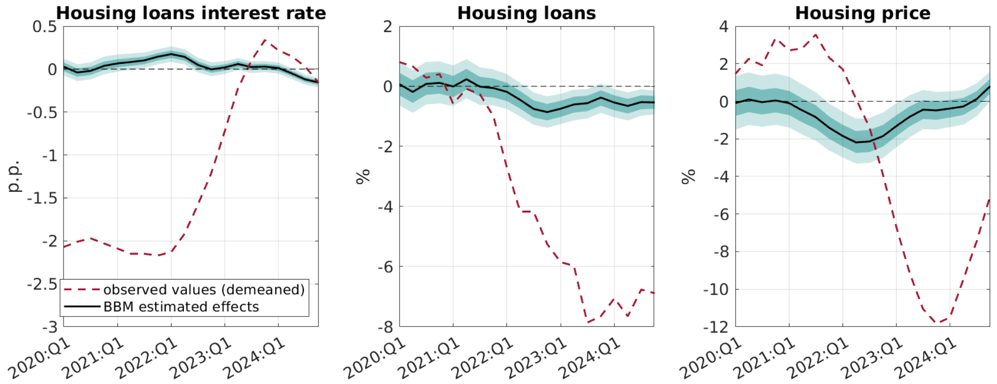
This paper studies the macroeconomic effects of such measures. Estimating these effects is challenging because borrower-based measures are typically introduced in response to prevailing macro-financial conditions, which complicates the identification of their causal aggregate impact. To address this issue, the paper develops a new macroeconometric framework that exploits a central feature of borrower-based measures: their effects are concentrated at specific points of the housing loan lending standards distribution. Loans close to the regulatory thresholds are directly affected, whereas those sufficiently distant are not. This creates distinctive distributional shifts. The paper builds on this insight to propose a new two-step framework that first estimates the macroeconomic effects of changes in lending standards in a vector autoregression model, and then uses the specific distributional shifts induced by borrower-based measures to isolate their aggregate effects. We refer to this methodology as a mesoeconometric strategy, which lies at the intersection of macroeconometric and microeconometric analysis.

The paper first establishes that changes in housing loan lending standards have economically meaningful effects on the French housing and credit cycle. A tightening raises housing loan borrowing interest rates, slows housing credit growth, and lowers house price growth. These effects are persistent and sizable. By contrast, the impact on broader macroeconomic variables is more limited , with no clearly significant effects. In particular, the estimated responses of real GDP and household income remain small. This suggests that lending standards changes operate primarily through housing and housing credit markets rather than via large aggregate spillovers.

Building on these results, the paper then quantifies the specific contribution of borrower-based measures. The findings indicate that their effects are statistically significant but economically limited. The BBM-induced component of lending standards tightening increases housing loan borrowing interest rates by about 0.15 to 0.20 percentage points at its peak, slows housing credit growth by around 0.8 percentage points, and lowers house price growth by about 2 to 3 percentage points at its trough. The estimated contribution remains limited relative to the overall market slowdown observed over the period. At the same time, the paper finds no statistically significant effects on real residential investment, household income, or real GDP. Figure 1 illustrates these estimated effects.

Overall, the findings suggest that borrower-based macroprudential measures can enhance the resilience of housing credit markets without generating large adverse effects on aggregate activity. In the French case, the measures appear to have worked as intended as a targeted instrument affecting the riskiest segments of the housing credit market, while leaving broader macroeconomic dynamics largely unaffected. Beyond the French application, the paper also proposes a tractable framework for evaluating policies that act through targeted constraints in the distribution of credit.

Figure 1. Macroeconomic effects of the borrower-based measures in France



Note: The figure reports the cumulative effects of the BBM-induced component of lending standards shocks on i) housing loan borrowing interest rates, ii) the annual growth rate of outstanding housing loan volumes and iii) the annual growth rate of house prices. Solid lines represent point estimates of the contribution of the BBM-induced component on the variable on top of the figure, while shaded areas represent 68% and 90% confidence bands. The red dashed line denotes the demeaned observed series for the corresponding variable.

Les effets macroéconomiques de l'encadrement de l'endettement des ménages : une approche mésoéconométrique

RÉSUMÉ

Nous développons un cadre mésoéconométrique permettant de quantifier les effets macroéconomiques des politiques visant à limiter l'endettement des ménages. Nous nous intéressons aux mesures macroprudentielles visant les emprunteurs (BBM), qui encadrent les conditions d'octroi des prêts à l'habitat. L'approche consiste à identifier des chocs de conditions d'octroi dans un modèle VAR structurel avec variable instrumentale externe (SVAR-IV), puis à exploiter les différences de réaction des emprunteurs aux BBM le long de la distribution des nouveaux crédits pour isoler la part de ces chocs attribuable aux BBM. Nous appliquons ce cadre à la France, qui a introduit en 2019 des plafonds de taux d'effort (DSTI) et de maturité des prêts. Nous montrons que les chocs de conditions d'octroi ont des effets persistants et économiquement significatifs sur la dynamique du marché du logement et du crédit. En revanche, la composante induite par les BBM a des effets statistiquement significatifs mais d'ampleur économique contenue. Concernant le marché du crédit, la mesure augmente les taux d'emprunt d'environ 0,15 à 0,20 points de pourcentage et ralentit la croissance de l'encours réel de crédits à l'habitat d'environ 0,8 points de pourcentage au maximum entre 2022 et 2023, période durant laquelle cet encours a reculé jusqu'à 8 %, principalement sous l'effet de la hausse des taux. Aucun effet significatif n'est mis en évidence sur l'investissement résidentiel réel, le revenu des ménages ou le PIB réel. Ces résultats indiquent que, conformément à leur objectif, les BBM affectent principalement la composante la plus risquée du marché du crédit immobilier, sans générer d'effets macroéconomiques plus larges, soulignant ainsi leur rôle d'instruments ciblés pour renforcer la résilience financière.

Mots-clés : politique macroprudentielle, chocs de conditions d'octroi, marché du logement, mesures emprunteur

1. Introduction

The Global Financial Crisis propelled household leverage to the forefront of policy debates. Excessive credit growth—particularly for housing—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, 2011; Jordà et al., 2015). More broadly, research highlights the procyclical nature of housing credit and its role in amplifying economic cycles, often leading to more severe financial instability during downturns (Schularick and Taylor, 2012). In response, governments and central banks around the world have increasingly implemented borrower-based macroprudential measures (BBMs) to contain excessive credit growth and safeguard financial stability, using tools such as caps on debt-service-to-income (DSTI) ratios or loan-to-value (LTV) ratios. Yet, assessing the macroeconomic effects of these measures remains empirically challenging. Understanding their aggregate impact is crucial to evaluate the policy trade-off between improving the safety of household credit and the potential costs in terms of reduced credit supply and economic activity.

To address these questions, we propose a novel two-step empirical framework that quantifies the macroeconomic effects of BBMs by exploiting their heterogeneous impact across the distribution of lending standards among newly originated housing loans. We refer to this methodology as a *mesoeconometric strategy*, which lies at the intersection of macroeconometric and microeconometric analysis. From December 2019 onward, amid growing vulnerabilities in the French housing credit market, the High Council for Financial Stability (HCSF)—France's macroprudential authority—introduced recommendations to limit DSTI ratios and loan maturities at origination, eventually making these guidelines legally binding in January 2022. This phased implementation strategy creates a unique setting in which the evolving measure induces continuous changes in lending standards that affect borrower segments close to the regulatory thresholds while leaving others largely unaffected, thereby generating the cross-sectional variation that underpins our identification strategy.

In the first stage, we construct an instrument variable based on responses from French banks to the euro area Bank Lending Survey and use it in a VAR model to identify exogenous changes in lending standards for housing loans. In the second stage, we exploit heterogeneous responses across segments of the loan distribution—contrasting loans close to the DSTI and maturity limits targeted by the measure with loans sufficiently far from these thresholds—to isolate the component of the lending standards shock attributable to BBMs. This step relies on French loan-level data on new housing credit originations. Building on this two-step framework, we estimate the dynamic causal effects of BBM-induced shocks on housing loan volumes, borrowing rates, house prices, and real activity.

We first document several key findings on the effects of lending standards shocks in France.

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 a substantial decrease in house prices. 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 variation in housing loan borrowing rates, house prices, and, to a lesser extent, outstanding housing loan volumes.

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. 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 overly affecting credit access and overall demand.

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, 2011; Mian et al., 2013) and its impact on consumer spending in the aftermath (Mian and Sufi, 2014). These insights gave rise to an important literature examining the macroeconomic and financial stability implications of ex ante leverage caps (Bianchi and Mendoza, 2010; Farhi and Werning, 2013; Korinek and Simsek, 2016).

Our analysis builds upon an important literature leveraging loan-level data to analyze the effects of regulatory constraints related to housing loan lending standards.These studies exploit the fact that such measures typically affect only a portion of the distribution of lending standards, identifying their effects by comparing loans constrained by the regulatory thresholds with otherwise similar counterfactual borrowers. DeFusco et al. (2020) study the effects of an implicit tax on housing credits with high debt-to-income (DTI) ratios in the United States and show that the policy led to an increase in interest rates and a significant reduction in the quantity of credit extended to constrained borrowers, consistent with a tightening of credit supply. Tzur-Ilan (2023) studies the effects of loan-to-value (LTV) limits in Israel and shows that, in addition to affecting the price and quantity of credit, the policy also led borrowers to choose housing units that were more affordable, located farther from the central business district, and situated in lower-socioeconomic neighborhoods. van Bekkum et al. (2024) use administrative household-level data and are able to track the effects of LTV limits on household balance sheets, notably on cash balances and consumption. They show that the policy leads to both deleveraging and lower cash balances to satisfy the LTV limit, reflecting an important solvency–liquidity trade-off, while nevertheless allowing households to better smooth consumption following income losses in the following years.[1] Our paper leverages loan-level data to identify constrained and unconstrained borrowers following the implementation of the measure. Our approach differs in that these groups are used to extract the component attributable to BBMs from lending standards shocks estimated within a VAR model.

Our analysis is also related to a literature using cross-country panel data to assess the aggregate effects of borrower-based macroprudential measures (BBMs). These papers exploit cross-country variation in the implementation of macroprudential policies, typically relying on policy indicators constructed as dummy variables (Kuttner and Shim, 2016; Cerutti et al., 2017; Akinci and Olmstead-Rumsey, 2018). Using this approach, they find that these measures are generally associated with slower housing credit growth and more moderate house price dynamics. Studies assessing the aggregate effects of borrower-based macroprudential measures that are closest to our approach include Alam et al. (2025) and Richter et al. (2019), which capture the intensity of changes in LTV limits. They show that BBMs are effective in containing excesses in housing and credit cycles, while the associated macroeconomic costs—in terms of consumption, inflation, and output—remain relatively modest. Fernández-Gallardo and Paya (2025) combine a narrative identification approach with a structural VAR framework to estimate the effects of macroprudential policy in the euro area. In contrast to our paper, they rely on a broad macroprudential policy index covering all categories of macroprudential instruments, in which policy actions are weighted according to a pre-defined scheme. By leveraging loan-level data, our approach focuses on a single country, thereby mitigating biases arising from cross-country differences in the design and implementation of BBMs and allowing us to directly map the share of constrained borrowers to their effects on the real economy.

From a theoretical perspective, 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 housing credit channel in macroeconomic transmission.

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[1] Acharya et al. (2022) and Peydró et al. (2024) exploit identification strategies based on banks' heterogeneous exposure to the regulatory constraint and show that banks reallocate lending within their portfolios across borrowers and geographies to conform to the new limits

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.

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, which also describes the methodology used to isolate the effects of BBMs. Section 5 presents our empirical results on the aggregate effects of lending standards shocks and BBMs. Section 6 concludes.

2. Institutional Background

In 2019, the HCSF, France's macroprudential authority, published an assessment of vulnerabilities in the residential real estate market, highlighting a progressive loosening of lending conditions over the preceding years. This loosening was reflected in rising DSTI ratios and longer loan maturities. In particular, the share of new housing loans originated with a DSTI above 35% or a maturity exceeding 25 years increased markedly after 2015, echoing patterns observed in the run-up to the 2008 global financial crisis. These developments were accompanied by a significant rise in aggregate household indebtedness, which increased household-sector vulnerability by making debt service more sensitive to adverse income shocks and, more broadly, heightening the economy's exposure to macroeconomic disturbances.

In response to the easing of lending standards and the rise in household debt, the HCSF sought to limit the build-up of systemic risks by implementing a borrower-based measure to tighten the conditions for housing loan origination[2]. The implementation of the measure was gradual, with the HCSF opting for a step-by-step approach to allow time for stakeholder adjustment (see Figure 1). 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 increasing 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, while leaving the core parameters of the measure unchanged: a DSTI cap of 35% and a maturity cap of 25 years[3].

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[2] Loan renegotiations, debt consolidation loans, and bridge loans are excluded from the scope of the measure, provided that they are aimed at lowering the borrower's DSTI ratio.

[3] Loans with a maturity of up to 27 years remain compliant when they finance construction or renovation works, provided that renovation costs exceed a specified threshold and that part of the repayments is deferred.

The changes concerned the operational implementation of the framework. Among these changes, banks were allowed to assess compliance over a three-quarter horizon when a limited breach of the flexibility margin occurred in a given quarter. The HCSF also increased the share of the flexibility margin that could be used freely from 20% to 30% by reducing the portion allocated to primary residences from 80% to 70%. The share allocated to first-time buyers remained unchanged at 30%[4]. These adjustments constitute a boon for our empirical analysis by introducing meaningful variation that facilitates identifying the measure's macroeconomic impact.

Table 1: Timeline and Main Features of the French Borrower-Based Measure

	2019 Recommendation	**2021 Recommendation and 2022 Binding Decision**	**Current Measure (since December 2023)**
DSTI limit	33%	35%	35%
Maturity limit	25 years	25 years, with limited exceptions	25 years, with limited exceptions
Flexibility margin	15% of quarterly loan production, of which at least 75% for owner-occupied primary residences	20% of quarterly loan production, of which at least 80% for owner-occupied primary residences and 30% for first-time buyers	20% of quarterly loan production, of which at least 70% for owner-occupied primary residences and 30% for first-time buyers

Notes: DSTI refers to the debt-service-to-income ratio at origination. The flexibility margin corresponds to the share of new lending allowed to deviate from the baseline limits.

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. This choice also reflects an important feature of the French housing finance system: housing loans are predominantly secured through third-party guarantees (*cautionnement*) rather than standard mortgages, reducing the relevance of LTV limits. 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 annual income at the time the loan is originated.

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[4] The 2023 reform introduced several additional technical adjustments to the implementation of the measure, including the exclusion of interest payments on bridge loans from the DSTI calculation when the bridge loan's LTV does not exceed 80% of the value of the property being marketed, as well as a lowering of the renovation threshold required for eligibility for the 27-year maturity limit.

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 (Lown and Morgan, 2006). To this end, we draw on the euro area Bank Lending Survey (BLS), which provides quarterly bank-level information on changes in credit standards and on banks' perceptions of credit demand. (Ciccarelli et al., 2013, 2015; Altavilla et al., 2019).

3.1. Measuring Changes in Lending Standards in the Bank Lending Survey

Each quarter since 2002, the BLS has collected from a representative sample of euro area banks—including 12 French banks—information on changes in housing loan lending standards. The relevant question is: "Over the past three months, how have your bank's credit standards as applied to the approval of loans to households for house purchase changed?" The possible responses are: tightened considerably, tightened somewhat, remained basically unchanged, eased somewhat, and 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 regarding lending standards, which are largely concentrated in three main outcome categories as shown in Figure 1. Following Lown and Morgan (2006) and related work, we derive from these qualitative responses a raw net percent tightening of credit standards, computed as:

$$\begin{aligned}\text{Net percent tightening at } t = &\left(\text{\% of banks reporting tightening at } t\right)\\ &-\left(\text{\% of banks reporting easing at } t\right).\end{aligned} \tag{1}$$

Endogenity concerns. A simple net percentage of reported tightening may conflate supply- and demand-driven factors and therefore requires further refinement to isolate exogenous changes in lending standards. A high positive value of the indicator may reflect a drop in demand and a deterioration in borrower quality rather than an exogenous contraction in the willingness of banks to lend. Controlling for demand factors is therefore essential. One way to illustrate this issue is to examine the relationship between net tightening and banks' perceived housing loan demand as

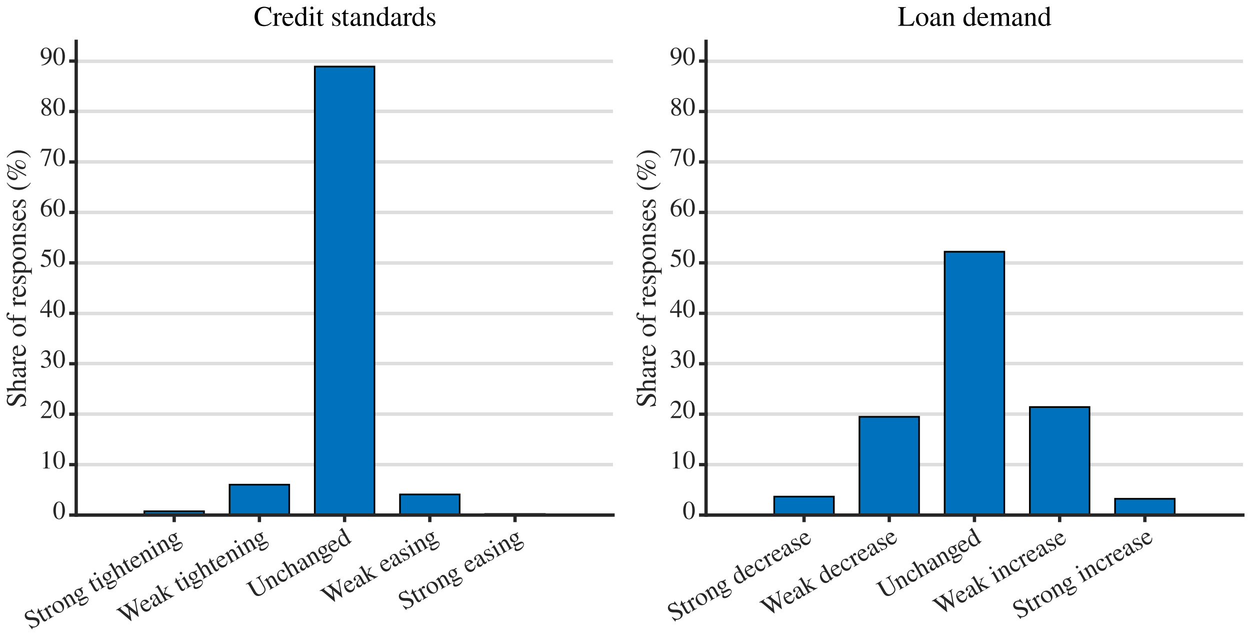

Figure 1: French banks' responses to the BLS regarding housing loan credit standards and demand, 2002Q4-2024Q2.

Notes: The figure reports the responses of French banks to the Bank Lending Survey regarding housing loan credit standards and demand. The sample period extends from Q4 2002 to Q2 2024.

reported in the BLS.[5] At the bank level, perceived demand is captured by a discrete variable taking the values 1, 0, and -1, corresponding respectively to a reported decline, no change, and an increase in housing loan demand (Figure 1) .[6] Aggregating these responses allows us to build a net percent demand indicator defined as the difference between the share (in %) of banks reporting an increase in demand and the share reporting a decline. Similarlty to Altavilla et al. (2019), we find that net tightening in lending standards is significantly negatively correlated with this net demand indicator (-0.36; Figure 2), confirming that raw survey responses on credit standards partly co-move with demand conditions.

3.2. Estimating Exogenous Changes in Lending Standards

Following Bassett et al. (2014) and Altavilla et al. (2019), we address this concern by estimating a model that relates the bank-level BLS responses to banks' perceived demand, as well as a wide range of macroeconomic variables. We define for each bank i in our sample and for quarter t a

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[5] The question is: "Over the past three months, how has the demand for loans to households for house purchase changed at your bank, apart from normal seasonal fluctuations?"

[6] The five original response categories are "declined considerably," "declined somewhat," "remained basically unchanged," "increased somewhat," and "increased considerably." As in the case of the lending standards question, we collapse these responses into three broader categories.

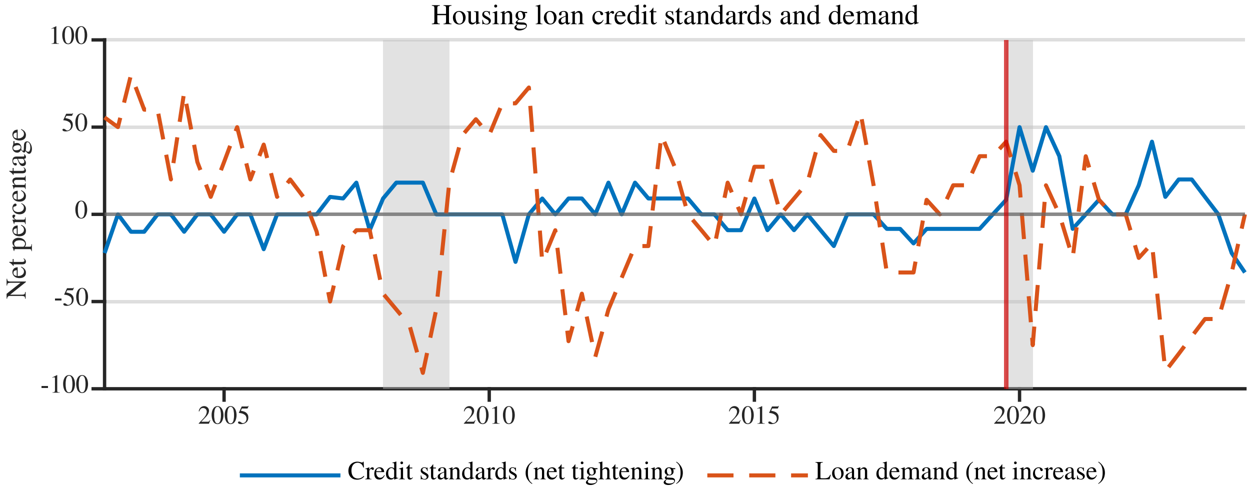

Figure 2: Net percentages, French banks, 2002Q4-2024Q2.

Notes: The figure reports net percentages, as defined in Equation 1, based on responses of French banks to the BLS regarding housing loan credit standards and demand. The sample period extends from Q4 2002 to Q2 2024. Shaded areas correspond to recessions, the vertical red line indicates the introduction of the borrower-based measure

variable:

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

where -1 indicates easing, 0 is neutral, and $+1$ represents tightening. We compute the moving average over four quarters of this indicator to smooth out short-term fluctuations.

We then estimate the following linear 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. Following the literature, we include the four-quarter moving average of the BLS-based discrete measures of credit demand perceived by bank i at quarter t ($D_{i,t}^{Demand,ma}$). The model also includes bank fixed effects.

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. By controlling for macroeconomic fundamentals and information about 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 only capture some metrics related to lending standards shocks. We then aggregate these bank-level residuals to obtain a single measure at the country level.

Table 2 presents the results for Equation 2, estimated using OLS. Column 1 includes only the BLS-based discrete demand variable averaged over four quarters, column 2 includes only macroeconomic and financial variables, and column 3 reports the full specification with all covariates. 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 2: Determinants of Changes in Housing Loan Lending Standards

	(1)	**(2)**	**(3)**
Bank-level Demand	-0.1312*** (0.0139)		-0.1219*** (0.0151)
Real GDP Growth		-1.1106*** (0.2091)	-0.9157*** (0.2760)
Change in Unemployment Rate		0.0353*** (0.0112)	0.0239** (0.0104)
Short-term Rate Change		0.0308*** (0.0094)	0.0308*** (0.0095)
VSTOXX Change		0.0006 (0.0010)	0.0006 (0.0008)
Constant	0.0308*** (0.0066)	0.0432*** (0.0072)	0.0415*** (0.0073)
Bank Fixed Effects	Yes	Yes	Yes
Observations	916	916	916
F-statistic	89.31	10.30	19.82
Prob > F	0.0000	0.0000	0.0000
R-squared	0.1481	0.1048	0.1754
Adj. R-squared	0.1368	0.0899	0.1608
Root MSE	0.2008	0.2062	0.1980

Notes: Sample period: Q3 2003-Q2 2024. Number of banks = 12. The dependent variable is the four-quarter moving average of banks' responses regarding credit standards, coded as 1 for tightening, 0 for unchanged, and -1 for easing. The bank-level demand factor is the four-quarter moving average of banks' responses on credit demand, coded as 1 for a decrease, 0 for no change, and -1 for an increase. For consistency with Altavilla et al. (2019) and Bassett et al. (2014), we reverse the sign of the coefficient so that higher values reflect higher demand. All specifications include bank fixed effects. Coefficients are reported with standard errors in parentheses. Asterisks denote significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

As expected, an increase in bank-level demand is associated with looser credit standards, as indicated by the negative and significant coefficient. Similarly, stronger real GDP growth reduces net tightening. The impact of labor market conditions (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 changes in the VSTOXX index 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 estimated residuals of Equation 2 according to:

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

where I is the number of banks in our sample ($I = 12$), $\hat{v}_{i,t}$ 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 3 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 2019Q4. It also shows that lending standards somewhat tightened around the 2008 financial crisis period.

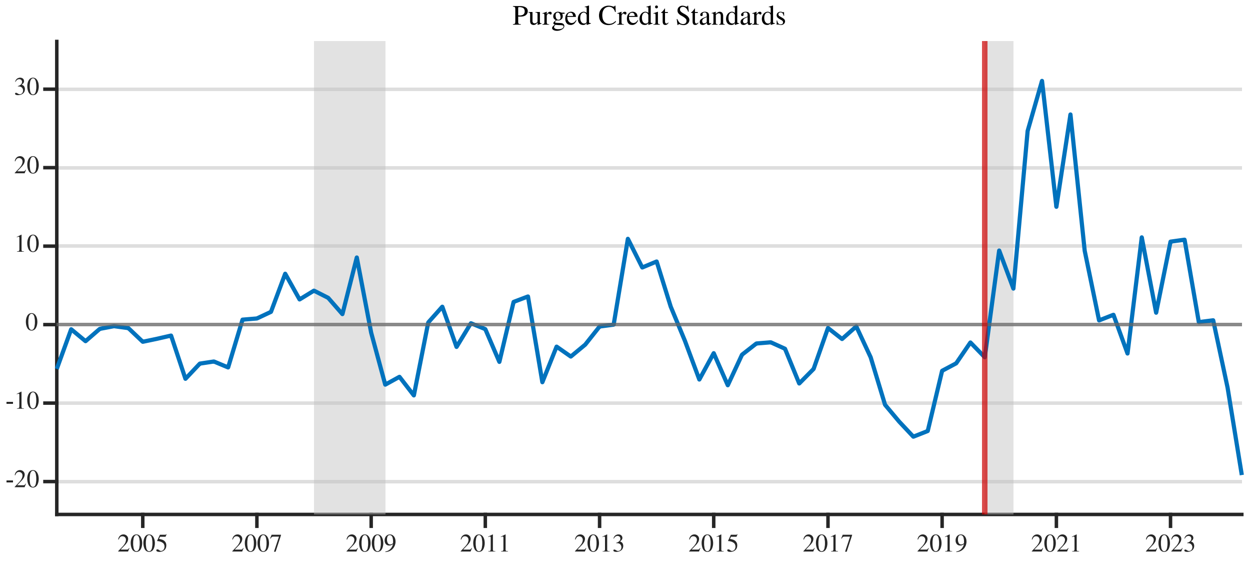

Figure 3: Estimated proxy for lending standards shocks

4. Econometric Framework

This section presents the econometric framework used to identify lending standards shocks attributable to borrower-based measures and to assess their effects on the real economy. Our empirical strategy proceeds in two steps. In the first step, we identify lending standards shocks. To do so, we estimate a reduced-form Bayesian vector autoregression (VAR) model incorporating seven French macroeconomic and financial variables, several of which capture developments in the housing and housing credit markets. Structural lending standards shocks are identified using the proxy derived from French banks' responses to the Bank Lending Survey (BLS), as discussed above. Since this proxy may be subject to measurement error and does not constitute a direct observation of the underlying shocks (Stock and Watson, 2018), we treat it as an external instrument in the VAR model rather than as the shock itself. In the second step, we isolate the component of lending standards shocks attributable to the borrower-based measure (BBM). This is achieved by exploiting differential dynamics across segments of new housing loan issuance, comparing loans directly targeted by the policy with those that are unaffected.

4.1. Identification of Lending Standards Shocks

4.1.1. Reduced-form VAR

We begin by specifying the reduced-form VAR that serves as the basis for the identification of lending standards shocks. Let $\mathbf{y}_t$ denote a vector of French macroeconomic and financial variables capturing developments on both the supply and demand sides of the housing and housing credit markets:

$$\mathbf{y}_t = (ri_t, hp_t, hc_t, lr_t, inc_t, gdp_t)'.$$

Here ri_t denotes real residential investment, hp_t real house prices, hc_t real outstanding housing credit, lr_t the nominal housing loan lending rate, inc_t real household disposable income, and gdp_t real GDP. Together, these variables reflect bank lending behavior, households' financing costs and purchasing power, and overall housing market conditions. The model also includes one exogenous variable, $\mathbf{z}_t$, namely the 10-year government bond yield, which serves as a proxy for banks' long-term funding costs. A detailed description of the data and their construction is provided in Appendix A.1.

We estimate the following reduced-form VAR:

$$\mathbf{y}_t = \mathbf{B}\mathbf{x}_t + \mathbf{u}_t, \qquad \mathbf{u}_t \sim \mathcal{N}(\mathbf{0}, \mathbf{\Sigma}_u), \tag{4}$$

where

$$\mathbf{x}_t = (\mathbf{y}'_{t-1}, \dots, \mathbf{y}'_{t-p}, \mathbf{z}'_t, \dots, \mathbf{z}'_{t-q}, 1)'$$

collects p lags of the endogenous variables, q lags of the exogenous variable, and a constant. We set $p = q = 4$ in all specifications. All variables are expressed in first differences of logarithms, except for the housing loan lending rate and the 10-year government bond yield, which enter the VAR in levels.

The choice of a VAR framework is primarily motivated by the relatively short sample period, which limits the feasibility of alternative approaches such as the local projection method proposed by Jordà (2005) (see also Jordà et al., 2015), as these require estimating separate instrumental-variable regressions for each impulse horizon.

4.1.2. Structural representation and invertibility

We assume that the data-generating process admits a structural representation linking the endogenous variables to a set of underlying structural shocks:

$$\mathbf{A}_0\mathbf{y}_t = \tilde{\mathbf{A}}\mathbf{x}_t + \boldsymbol{\varepsilon}_t, \qquad \boldsymbol{\varepsilon}_t \sim \mathcal{N}(\mathbf{0}, \boldsymbol{\Omega}), \tag{5}$$

where $\boldsymbol{\varepsilon}_t$ is an $n_\varepsilon \times 1$ vector of mutually uncorrelated structural shocks with zero mean and covariance matrix $\boldsymbol{\Omega}$, which is diagonal. Without loss of generality, the shocks are normalized such that $\boldsymbol{\Omega} = I_{n_\varepsilon}$.

Recovering this structural representation from the reduced-form VAR requires the standard *invertibility* assumption (see Plagborg-Møller and Wolf, 2022). The system is invertible with respect to $\mathbf{y}_t$ if the number of structural shocks equals the number of endogenous variables, $n_\varepsilon = n_y$, and if the shocks are spanned by current and past values of $\mathbf{y}_t$. Under this assumption, relaxed in some of our robustness exercises, and provided the VAR lag order is correctly specified, the contemporaneous matrix $\mathbf{A}_0$ is invertible and the reduced-form innovations can be expressed as linear combinations of the structural shocks. Defining the *impact matrix* $\mathbf{S} \equiv \mathbf{A}_0^{-1}$, we obtain

$$\mathbf{u}_t = \mathbf{S}\boldsymbol{\varepsilon}_t, \qquad \boldsymbol{\Sigma}_u = \mathbf{S}\mathbf{S}', \qquad \mathbf{B} = \mathbf{S}\tilde{\mathbf{A}}. \tag{6}$$

The matrix $\mathbf{S}$ maps structural shocks into reduced-form innovations, so that each column of $\mathbf{S}$ represents the contemporaneous effect of a structural shock on $\mathbf{y}_t$. We focus on the *lending standards shock*. Without loss of generality, let $\varepsilon_t^{LS} \equiv \varepsilon_{1,t}$ denote this shock and let $\mathbf{s}_1$ denote the first column of $\mathbf{S}$. Identifying $\mathbf{s}_1$ allows us to trace the dynamic effects of exogenous changes in lending standards on $\mathbf{y}_t$.

4.1.3. External instrument approach

Equation 6 shows that the reduced-form covariance matrix $\boldsymbol{\Sigma}_u$ does not uniquely determine the impact matrix $\mathbf{S}$. In particular, $\boldsymbol{\Sigma}_u$ provides only $\frac{n_y(n_y+1)}{2}$ distinct moments, whereas $\mathbf{S}$ contains n_y^2 unknown coefficients. Identifying restrictions are therefore required to recover the structural shocks.

A widely used identification strategy in empirical macroeconomics is the *external instrument* approach, implemented in a proxy-VAR framework (SVAR-IV) following Mertens and Ravn (2013). This strategy relies on a proxy that is correlated with the structural shock of interest but uncorrelated with other structural innovations. A key requirement for the validity of the external instrument approach is that the structural shock be invertible. When this condition fails, especially in the presence of measurement error (see below), the recovery of the structural shock and the associated impulse responses may be compromised. We assess this assumption below and consider alternative identification strategies.

We build on the proxy variable Z_t defined and estimated in Equation (3). Because Z_t may contain predictable components, we extract its innovation by projecting it onto its own lags, the lags of the endogenous macroeconomic variables $\{\mathbf{y}_\tau\}_{-\infty<\tau<t}$ and the current and lagged values of the exogenous variables $\{\mathbf{z}_\tau\}_{-\infty<\tau\leq t}$, concatenated into $\{\mathbf{x}_\tau\}_{-\infty<\tau\leq t}$. Denoting the resulting residual by $\tilde{Z}_t$, we have:

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

We use $\tilde{Z}_t$ as the external instrument. Validity requires:

- $\mathbb{E}[\tilde{Z}_t\, \varepsilon_{1,t}] \neq 0 \quad \text{(relevance)},$
- $\mathbb{E}[\tilde{Z}_t\, \varepsilon_{j,t}] = 0,\ \forall j \neq 1 \quad \text{(exogeneity)}.$

Under these conditions, the covariance between reduced-form innovations and the instrument identifies the corresponding impact vector up to a scale factor:

$$\mathbb{E}[\mathbf{u}_t \tilde{Z}_t] = \mathbf{s}_1\, \pi_1, \tag{7}$$

where $\pi_1 = \mathbb{E}[\varepsilon_{1,t}\tilde{Z}_t]$.

For each bootstrap draw, 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 $\mathbf{S}$ ($\mathbf{s}_1$), using two-stage least squares (2SLS) (Mertens and Ravn, 2013). Specifically, we instrument $\hat{u}_{1,t}$ with $\tilde{Z}_t$ and use the fitted values to project the remaining residuals. This yields an estimate of $\mathbf{s}_1$ proportional to

$$\mathbf{s}_1 \propto \frac{\mathbb{E}[\tilde{Z}_t \mathbf{u}_t]}{\mathbb{E}[\tilde{Z}_t u_{1,t}]}. \tag{8}$$

This approach is valid provided that $\mathbb{E}[\tilde{Z}_t u_{1,t}] \neq 0$, that is, 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.

4.2. Invertibility, Measurement Error, and Recoverability

We next discuss potential limitations of the external instrument approach.

Imperfect instruments and the issue of non-invertibility. Proxy variables are rarely perfect measures of the structural shocks. A natural representation is

$$\tilde{Z}_t = \pi_1 \, \varepsilon_{1,t} + j_\chi \, \chi_t, \quad \forall t, \tag{9}$$

where j_χ is a non-negative scalar capturing the loading of the proxy variable on the measurement error, χ_t, that is orthogonal to the structural shocks. This representation clarifies what proxy-SVAR methods do and do not require. For impulse responses, proxy-SVAR identification is driven by the signal component $\pi_1 \, \varepsilon_{1,t}$, and measurement error affects efficiency. For historical decompositions and shock importance, however, scale and measurement error become first-order objects.

Under standard assumptions, the external instrument approach delivers point identification of the lending standards shock $\varepsilon_{1,t}$ and the associated structural objects of interest, including impulse responses and historical decompositions. However, point identification fails if both i) the instrument $\tilde{Z}_t$ is measured with error (i.e., $\chi_t \neq 0$) and ii) the system is non-invertible. Three cases arise:

1. If the proxy variable is a direct measure of the structural shock (i.e., perfectly correlated with $\varepsilon_{1,t}$ up to scale), identification is immediate, as the shock is directly observed.

2. If the proxy is not a direct measure of the shock but the system is invertible, point identification is still achieved. In this case, invertibility ensures that the structural shock is spanned by current and past values of the observed variables, so that the reduced-form residuals estimated via the VAR contain the structural innovations. The external instrument then isolates, within these residuals, the component attributable to $\varepsilon_{1,t}$, thereby delivering point identification. As a result, the proxy-SVAR recovers a unique shock series and associated impulse responses.

3. By contrast, when the proxy is measured with error and the system is non-invertible, point identification fails. Measurement error implies that the proxy does not directly recover the structural shock, while non-invertibility implies that the shock is not spanned by current and past observables in the VAR (Stock and Watson, 2018; Mertens and Ravn, 2013). In that

case, multiple observationally equivalent shock processes generate the same reduced-form dynamics, and the structural objects of interest are not uniquely determined. An alternative identification strategy is the *internal instrument approach*, described in Appendix B.1.1. While this approach does not require invertibility, it only identifies impulse responses up to scale, i.e. relative impulse functions, and does not recover a point-identified shock series. As a result, it does not permit the construction of historical decompositions. In our empirical analysis, we therefore assess the robustness of our results by comparing the relative impulse response functions obtained under the external instrument approach with those derived from the internal instrument approach.

Both features, measurement error in the proxy variable and non-invertibility, are plausible in our setting. Lending standards shocks are only imperfectly captured by responses to the Bank Lending Survey, introducing measurement error in the proxy. Non-invertibility may also arise in the context of lending standards and macroprudential policy. Private agents may form expectations about future policy actions based on political or institutional information not captured by the VAR, while policymakers may respond to information about economic conditions that is unobserved by the econometrician. Such informational frictions generate non-invertible moving-average representations and undermine point identification.

Invertibility and recoverability tests. We implement the tests proposed by Plagborg-Møller and Wolf (2022) to assess whether the lending standards shock identified from banks' responses to the Bank Lending Survey is invertible or, more weakly, recoverable. The degree of invertibility for the shock $\varepsilon_{1,t}$ is summarized by

$$R^2_{0,1} \equiv \mathrm{Var}\big(\mathbb{E}[\varepsilon_{1,t} \mid \{\mathbf{x}_\tau\}_{\tau \leq t}]\big)\,, \tag{10}$$

while the degree of recoverability is given by

$$R^2_{\infty,1} \equiv \mathrm{Var}\big(\mathbb{E}[\varepsilon_{1,t} \mid \{\mathbf{x}_\tau\}_{\tau \in \mathbb{Z}}]\big)\,. \tag{11}$$

Invertibility requires $R^2_{0,1} = 1$, whereas recoverability requires only $R^2_{\infty,1} = 1$, i.e., that the shock is spanned not only by current and past, but also by future values of the observed macroeconomic variables ($E\left(\varepsilon_{1,t} \mid \{y_\tau, x_\tau\}_{-\infty<\tau<\infty}\right) = \varepsilon_{1,t}$). Recoverability is therefore weaker and accommodates environments in which agents or policymakers observe information about future fundamentals. Using the instrument constructed in Section 3 as a proxy, the procedure delivers identified sets and upper bounds for $R^2_{0,1}$ and $R^2_{\infty,1}$. In our application, while the bounds reject invertibility assumption of the lending standards shock at the 90% confidence level, they indicate that our lending standards shock is recoverable. Table 3 reports the results.

These findings guide our baseline identification. Although invertibility fails, point identification

Table 3: Test for invertibility and recoverability of the lending standards shock

	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]

can be restored under the weaker *recoverability* assumption (Plagborg-Møller and Wolf, 2022). Using the residualized proxy $\tilde{Z}_t$ defined above, we construct a recoverability-based proxy by projecting $\tilde{Z}_t$ onto the space spanned by current and future values of the endogenous and exogenous variables:

$$\tilde{Z}_t^\dagger = \mathbb{E}\left[\tilde{Z}_t \mid \{\mathbf{y}_\tau, \mathbf{z}_\tau\}_{\tau \geq t}\right]. \tag{12}$$

Under recoverability, $\tilde{Z}_t^\dagger$ is proportional to the structural shock $\varepsilon_{1,t}$ and is purged of measurement-error components that cannot be recovered from macroeconomic observables. In particular, the structural shock is identified up to scale as

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

In practice, we approximate the projection in (12) using four leads of $\mathbf{y}_t$. Figure 11 plots the estimates of $\tilde{Z}_t^\dagger$ which is used as the instrument in the proxy-SVAR and restores point identification under recoverability. This specification serves as our benchmark.

4.3. Identification of Macroprudential Policy Effects

Having identified the aggregate lending standards shock, we now turn to its decomposition into bank-driven and policy-induced components. Specifically, we decompose the lending standards shock series $\varepsilon_{1,t}$ into two components in the period following the implementation of the measure: i) a regular bank-driven component and ii) a BBM-induced component. Identification of these components relies on four key assumptions, presented below.

4.3.1. Decomposition of the Lending Standards Shock

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

Assumption A.1: *Let T^* denote the implementation date of the BBM (in our application, $T^* =$ 2019Q4). For $t < T^*$, the observed shock reflects only the bank-driven component, denoted $\widetilde{\varepsilon}_{1,t}$.*

For $t \geq T^*$, the observed shock is given by the sum of the two components:

$$\varepsilon_{1,t} = \begin{cases} \widetilde{\varepsilon}_{1,t}, & t < T^*, \\ \widetilde{\varepsilon}_{1,t} + \varepsilon_{1,t}^{BBM}, & t \geq T^*. \end{cases} \tag{13}$$

Thus, after T^*, estimated lending standards shocks reflect both endogenous bank behavior and the effects of regulatory constraints. We allow the two components, $\widetilde{\varepsilon}_{1,t}$ and $\varepsilon_{1,t}^{\mathrm{BBM}}$, to be correlated.

4.3.2. Treatment and Control Groups

To isolate the BBM-induced component from the regular bank-driven component, we exploit the fact that the macroprudential measure binds at specific regulatory thresholds. As a result, its effects are expected to be concentrated in credit segments located around these thresholds, while segments sufficiently distant from them should remain largely unaffected. This differential exposure provides the basis for our identification strategy.

Definition of treatment and control groups. In the French case, the borrower-based measure targets both the debt service-to-income (DSTI) ratio and loan maturity. We therefore define two *treatment groups*: (i) the share of loan volumes with a DSTI above 35%, and (ii) the share with maturities exceeding 25 years. [7] These segments are directly exposed to the policy and are expected to respond contemporaneously to its implementation. As control groups, we consider (iii) loans with a DSTI below 20%, and (iv) loans with maturities between 10 and 15 years. These segments lie well below the regulatory thresholds and are thus unlikely to be materially affected by the measure.

Empirical patterns. Figure 4 plots the evolution of these four series over time, constructed from loan-level data. A detailed description of these data and their construction is provided in Appendix A.2. The top panels report the share of newly issued housing loans exceeding the BBM regulatory thresholds, namely, loans with a DSTI above 35% and maturities beyond 25 years. These series capture borrower segments directly targeted by the policy. Both exhibit a sharp and immediate decline following the introduction of the borrower-based measure, indicating a strong adjustment in lending activity at the regulatory thresholds.

A notable feature of the data is the change in co-movement across segments around the policy implementation. Prior to the BBM, treated and control series exhibit a marked negative co-movement: increases in the share of loans above the regulatory thresholds are mirrored by declines

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[7] We exclude loans with maturities between 25 and 27 years that remain compliant under specific conditions; see Section 2.

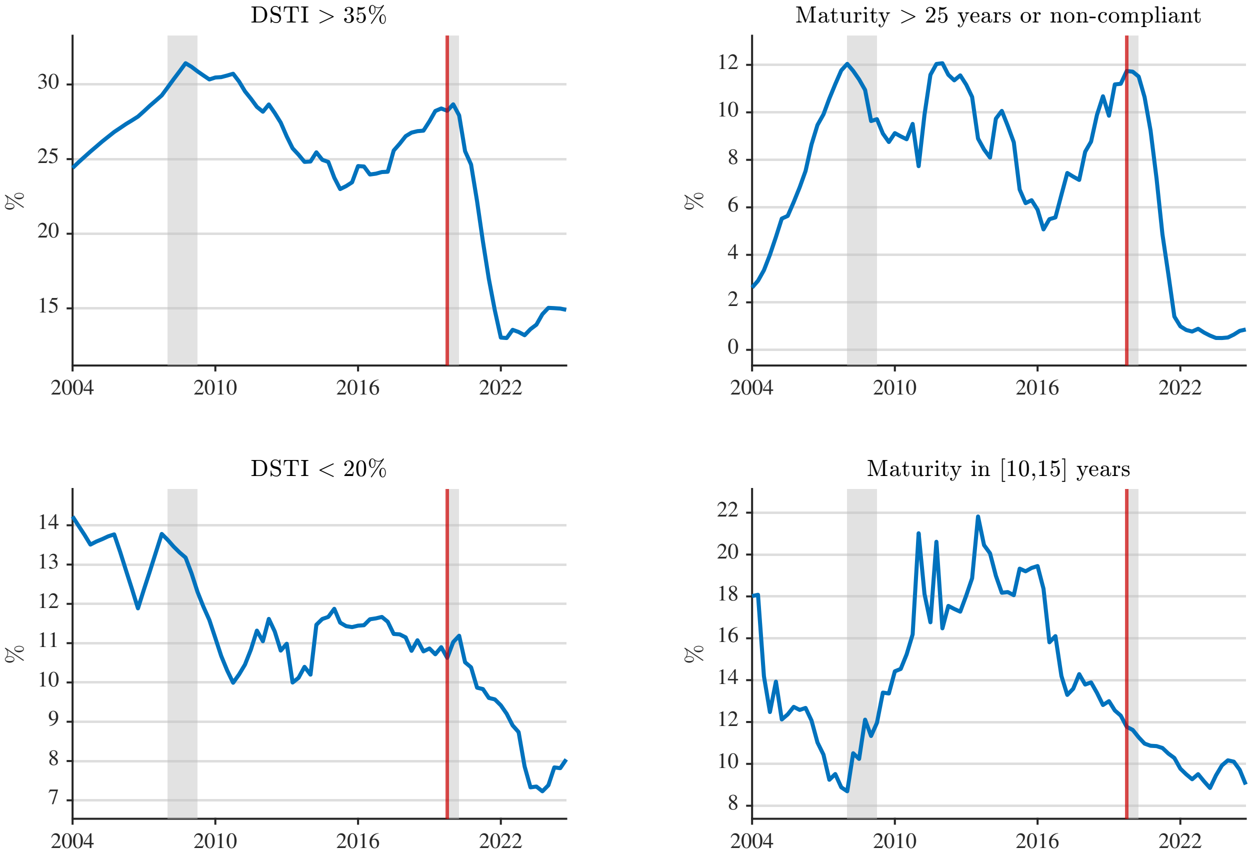
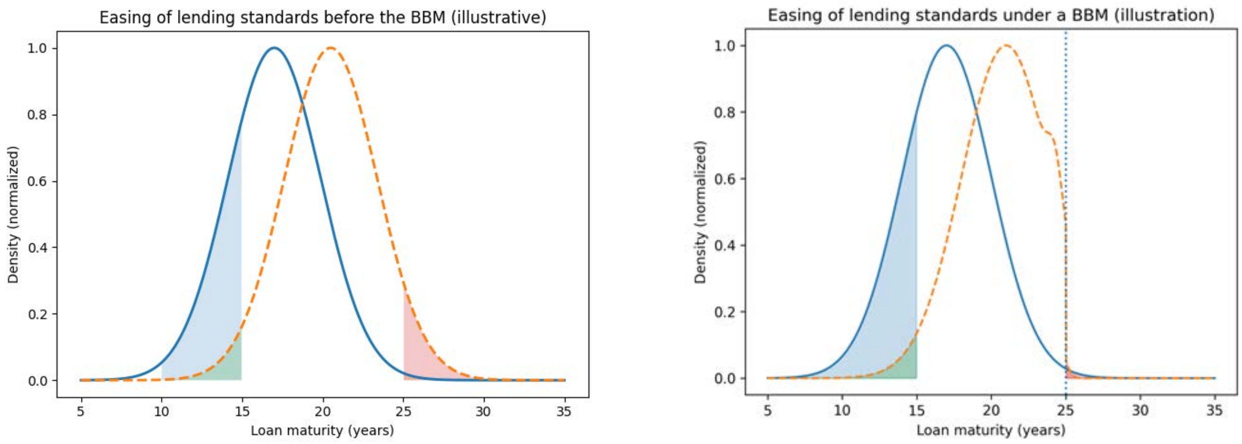


Figure 4: Distribution of lending standards.

in the share of loans well below them, both along the DSTI and maturity dimensions. Following the introduction of the measure, this pattern weakens and partially reverses, consistent with a compression of the distribution induced by the binding regulatory constraints.

Distributional mechanism. This change in co-movement reflects the underlying distributional mechanism induced by the policy. To further illustrate the underlying mechanism, Figure 5 provides a stylized example of how the distribution of loan maturities adjusts in the absence and in the presence of a binding borrower-based measure. In the unconstrained case (left panel), an easing of lending standards shifts the distribution to the right, increasing the mass of loans in the treatment region (i.e., above the regulatory threshold) while reducing the share of loans in the control region (well below the threshold). By contrast, when a maturity cap is imposed (right panel), the distribution becomes truncated at the policy threshold. As a result, further easing no longer translates into a higher share of loans in the treatment group. Instead, mass is reallocated toward loans just below the threshold, while the control group—located sufficiently far from the constraint—remains largely unaffected. This induces a compression of the distribution around the regulatory limit and alters the co-movement between treatment and control groups.



(a) Unconstrained case

(b) With BBM constraint

Figure 5: Effect of a Borrower-Based Measure on the Distribution of Loan Maturities

Notes: The figure illustrates how a borrower-based measure affects the distribution of loan maturities. In the absence of a constraint (left panel), an easing of lending standards shifts the distribution to the right, increasing the share of loans above the regulatory threshold and reducing the share well below it. When a binding constraint is introduced (right panel), the distribution becomes truncated at the threshold, preventing further expansion of the treatment region and inducing a reallocation of mass just below the constraint, while the control region remains largely unaffected.

4.3.3. Identification of the BBM-Induced Component

We now formalize this intuition by linking the dynamics of loan shares in treatment and control groups to the underlying structural lending standards shocks. For each borrower characteristic of interest, let $f^j_{i,t}$ denote the share of new loans in category i at time t, where $i \in \{DSTI, Mat\}$ indexes the lending standard (DSTI ratio or maturity) and $j \in \{C, T\}$ indicates whether the observation belongs to the control or treatment group. We decompose each series into a predictable component and an innovation:

$$f^j_{i,t} = E\left(f^j_{i,t} \mid \mathcal{I}_t\right) + \tilde{f}^j_{i,t}, \tag{14}$$

where $\mathcal{I}_t = \{\mathbf{y}_\tau, \mathbf{z}_\tau, f^j_{i,\tau}\}_{\tau<t} \cup \{\mathbf{z}_t\}$ denotes the information set consisting of lagged endogenous macroeconomic variables, current and lagged exogenous variables, and past realizations of $f^j_{i,t}$. The residual $\tilde{f}^j_{i,t}$ captures the unpredictable component of lending standards in group j, reflecting innovations in macroeconomic conditions, including shocks to lending standards.

Exclusion restriction. Next, we decompose the innovation $\tilde{f}^j_{i,t}$ into three components: one driven by the bank-driven 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 linear combinations of two components as follows:

$$\tilde{f}_{i,t}^{j} = \alpha_i^j\, \widetilde{\varepsilon}_{1,t} + \beta_i^j\, \varepsilon_{1,t}^{\text{BBM}} + \zeta_{i,t}^{j}, \tag{15}$$

where $\zeta_{i,t}^{j}$ represents the residual macroeconomic and segment-specific disturbances.

Assumption A.2: *The control series are unaffected by the BBM-induced component such that:*

$$\beta_i^C = 0, \;\; \forall i \in \{DSTI, Mat\} \tag{16}$$

whereas for the treatment series we allow:

$$\beta_i^T \neq 0, \;\; \forall i \in \{DSTI, Mat\} \tag{17}$$

Accordingly, the treatment series load on both $\widetilde{\varepsilon}_{1,t}$ and $\varepsilon_{1,t}^{\text{BBM}}$, while the control series load solely on $\widetilde{\varepsilon}_{1,t}$. Assumption A.2 states that some borrower segments are sufficiently far from regulatory limits and are not directly affected by the borrower-based measure.

Elasticity stability across periods. To implement our identification strategy, we impose an additional assumption on the stability of the relationship between bank-driven lending standards shocks and loan shares across regimes, before and after the introduction of the BBM.

Assumption A.3: *The sensitivity of loan shares to the bank-driven lending standards component is stable across periods. In particular, for the control group, the loading on the bank-driven component is constant before and after the implementation of the borrower-based measure:*

$$\alpha_i^C \textit{ is constant over time and } \alpha_i^C \neq 0, \quad \forall i \in \{DSTI, Mat\}. \tag{18}$$

Assumption A.3 implies that the response of control-group loan shares to bank-driven lending standards shocks remains unchanged across regimes. Since these segments are not directly affected by the borrower-based measure, they provide a stable benchmark for identifying the additional variation induced by the BBM. This assumption is related to identification strategies based on regime shifts, such as heteroskedasticity-based identification (Rigobon, 2003). Consistent with this assumption, we expect the control-group loadings to be positive and stable, reflecting a positive response to bank-driven lending standards shocks. By contrast, for the treatment group, we expect negative loadings on both the bank-driven and BBM-induced components, as tighter lending standards reduce the share of loans located above the regulatory thresholds. Appendix C.3 tests the relevance of this assumption.

Proportionality restriction. To achieve point identification of the BBM-induced component, we impose an additional auxiliary assumption linking it to the aggregate lending standards shock.

Assumption A.4 (Proportionality restriction): *The BBM-induced component is proportional to the aggregate lending standards shock after the implementation of the borrower-based measure:*

$$\varepsilon_{1,t}^{\text{BBM}} = \begin{cases} 0, & t < T^*, \\ k\,\varepsilon_{1,t}, & t \geq T^*, \end{cases} \tag{19}$$

where k is a constant parameter.

This assumption implies that the BBM component scales the aggregate lending standards shock in the post-policy period. Combined with the additivity assumption (Assumption A.1), it follows that the bank-driven component is also proportional to the aggregate shock, with coefficient $(1-k)$. As a result, both components can be expressed as constant multiples of the observed lending standards shock.

Estimation and identification of k. Under Assumptions A.1–A.4, the model implies that the response of control-group loan shares to lending standards shocks differs across regimes due to the scaling induced by the BBM. In particular, comparing the sensitivity of control-group series before and after the implementation of the measure allows us to identify the parameter k:

$$k = 1 - \frac{\gamma_{i,\text{post}}^{C}}{\gamma_{i,\text{pre}}^{C}}. \tag{20}$$

where $\gamma_{i,\text{pre}}^{C}$ and $\gamma_{i,\text{post}}^{C}$ denote the estimated responses of control-group loan shares to lending standards shocks in the pre- and post-BBM periods, respectively. A detailed derivation of this result and the associated system of equations are provided in Appendix B.1.3.

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 instrument are filled with zeros (McKay and Wolf, 2023). We use data about the distribution of lending standards from 2004Q1 to 2024Q4 and purge the series from the expected component, as specified in Equation (14). 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. We first analyze the dynamic responses of macroeconomic variables to a contractionary lending standards shock. We then quantify the importance of these shocks using forecast variance ratios (FVRs), before examining their historical contributions. Finally, we assess the macroeconomic effects of borrower-based macroprudential measures. Throughout, we evaluate the robustness of our benchmark specification, based on an external instrument ($\tilde{Z}_t^{\dagger}$) under recoverability, by comparison with an internal instrument approach when possible.

5.1. Dynamic Effects of a Lending Standards Shock

Figure 6 reports the cumulative responses of the main macroeconomic variables to a contractionary lending standards shock.

Interpretation of lending standards shocks. The shock is associated with a tightening in credit conditions, reflected in both borrowing costs and credit quantities. Housing loan interest rates increase by up to about 10 basis points after two quarters and remain elevated for two years. At the same time, the growth of outstanding housing credit declines gradually and persistently over the entire horizon, with no evidence of a rebound, leading to a cumulative reduction of about 1.5 percentage points after five years. Taken together, the simultaneous increase in borrowing costs and contraction in credit volumes indicate that the identified disturbance takes the form of a tightening in credit supply conditions.

Composition vs. competition effects. The joint response of lending rates and credit volumes reflects two opposing forces. On the one hand, tighter lending standards exclude riskier borrowers, improving average borrower quality and exerting downward pressure on lending rates (*composition effect*). On the other hand, reduced credit access intensifies competition among borrowers, allowing banks to raise lending rates (*competition effect*). While both mechanisms reinforce the contraction in credit quantities, they operate in opposite directions on lending rates. The observed increase in rates indicates that the competition effect dominates.

The tightening in credit supply propagates primarily through the housing sector. Residential investment declines in the short run and remains below baseline throughout the horizon, reaching about -1 percentage point after one year. House price growth also decreases persistently, with a cumulative decline of roughly 2.5 percentage points over the medium run, reflecting weaker housing demand and reduced credit availability. By contrast, the effects on broader macroeconomic aggregates are limited and not statistically significant. Real household income declines modestly on impact (around -0.3 to -0.4 percentage points) and remains slightly below baseline, while real GDP exhibits a small and short-lived contraction.

Overall, these results identify lending standards shocks as an important and persistent driver of housing and housing credit market dynamics, with non-negligible effects on both borrowing costs and credit quantities that accumulate over time. In contrast, their impact on broader macroeconomic aggregates remains limited, indicating that the transmission of these shocks is largely confined to the housing sector.

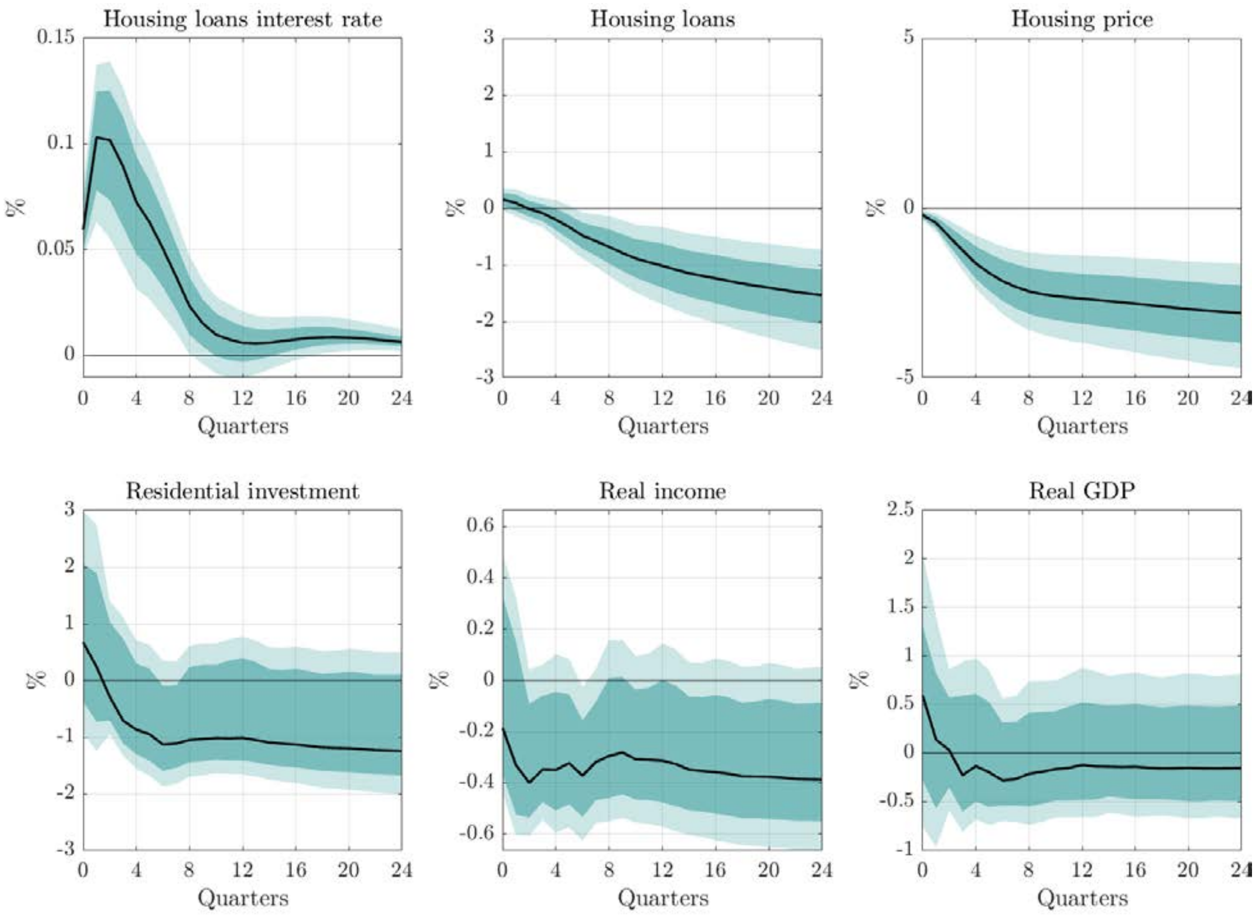


Figure 6: Dynamic Effects of a Contractionary Lending Standards Shock

Notes: The figure reports the cumulative responses of housing and macroeconomic variables to a contractionary lending standards shock. Black solid lines denote posterior median responses, while shaded blue areas represent the 16th–84th and 5th–95th percentile credible intervals. Estimates are obtained from a proxy-SVAR using the external instrument $\tilde{Z}_t^{\dagger}$, constructed under the recoverability assumption.

Instrument strength. The relevance of the external instrument is supported by the first-stage statistics. The corresponding F-statistic is equal to 11.03, exceeding the conventional rule-of-thumb threshold of 10 for weak instruments (Staiger and Stock, 1997; Stock and Yogo, 2005; Andrews et al., 2019). This suggests that weak-instrument concerns are unlikely to materially affect inference

External vs. internal instrument approaches. Figure 7 compares the responses obtained from our benchmark external instrument approach with those derived from an internal instrument approach. The latter relaxes both invertibility and recoverability assumptions but identifies relative impulse responses, i.e., only up to scale. Despite these differences, the estimated responses are remarkably similar across the two approaches. This comparison provides additional support for the robustness of our baseline results.

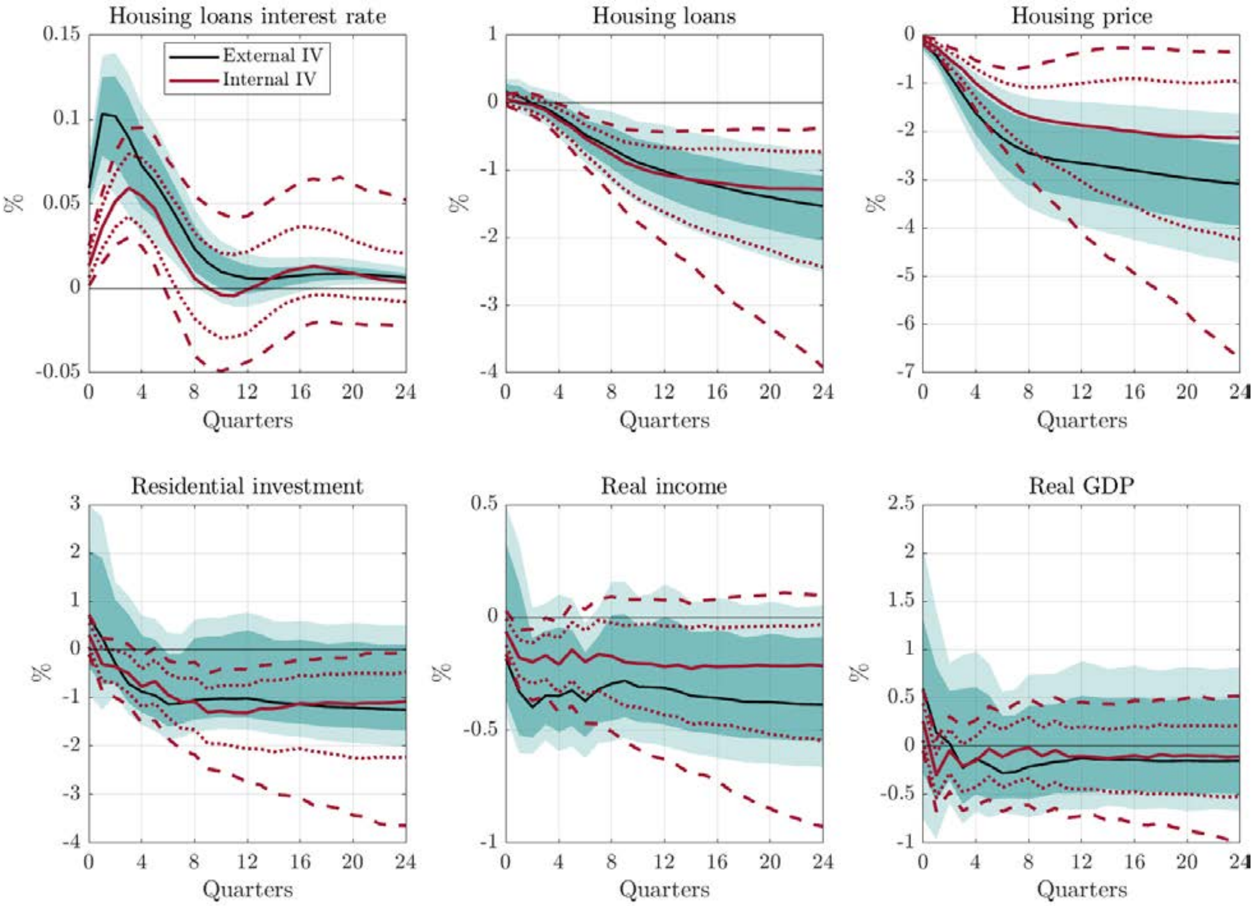


Figure 7: External vs. Internal Instrument Estimates of Relative Impulse Responses

Notes: The figure compares relative impulse responses to a contractionary lending standards shock obtained using the external and internal instrument approaches. Black solid lines (with blue shaded bands) denote the posterior median and confidence intervals from the benchmark external instrument approach using $\tilde{Z}_t^{\dagger}$. Red lines (with dashed and dotted bands) correspond to estimates from the internal instrument approach, which identifies responses up to scale.

5.2. Lending Standards Shocks Drive Borrowing Costs and House Price Fluctuations

To quantify the importance of lending standards shocks in driving macroeconomic fluctuations, we use the forecast variance ratio (FVR), which measures how much forecast uncertainty about a variable is reduced when the future path of the shock is known. Formally, for variable i at horizon

h,

$$\mathrm{FVR}_{i,h} \;=\; 1 - \frac{\mathrm{Var}\Big(y_{i,t+h} \,\Big|\, \{y_\tau\}_{-\infty<\tau\le t},\ \{\epsilon_{1,\tau}\}_{t<\tau<\infty}\Big)}{\mathrm{Var}\Big(y_{i,t+h} \,\Big|\, \{y_\tau\}_{-\infty<\tau\le t}\Big)}. \tag{21}$$

Figure 8 reports the corresponding estimates. Lending standards shocks account for a sizeable share of fluctuations in borrowing costs and housing prices. In particular, they explain around 50 to 60 percent of the forecast error variance of housing loan interest rates at medium horizons and about 35 to 40 percent of the variation in house price growth.

By contrast, their contribution to credit quantities is more moderate, accounting for roughly 15 to 20 percent of the variation in housing loan growth. This indicates that, while lending standards play an important role, other factors, such as demand conditions and monetary policy, also contribute to fluctuations in credit volumes.

The explanatory power of lending standards shocks is considerably weaker for broader macroeconomic aggregates. They account for less than 10 percent of the variation in residential investment, real income, and real GDP across horizons, with relatively wide confidence bands. Overall, the effects of lending standards shocks are concentrated in housing and housing credit markets, with limited spillovers to aggregate activity.

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 C.2.

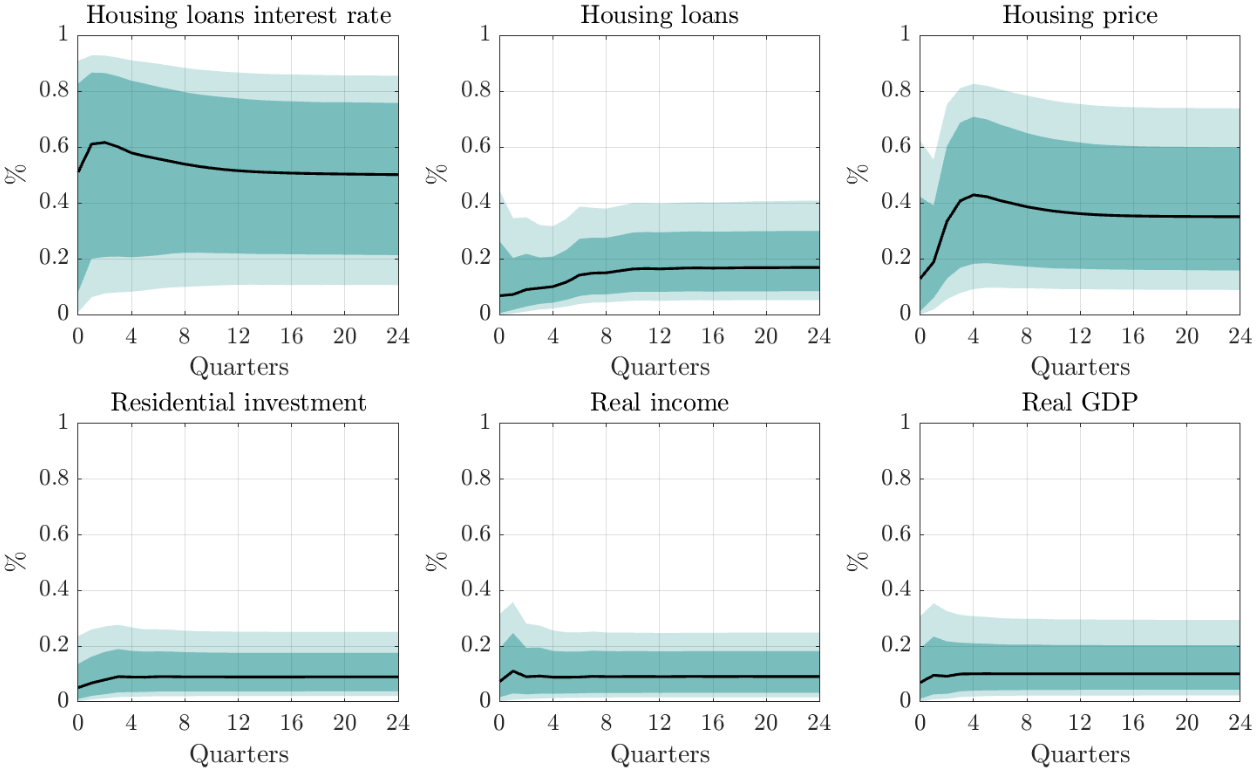


Figure 8: Contribution of Lending Standards Shocks to Forecast Error Variance

Notes: The figure reports the share of the forecast error variance of each variable attributable to the identified lending standards shock at different horizons. Solid lines denote point estimates, while shaded areas correspond to the 16th–84th and 5th–95th percentile bootstrap confidence bands. Estimates are obtained from a proxy-SVAR using the external instrument $\tilde{Z}_t^{\dagger}$, constructed under the recoverability assumption.

5.3. Historical Contribution of Lending Standards Shocks to Housing Market Fluctuations

Figure 9 reports the cumulative historical contribution of lending standards shocks to key housing and housing credit market variables, namely housing loan interest rates, real outstanding housing loan (year-on-year) growth, and real house price (year-on-year) growth.

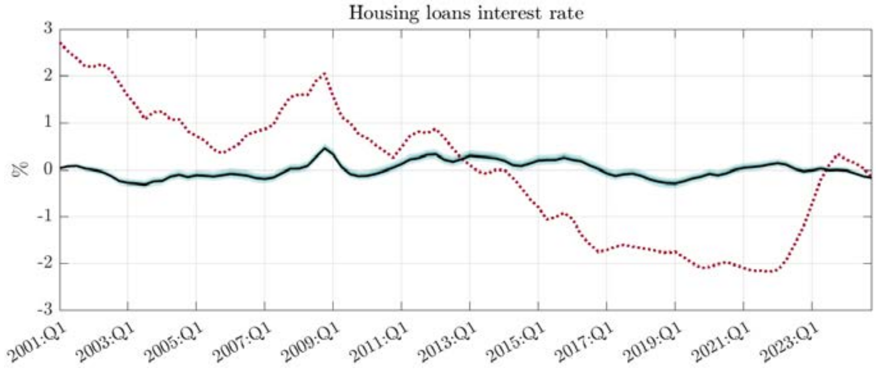
Lending standards shocks account for sizable fluctuations in housing prices and credit over the sample, particularly during periods of financial stress and credit expansion. During the Global Financial Crisis (2008–2009), they contributed to a cumulative decline in house price growth of about 4 to 6 percentage points at the trough and to a reduction in housing loan growth of roughly 2 to 3 percentage points. A similar, though less pronounced, pattern is observed during the euro area sovereign debt crisis.

In contrast, during the post-2015 period and up to the Covid crisis, lending standards shocks contributed positively to housing dynamics. At their peak, they account for an increase in house price growth of around 3 to 4 percentage points and about 1 to 2 percentage points for housing loan growth, consistent with a period of easing credit conditions.

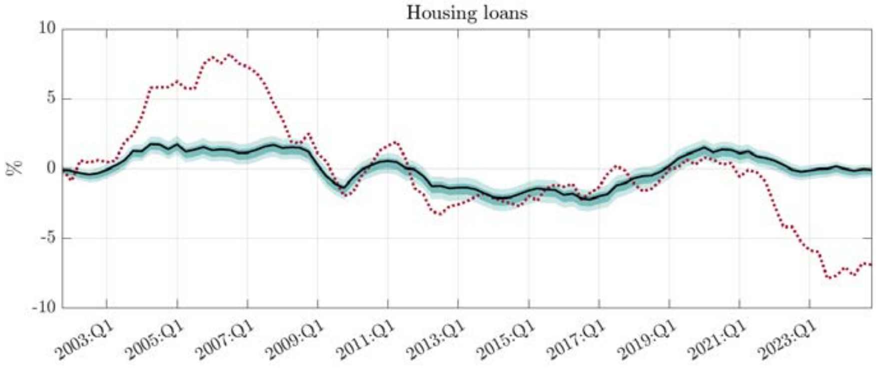
By comparison, the recent downturn in the housing market following the Covid period appears to be only weakly related to lending standards shocks. Their contribution to house price growth remains limited—generally within a range of ±2 percentage points—suggesting that other factors, such as monetary policy tightening and broader macroeconomic conditions, play a dominant role.

Across all periods, lending standards shocks have comparatively limited explanatory power for housing loan interest rates. Their contribution remains small throughout the sample, typically within ±0.3 to 0.4 percentage points, indicating that lending rates are largely driven by other macro-financial factors.

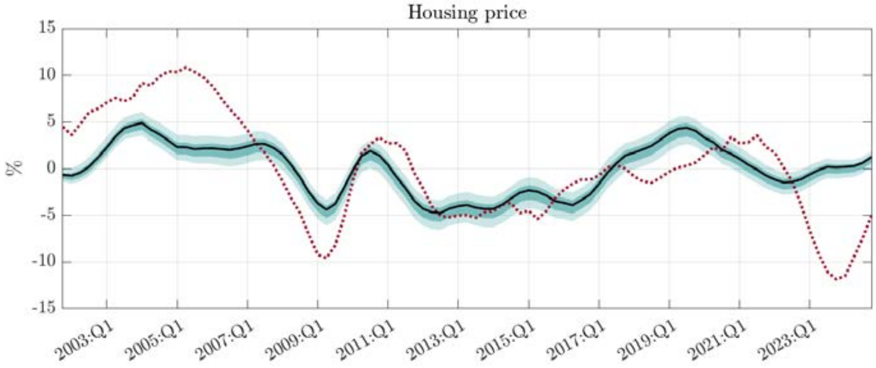
Overall, these results indicate that lending standards shocks are an important driver of fluctuations in housing credit and house prices, particularly during episodes of tightening and easing credit conditions, while their influence on lending rates remains limited.



(a) Housing loan interest rate



(b) Housing loans



(c) Housing prices

Figure 9: Historical Contribution of Lending Standards Shocks

Notes: The figure reports the cumulative historical contribution of identified lending standards shocks to housing loan interest rates, housing loan growth, and house price growth. Black solid lines denote the estimated contribution of the shock, while shaded areas represent the 68% and 90% confidence bands. Red dotted lines correspond to the observed series (demeaned). Contributions are expressed in percentage points.

5.4. Macroeconomic Effects of Borrower-Based Measures

We now quantify the macroeconomic effects of the borrower-based measure (BBM) by decomposing the identified lending standards shock into its bank-driven and policy-induced components, as described in Section 4.3. The estimation yields a value of $k = 1.04$, indicating that the BBM-induced component largely offsets the underlying bank-driven variation in lending standards in the post-policy period.

Figure 10 reports the cumulative historical contribution of the BBM component to key housing and macroeconomic variables. The BBM exerts statistically significant but quantitatively modest effects on housing and credit market outcomes, with a time-varying impact that is particularly pronounced around the implementation period. For housing loan interest rates, the BBM contributes positively to borrowing costs, with an increase of up to about 0.15 to 0.20 percentage points at its peak in 2022. This suggests that the tightening induced by the measure translates into higher effective lending rates.

For housing credit, the contribution of the BBM is initially negative and becomes increasingly contractionary over time. At its trough in 2023–2024, the BBM accounts for a decline in housing loan growth of approximately 0.8 percentage points, accounting for roughly 10 percent of the observed decline in housing credit growth over the same period. This effect is persistent and aligns with the tightening in borrower constraints.

House price dynamics display a similar pattern. The BBM contributes to a decline in house price growth of about 2 to 3 percentage points at its trough, reflecting the combined effect of reduced credit availability and weaker housing demand. This contraction is followed by a gradual attenuation, consistent with the adjustment of the housing market over time.

By contrast, the effects on broader macroeconomic aggregates remain limited. The contribution of the BBM to residential investment fluctuates within a relatively wide range but remains centered around zero, while its impact on real income and real GDP is small and imprecisely estimated throughout the sample.

Overall, these findings indicate that borrower-based macroprudential policy has non-negligible and persistent effects on housing and housing credit market outcomes, particularly on credit volumes and house prices, while its spillovers to aggregate economic activity remain limited.

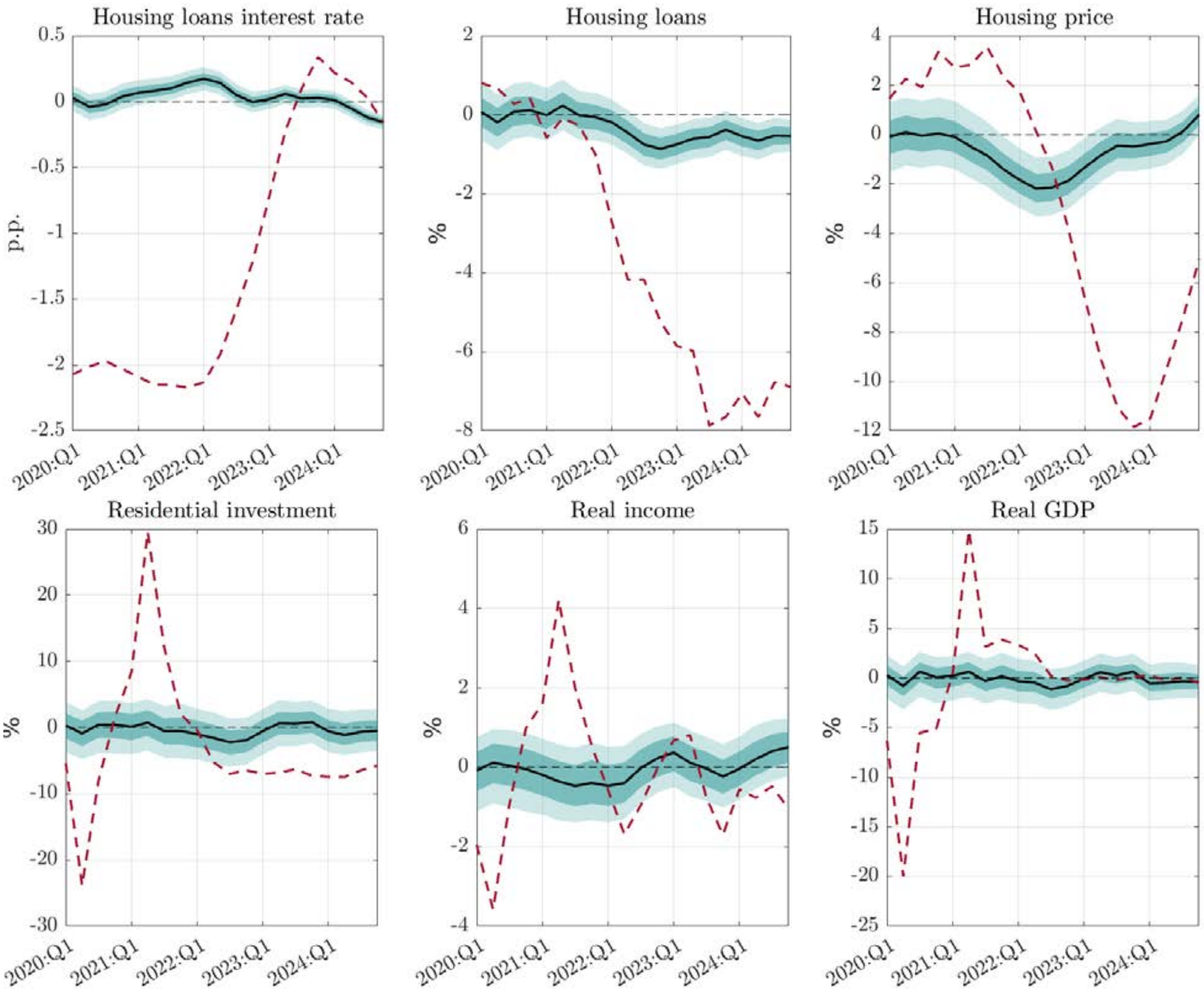


Figure 10: Macroeconomic effects of borrower-based measures (BBM)

Notes: The figure reports the cumulative contribution of the BBM-induced component of lending standards shocks to housing and macroeconomic variables. Solid lines denote point estimates, and shaded areas represent 68% and 90% confidence bands. The red dashed line corresponds to the demeaned observed series. Estimates are based on the decomposition of lending standards shocks under the proportionality restriction ($k = 1.04$).

6. Conclusion

This paper develops a novel two-step macroeconometric framework to assess the macroeconomic effects of macroprudential policies that target household leverage. In the first step, we construct a survey-based instrument to identify lending standards shocks in a VAR framework. In the second step, we exploit heterogeneous responses across borrower segments to isolate, within lending standards shocks, the component attributable to borrower-based macroprudential measures

(BBMs). This approach, which we label *mesoeconometrics*, allows us to provide new quantitative evidence on the effects of these measures on housing and credit markets.

Our results indicate that the BBM-induced component of lending standards shocks has statistically significant but economically moderate effects concentrated in credit and housing market outcomes. At their peak, these measures increase housing loan interest rates by about 15 to 20 basis points and reduce housing loan growth by approximately 0.8 percentage points, corresponding to roughly 10 percent of the observed contraction in credit over the same period. House price growth declines by about 2 to 3 percentage points at its trough. By contrast, we find little to no statistically significant impact on real residential investment, household income, or real GDP. This pattern suggests that the transmission of BBMs operates through specific segments of the economy rather than generating broad-based macroeconomic effects.

Collectively, these findings support the view that borrower-based macroprudential policies can enhance the resilience of household credit markets while limiting unintended consequences for aggregate economic activity. More broadly, our mesoeconometric framework provides a tractable and data-efficient approach to evaluating the aggregate effects of policies that operate through distributional constraints, and can be readily applied to other macroprudential settings.

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A. Data sources

A.1. VAR variables

Table 4: Variable definitions and sources

Variable	Definition	Source
Housing loan interest rate	Interest rate on new loans to households for house purchase with an initial rate fixation period of more than 10 years	Banque de France
Housing loans	Outstanding stock of housing loans granted to households, deflated by the CPI	Banque de France
House prices	Nominal house price index divided by the consumer expenditure deflator	OECD
Residential investment	Gross fixed capital formation by asset: dwellings (gross), chain-linked volumes	OECD
Real income	Real gross disposable income of households and non-profit institutions serving households	OECD
Real GDP	Gross domestic product, volumes	OECD
10-year OAT yield	Yield on 10-year French government bonds	Banque de France

A.2. Lending standards data

DSTI. The quarterly series on the distribution of new housing loans by DSTI ratio combine several data sources. From 2012Q1 to 2024Q4, the baseline source is the French bank-level reporting CREDITHAB, which covers all new housing loans in France. This dataset displays a break in 2020Q1 following a change in reporting scope. To correct for this break, we rely on confidential loan-level data communicated to the French supervisory authority (ACPR), covering approximately one third of the market. Specifically, we use the growth rate observed in the confidential loan-level data between 2019Q4 and 2020Q1 to infer a consistent 2019Q4 value under the post-2020 reporting scope, and then retropolate the series back to 2012Q1 using the dynamics of the CREDITHAB data. For the earlier period, we use bank-level annual supervisory data published by the ACPR, which also cover all new housing loans. We interpolate these annual observations to quarterly frequency and use them to extend the CREDITHAB series back to 2001Q4.

Maturity. From 2020Q1 to 2024Q4, the quarterly maturity series come from CREDITHAB reporting. Before 2020Q1, we retropolate them using confidential, representative loan-level data reported to the Banque de France. A caveat is that the confidential series available prior to 2020 capture loans with maturities of 25 years or more, whereas the post-2020 CREDITHAB series capture loans classified as non-compliant with the BBM, namely loans with maturities strictly exceeding 25 years, except for specific exemptions applying to loans with maturities between 25 and 27 years.

All series are seasonally adjusted.

B. Additional Identification and Estimation Details

B.1. More on the Identification of Lending Standards Shocks

B.1.1. Internal instrument approach

This appendix describes the *internal instrument* approach, which relaxes the invertibility assumption in (5). In addition to satisfying the relevance and exogeneity conditions in (4.1.3), the instrument Z_t must be orthogonal to all leads and lags of 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, the approach incorporates it directly into the system by augmenting the VAR and placing Z_t first in the ordering. Specifically, the augmented vector is defined as

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

A Cholesky decomposition of the covariance matrix of $\bar{\boldsymbol{y}}_t$, denoted $\boldsymbol{\Sigma}^*$, then delivers the impulse responses to the structural shock of interest from its first column, normalized by its first element:

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

This approach does not require invertibility of the original VAR and remains valid in the presence of measurement error in the instrument or non-invertible shocks (Ramey, 2011; Plagborg-Møller and Wolf, 2021). However, it identifies impulse responses only up to scale and does not recover a point-identified series for the structural shock.

B.1.2. Recoverable Instrument

Figure 11 shows the recoverable instrument $\tilde{Z}_t^{\dagger}$ used after purging out the measurement error following equation (12).

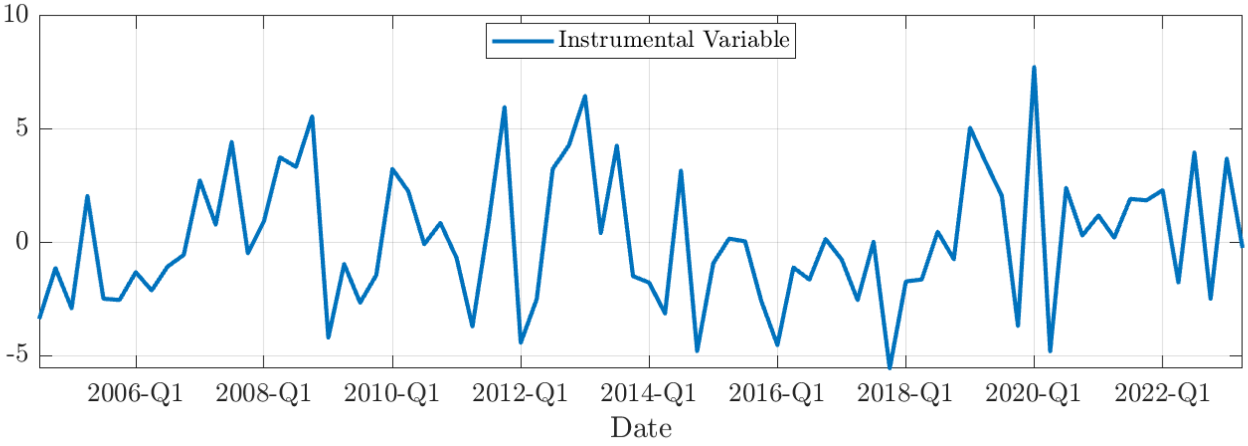

Figure 11

B.1.3. Closed-form derivation of the estimator for k

This subsection derives the closed-form expression used to identify the parameter k, which governs the relative contribution of the BBM-induced component to the aggregate lending standards shock. The derivation relies on the identifying assumptions stated in the main text, namely the additive decomposition (Assumption A.1), the exclusion restriction (Assumption A.2), and the proportionality restriction (Assumption A.4).

Pre-BBM period. For $t < T^*$, the lending standards shock coincides with the bank-driven component. Using Equation (15), the dynamics of loan shares for control and treatment groups can be written as:

$$\begin{cases} \tilde{f}_{i,t}^{C} = \alpha_{i,1}^{C}\, \varepsilon_{1,t} + \zeta_{i,t}^{C}, \\ \tilde{f}_{i,t}^{T} = \alpha_{i,1}^{T}\, \varepsilon_{1,t} + \zeta_{i,t}^{T}. \end{cases} \tag{22}$$

Post-BBM period. For $t \geq T^*$, the lending standards shock is decomposed into a bank-driven and a BBM-induced component. Under the proportionality restriction, we have $\varepsilon_{1,t}^{\text{BBM}} = k\, \varepsilon_{1,t}$, implying that the bank-driven component is given by $(1-k)\varepsilon_{1,t}$. Substituting into Equation (15), we obtain:

$$\begin{cases} \tilde{f}_{i,t}^{C} = \alpha_{i,1}^{C}\, (1-k)\, \varepsilon_{1,t} + \zeta_{i,t}^{C}, \\ \tilde{f}_{i,t}^{T} = \left[\alpha_{i,1}^{T}(1-k) + \alpha_{i,2}^{T} k\right] \varepsilon_{1,t} + \zeta_{i,t}^{T}. \end{cases} \tag{23}$$

Estimation and identification of k. We estimate the relationship between loan share innovations and the lending standards shock by regressing $\tilde{f}_{i,t}^{j}$ on $\varepsilon_{1,t}$ separately over the pre- and post-BBM periods. Let $\gamma_{i,\text{pre}}^{C}$ and $\gamma_{i,\text{post}}^{C}$ denote the corresponding OLS coefficients for the control group. From Equations (22) and (23), these coefficients satisfy:

$$\begin{cases} \gamma_{i,\text{pre}}^{C} = \alpha_{i,1}^{C}, \\ \gamma_{i,\text{post}}^{C} = \alpha_{i,1}^{C}\,(1-k). \end{cases}$$

Taking the ratio of these coefficients yields:

$$k = 1 - \frac{\gamma_{i,\text{post}}^{C}}{\gamma_{i,\text{pre}}^{C}}. \tag{24}$$

This expression provides a closed-form estimator for k, which can be used to recover the BBM-induced component $\varepsilon_{1,t}^{\text{BBM}}$ and the bank-driven component $\widetilde{\varepsilon}_{1,t}$, both of which are proportional to the aggregate lending standards shock.

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.

C.1. Log-Level Impulse Responses

Figure 12 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.

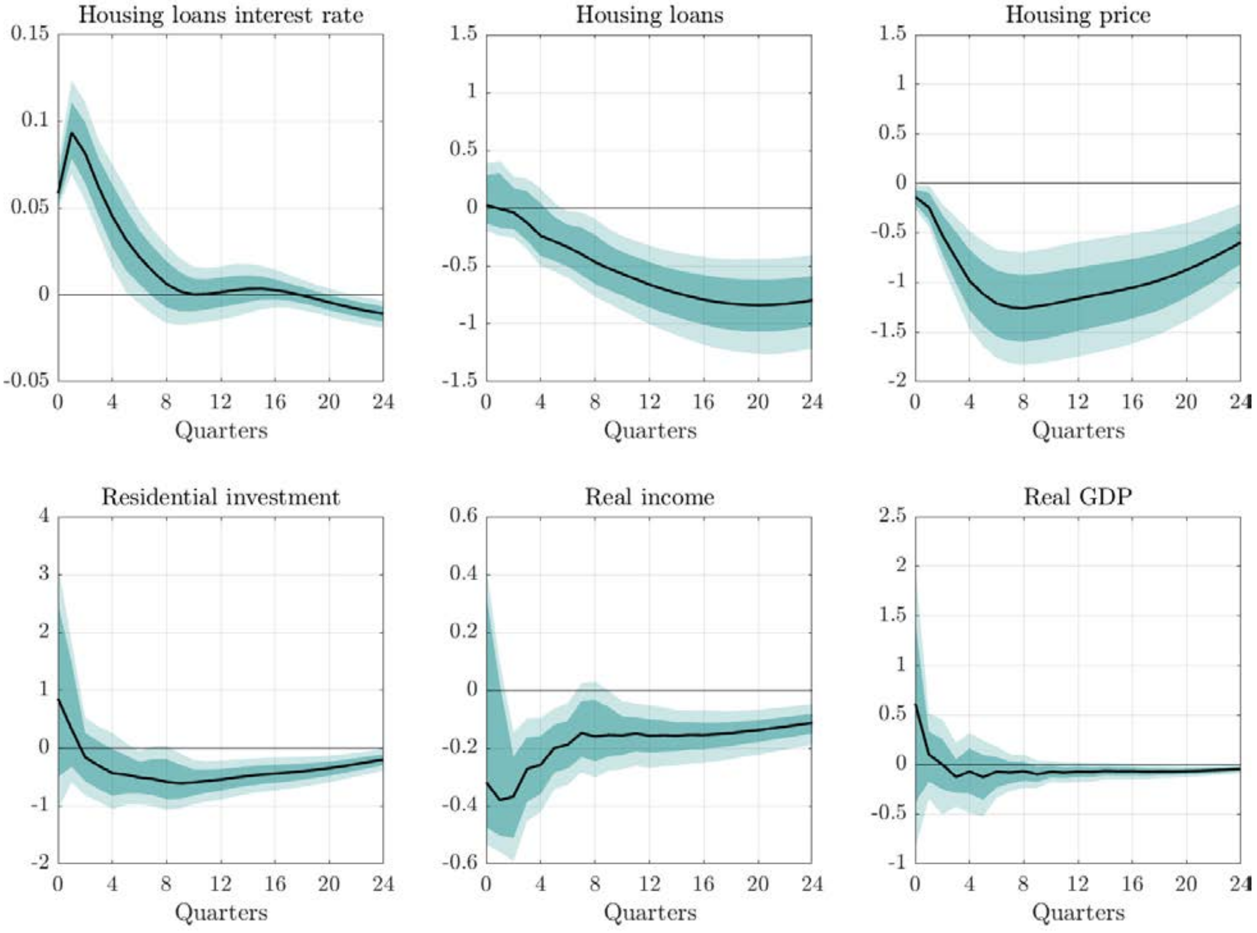

Figure 12: Impulse response functions to a negative lending standards shock estimated in log levels. Black: posterior median (solid) and 16th, 84th, 5th, and 95th percentile bands (shaded).

C.2. 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 13 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.

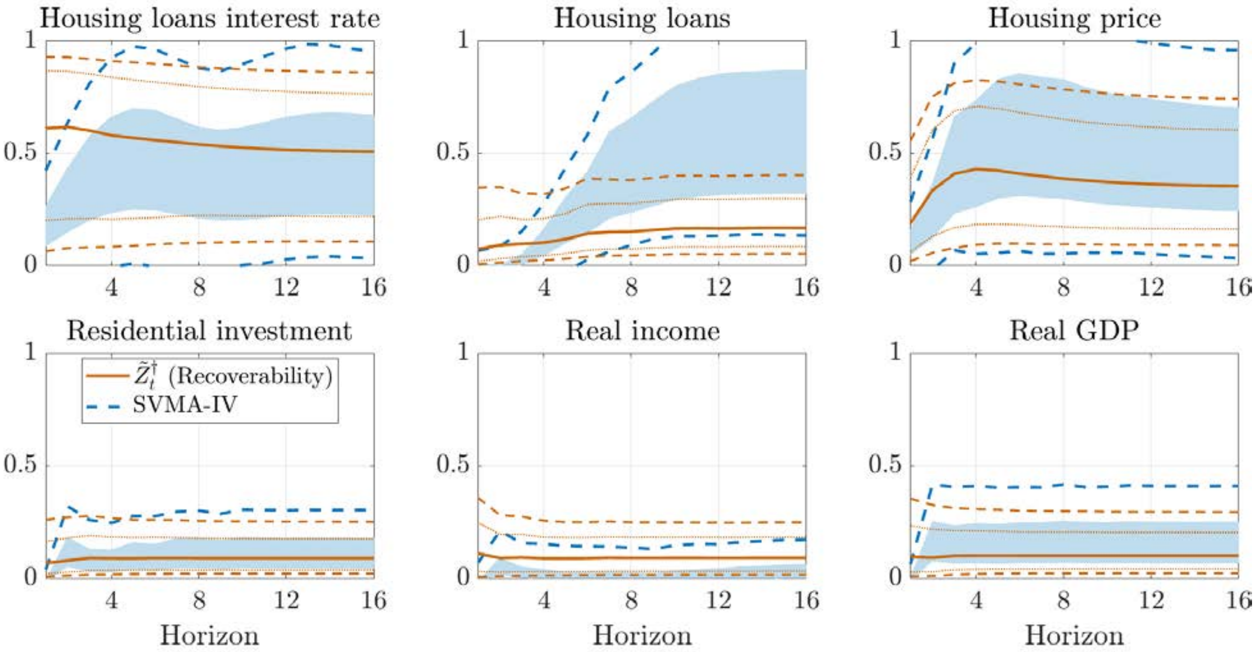

Figure 13: Forecast Variance Ratio (FVR) Estimates. The graph displays the FVR estimated from two strategies: (i) the benchmark SVAR-IV model using the recoverable instrument $\tilde{Z}_t^\dagger$, shown with orange lines and associated 68 and 90% confidence bands; and (ii) the invertibility-robust SVMA-IV 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.

C.3. Testing the validity of the identifying framework

A key identifying assumption of our framework is that the response of the control group to bank-driven lending standards shocks is stable over time (Assumption A.3). Because the control group consists of borrowers sufficiently far from the regulatory thresholds, it is not directly affected by the BBM. Consequently, in the absence of the BBM, the relationship between the control group and lending standards shocks should remain stable. Any change in this relationship following the implementation of the BBM can therefore be attributed to the BBM component, allowing us to recover $\varepsilon_{1,t}^{\text{BBM}}$. By contrast, a change in this relationship prior to the implementation of the BBM would weaken the credibility of the identification strategy.

To assess the empirical relevance of our framework, we estimate the following regression:

$$\begin{aligned} f_{\text{Mat},t}^{\text{Control}} &= \alpha\widetilde{\varepsilon}_{1,t} + \delta_{\text{pre}}\mathbf{1}\{t \in \text{Pre}_{4y}\} + \delta_{\text{post}}\mathbf{1}\{t \in \text{Post}_{4y}\} \\ &\quad + \gamma\widetilde{\varepsilon}_{1,t} \times \mathbf{1}\{t \in \text{Pre}_{4y}\} + \beta\widetilde{\varepsilon}_{1,t} \times \mathbf{1}\{t \in \text{Post}_{4y}\} + u_t. \end{aligned} \tag{25}$$

In this exercise, we focus on maturity, where $f_{\text{Mat},t}^{\text{Control}}$ denotes the share of loans with a maturity between 10 and 15 years, and $\widetilde{\varepsilon}_{1,t}$ denotes the lending standards shock identified in the first step of the analysis. The indicator variables correspond to four-year windows before and after the implementation of the BBM.

Equation 25 yields three important results. First, the coefficient α captures the baseline relationship between lending standards shocks and the control group. A tightening of lending standards should shift the DSTI and maturity distributions toward safer loans, implying a positive and statistically significant coefficient. Second, the interaction coefficient γ provides a placebo test of the stability of the control group's loading on lending standards shocks prior to the introduction of the BBM. Under Assumption A.3, this coefficient should not be statistically significant. Third, the coefficient β captures the change in this relationship after the implementation of the BBM. Because the aggregate lending standards shock combines both bank-driven and regulatory components once the policy is introduced, the observed relationship between the control group and the aggregate shock should weaken. Accordingly, the interaction coefficient β is expected to be negative.

Figure 14 reports the main coefficients estimates. We find a significant pre-treatment relationship between the control group and lending standards shocks. The placebo interaction term, corresponding to the four-year period before implementation, is not statistically significant, indicating that the loading of the control group on lending standards shocks is stable prior to the introduction of the BBM. Finally, the post-treatment interaction term is negative, consistent with a weakening of the observed relationship once the BBM becomes active. Taken together, these results support the validity of our identification strategy.

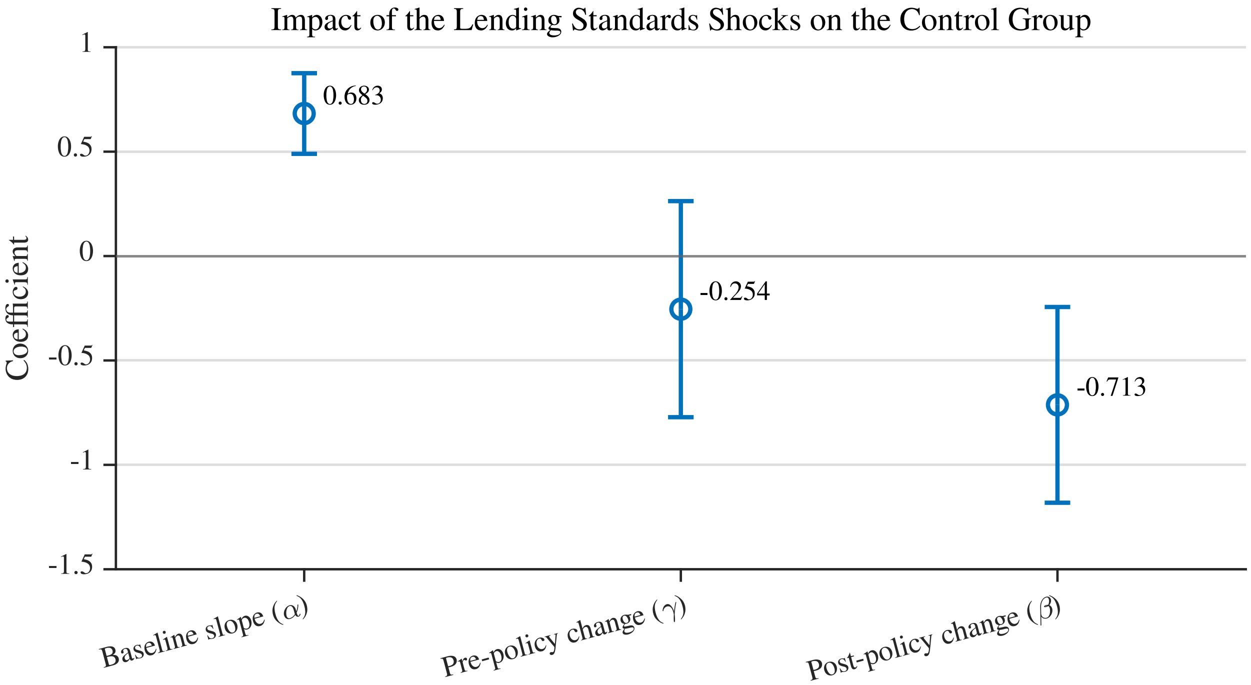

Figure 14: Estimates of coefficients α, γ and β of equation 25. Whiskers indicate 68% confidence intervals.