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Abstract

Borrower-based mortgage limits are designed to make lending safer, but they may not affect all households in the same way. We study how tighter loan-to-value and debt-service-to-income limits are associated with access to new mortgages across the income distribution. We combine household-level data from the Household Finance and Consumption Survey with hand-collected information on policy actions in 17 European countries over 2008–2019. We find that middle-income households are disproportionately affected. Following tightening, they are approximately 2 percentage points less likely than households in the top income decile to obtain a first mortgage on their main residence. The pattern is driven mainly by loan-to-value tightening. Among middle-income households, the differential effect is stronger for younger households, which typically have less accumulated savings and housing equity.

JEL Codes: E58, D31, G21, G28.
Keywords: Borrower-based measures, distributional effects, household borrowing, macroprudential policy, household finance and consumption survey.

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1. Introduction

Borrower-based macroprudential measures (BBMs) set limits on the terms under which households can obtain mortgage credit. The most common are limits on loan-to-value (LTV) ratios, which restrict the size of a loan relative to the value of the property, and limits on debt-service-to-income (DSTI) ratios, which restrict monthly repayments relative to household income. These measures are intended to curb excessive household indebtedness and make banks and borrowers more resilient to housing market downturns. Evidence suggests that they can contain credit growth and house price pressures (Araujo et al., 2024; Biljanovska et al., 2022). But they can also make it harder for some households to obtain a mortgage.

Consider two households trying to buy similarly priced flats. One has enough savings to increase its down payment when the LTV limit is tightened. The other does not. For the first household, the new limit may have little effect. For the second, it may mean postponing the purchase or choosing a cheaper property. A DSTI limit can work in a similar way: households with less room in their monthly budgets are more likely to be affected when the ceiling becomes stricter.

The distributional effect is not necessarily strongest at the bottom of the income distribution. Low-income households may have limited access to mortgage credit even in the absence of regulation. Tightening may instead bind most strongly for households that were close to qualifying for a mortgage before the policy change. These may be middle-income households, especially younger households with limited savings and little accumulated housing equity.

This distributional dimension matters for policy. By limiting leverage, BBMs can reduce household vulnerability and lower the costs of financial crises, which tend to fall disproportionately on lower-income households (Jenkins et al., 2012; Vacas-Soriano and Fernández-Macías, 2018; Bridges et al., 2021). At the same time, tighter borrowing limits may delay or prevent entry into owner-occupied housing for some households. Because housing is a major component of household wealth, unequal access to mortgage credit may also affect opportunities to accumulate wealth over time (Arrondel et al., 2014; Du Caju et al., 2014). In this paper, we focus on the first part of this process: access to new mortgage credit.

We study whether the relationship between BBM tightening and new mortgage origination differs across the household income distribution. We combine harmonised household-level data from the Household Finance and Consumption Survey (HFCS) with hand-collected information on LTV and DSTI policy actions for 17 European countries. The baseline analysis covers the first three HFCS waves, spanning 2008–2019. We exclude the fourth wave from the baseline because it overlaps with the COVID-19 pandemic and the extraordinary support measures introduced during that period. We focus on new mortgage originations and exclude refinanced loans from the baseline outcome. The HFCS records completed loans rather than mortgage applications or rejections, so our outcome captures the probability of observing a new origination. We estimate linear probability models with country-by-wave fixed effects on a matched sample of households.

We find that BBM tightening is associated with a relative reduction in access to first mortgages secured against the household main residence for middle-income households. Compared with households in the top income decile, households in the middle of the distribution experience a reduction of approximately 2 percentage points in the probability of obtaining a new first HMR mortgage. We do not find the same pattern for the other mortgage categories. The income gradient is driven mainly by LTV tightening. DSTI tightening produces estimates in a similar direction, but with lower precision. Within the middle-income group, the differential effect is stronger for younger households. This is consistent with younger households being more exposed to tighter borrowing constraints because they typically have less accumulated savings and housing equity. The HFCS does not allow us to identify first-time buyers directly.

The paper contributes to the literature in three ways. First, it provides household-level evidence on how BBM tightening is associated with mortgage access across the income distribution in a multi-country setting. Second, it distinguishes between first HMR mortgages and other mortgage categories, showing that the main result is concentrated in the loan type most closely linked to access to owner-occupied housing. Third, it separates LTV and DSTI tightening and examines which household groups account for the observed income gradient.

The remainder of the paper is organised as follows. Section 2 reviews the related literature. Section 3 describes the HFCS data, the BBM policy indicators, and the construction of the analytical sample. Section 4 presents the empirical framework. Section 5 reports the baseline results, extensions, and robustness checks. Section 6 concludes and discusses policy implications.

2. Related Literature

Most studies of macroprudential policy focus on aggregate outcomes. The literature generally finds that borrower-based and sectoral measures can contain credit growth and house price pressures (Araujo et al., 2024; Biljanovska et al., 2022). Less is known about how these measures affect different types of households. This contrasts with the monetary policy literature, where distributional effects have been studied more extensively, including with HFCS data (Lenza and Slacalek, 2018; Casiraghi et al., 2018; Xu, 2021; Lee, 2020). The mechanisms are different, however. Borrower-based measures act directly on the terms under which households can obtain mortgage credit.

One strand of the macroprudential literature studies this trade-off using macroeconomic models and microsimulations. Georgescu and Martín (2021) show that borrower-based limits can make households more resilient during crises, but may also exclude some of them from the housing market. Carpantier and Van Kerm (2018) and Frost and van Stralen (2018) link high LTV ratios at mortgage origination to later wealth inequality. Other studies focus mainly on the resilience benefits of macroprudential policy (Gross and Población, 2017; Jurča et al., 2020). Taken together, these papers show that tighter borrowing limits involve a trade-off: they may reduce financial vulnerability, but they may also make access to housing finance more unequal.

A second strand studies specific policy changes. The results suggest that the effects depend on the instrument and the country context. For example, Peydró et al. (2020) and Acharya et al. (2022) find that borrowing limits in the UK and Ireland shifted credit towards higher-income borrowers. Park and Kim (2023) find that LTV ceilings in South Korea increased household wealth inequality and changed housing market expectations. Looking across 17 transition economies, Konstantinou et al. (2022) show that the distributional effects depend on financial openness and development. At the same time, macroprudential policy may reduce inequality over a longer horizon by lowering the costs of financial crises (Bridges et al., 2021).

An adjacent literature examines lender-based instruments. Biljanovska and Chen (2025) show that their distributional effects also depend on the tool used. Levies on financial institutions and tighter capital requirements affect different groups of borrowers through different channels. This reinforces a broader point: the distributional effects of macroprudential policy cannot be inferred from its aggregate effects alone.

3. Data

We combine two data sources: household-level data from the Household Finance and Consumption Survey (HFCS) and country-month data on borrower-based macroprudential policy actions. This section describes both sources and the construction of the analytical sample.

3.1 Household Finance and Consumption Survey

The household-level data come from the Household Finance and Consumption Survey (HFCS), a harmonised survey coordinated by the European Central Bank together with national central banks and statistical institutes in euro area member states and several other European countries.[1] The HFCS provides information on household balance sheets, income, consumption, and socio-demographic characteristics. This makes it well suited for studying differences in mortgage origination across the income distribution.

We use four HFCS waves with fieldwork periods spanning from late 2008 to early 2022. The first wave covered 15 euro area countries. Country coverage expanded in later waves, reaching 22 countries in waves 3 and 4. Table A1 in the appendix provides an overview of the fieldwork periods, the number of participating households, and country coverage in each wave. We use the household-level component of the HFCS, namely the H and D files, and do not use person-level data. Socio-demographic characteristics refer to the household reference person identified during the interview.

The HFCS records up to three mortgages secured against the household main residence (HMR), defined as the property in which the household lives for most of the time. It also records up to three mortgages secured against each of up to three other properties.[2] For each mortgage, the survey reports the initial loan amount, the outstanding balance, the interest rate, whether the loan is a refinancing, and the year of origination. This allows us to identify recent mortgage originations at the household level.[3]

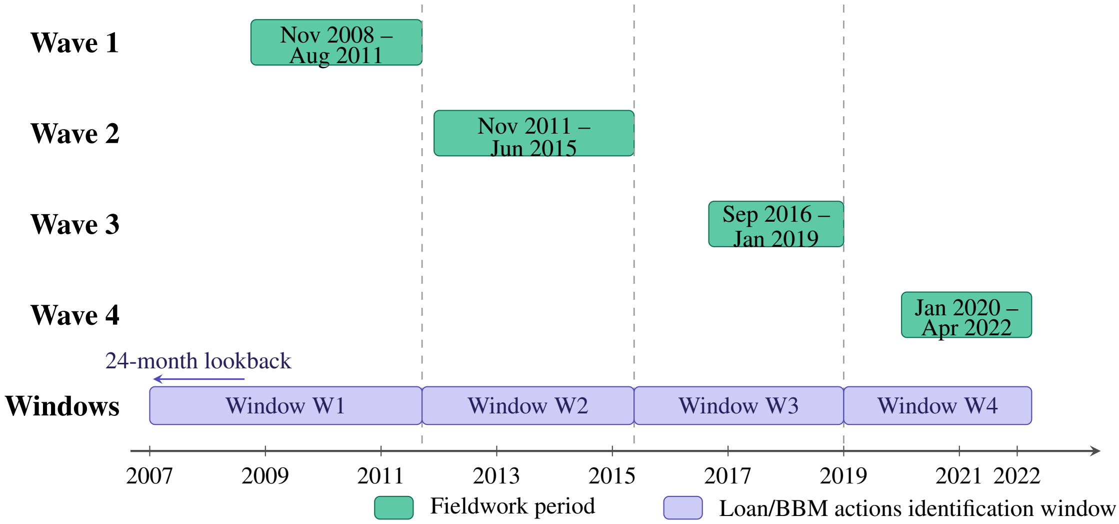
We define a mortgage as new if its year of origination falls within a wave-specific identification window. For waves 2 to 4, the window runs from the end of the fieldwork period of the previous wave to the end of the fieldwork period of the current wave. For wave 1, and for countries entering the survey for the first time, the window extends 24 months back from the end of the fieldwork period. This captures recent originations when no previous survey wave is available. The country-specific fieldwork periods are taken from the ECB methodological reports for the individual waves. Figure 1 illustrates the construction of the windows.

[1] For a detailed description of the survey methodology, objectives, and data availability, see `https://www.ecb.europa.eu/stats/ecb_surveys/hfcs/html/index.en.html`.

[2] Other properties include secondary residences, investment properties, agricultural land, garages, commercial premises, and warehouses. Some of these assets are non-residential and may not be subject to LTV or DSTI limits in the same way as mortgages secured against the household main residence. Results for the other real estate category should therefore be interpreted with caution.

[3] The HFCS records completed mortgage transactions only. We therefore observe the joint outcome of a household's decision to apply for a mortgage and a lender's decision to grant it. We do not observe unsuccessful applications.

Figure 1: HFCS Survey Waves and Loan/BBM Actions Identification Windows



Note: The figure illustrates the fieldwork periods of the four waves of the Household Finance and Consumption Survey (HFCS) and the corresponding identification windows used to classify new mortgage loan originations and borrower-based macroprudential (BBM) policy actions. Green bars indicate the fieldwork period of each wave, defined by the earliest start and latest end of data collection across all participating countries. Light purple bars indicate the identification windows, which are defined separately for each country using that country's own start and end dates of fieldwork. The same windowing logic is applied to aggregate monthly BBM tightening indicators to the country-wave level.

We construct two versions of the new-mortgage indicator. The first includes refinanced loans, while the second excludes them. Our preferred outcome excludes refinancing. Refinancing may reflect interest rate developments, changes in household circumstances, or adjustments to loan maturity, rather than entry into the mortgage market. Excluding these loans therefore provides a cleaner measure of new mortgage origination. At the same time, refinancing remains informative because tighter borrowing limits may also affect its feasibility. We consequently report results including refinanced loans alongside the baseline.

Before merging the HFCS data with the policy indicators, we make several adjustments. We winsorize all volume variables at the 0.5th and 99.5th percentiles and convert monetary values to constant prices using country-wave-specific inflation adjustment factors. Values are expressed in prices of the last available wave. We exclude households with missing information on gross household income, net wealth, household type, or the employment status, gender, age, or education of the household reference person.[4]

3.2 Borrower-Based Macroprudential Policy Data

We collect information on the tightening of borrower-based macroprudential measures, focusing on loan-to-value (LTV) and debt-service-to-income (DSTI) limits. The dataset combines information from three sources.

[4] For waves 1 and 2, education is recoded into four categories consistent with the International Standard Classification of Education (ISCED) to ensure comparability across waves.

Our main source is the Integrated Macroprudential Policy (iMaPP) Database maintained by the International Monetary Fund and introduced by Alam et al. (2019). The database provides indicators of tightening and loosening actions across a broad range of macroprudential instruments, together with a narrative description of each policy change. We use these descriptions to identify changes that directly alter the numerical value of an LTV or DSTI limit. For example, a reduction in the statutory LTV ceiling from 90 to 80 percent is classified as a tightening action.

Changes that do not directly modify the numerical limit are coded as zero. This includes, for example, changes in the share of new loans that banks may issue above a given LTV threshold while leaving the threshold itself unchanged. We exclude such actions because they are less directly visible to households and less likely to affect borrowing decisions at the time of origination.

We cross-check all identified actions against two additional sources: the ESRB Macroprudential Measures Database (European Systemic Risk Board, 2025) and the Macroprudential Policies Evaluation Database (MaPPED) developed by Budnik and Kleibl (2018). Both databases provide detailed descriptions of borrower-based measures and help verify the nature and timing of individual policy changes.

For each action, we identify the month in which the tightening became effective whenever this information is available. Where possible, we also collect the announcement date. This allows us to construct two versions of the BBM indicators. The baseline version records actions in the month in which the new limit takes effect. The alternative version records the announcement month and is used as a robustness check. It allows for the possibility that households adjust their borrowing decisions before the measure becomes binding.[5]

The resulting dataset is organised at the country-month level. For each country and month, it records whether at least one LTV or DSTI tightening action occurred. We construct a combined BBM indicator as well as separate indicators for LTV and DSTI tightening. The separate indicators are used in Section 5.2. We also collect information on loosening actions, but these events are relatively rare in the sample period and are not the main focus of the analysis.

3.3 Aggregation and Merging

We restrict the country sample to countries that used at least one borrower-based macroprudential measure during the sample period. Austria, Germany, Spain, Greece, Italy, and Croatia are excluded because they show no BBM activity within the period covered by the analysis. Including these countries would mix the absence of a tightening action with a broader absence of active BBM policy. Some of them introduced borrower-based measures in 2023, 2024, or 2025, but these actions fall outside our sample. The resulting dataset covers 17 countries.[6]

To merge the policy data with the HFCS, we aggregate the monthly BBM indicators to the country-wave level using the same identification windows as for new mortgage originations. These windows are described in Section 3.1 and illustrated in Figure 1. A country-wave cell is assigned a value of one if at least one tightening action occurred within the relevant window, and zero otherwise.

[5] Announcement dates should be interpreted with caution. If a measure is announced in one survey wave but becomes effective only in the next, an indicator based only on the announcement date may understate the policy environment in the later period.

[6] Belgium (BE), Cyprus (CY), the Czech Republic (CZ), Estonia (EE), Finland (FI), France (FR), Hungary (HU), Ireland (IE), Latvia (LV), Lithuania (LT), Luxembourg (LU), Malta (MT), the Netherlands (NL), Poland (PL), Portugal (PT), Slovenia (SI), and Slovakia (SK).

We apply this procedure separately to the effective-date and announcement-date versions of the indicators, and separately to the combined BBM indicator and the LTV- and DSTI-specific indicators. Table A2 in the appendix reports the distribution of tightening actions across countries and waves. The resulting country-wave indicators are then merged with the household-level HFCS data by country and wave.

3.4 Propensity Score Matching and Baseline Sample

To estimate differences in the probability of obtaining a new mortgage, we need to compare households observed in country-wave cells with and without BBM tightening. These households may differ in characteristics that are also related to mortgage borrowing. We therefore use propensity score matching to construct a more comparable sample.

The treatment indicator equals one if the household is observed in a country-wave cell with at least one BBM tightening action during the relevant identification window, and zero otherwise. We use 1:1 nearest-neighbour matching with a caliper of 0.05. Each household in a treated country-wave cell is matched to the most similar household in a control cell within the specified distance in propensity score space.[7]

The propensity score model includes household characteristics that are related to mortgage borrowing but should not be directly affected by current BBM tightening: decile position in the within-country distribution of gross household income, decile position in the within-country distribution of net wealth, age of the household reference person and its square, gender, education, employment status, and household type. Detailed variable definitions are reported in Table A3 in the appendix. We exclude current debt, existing mortgage status, household savings, and other financial variables that may themselves respond to macroprudential policy.[8]

Matching is performed on the country-restricted dataset described in Section 3.3, using all four HFCS waves. The matched sample contains 92,190 households observed in treated country-wave cells and the same number of matched control households. A further 38,373 households, corresponding to 17% of the original sample, remain unmatched. Appendix A.3 reports the balance diagnostics. After matching, all standardized mean differences are below 0.02 in absolute value, the variance ratios for continuous covariates are close to one, and the propensity score distributions show broad common support (Table A4, Figure A1, and Figure A2, Panel A).

The baseline outcome analysis is restricted to waves 1–3. Wave 4 covers fieldwork conducted between January 2020 and April 2022 and therefore overlaps with the COVID-19 pandemic. During this period, household borrowing was affected by exceptional measures, including payment moratoria, government-backed credit guarantees, and large fiscal transfers. We cannot fully account for these interventions in our setting. Including wave 4 in the baseline could therefore confound the relationship between BBM tightening and mortgage origination with the effects of temporary crisis measures. This concern is also noted by Siranova et al. (2025), who exclude wave 4 from their analysis because the period was subject to exemptions from the standard

[7] We use 1:1 matching because the number of suitable control observations is not sufficient to support a wider matching ratio without reducing match quality.

[8] Survey weights are not used in the propensity score estimation. Including them leads to numerically unstable logit estimates because the weights inflate effective sample sizes in some covariate cells and make rare categories effectively deterministic. Previous studies also show that the use of survey weights in the matching stage does not materially improve covariate balance (DuGoff et al., 2014; Lenis et al., 2019; Austin et al., 2018).

macroprudential framework. The effects of the pandemic on HFCS households are documented by HFCN (2023b). We therefore use wave 4 only as a robustness check.

3.5 Summary Statistics

Table 1 reports the number and share of new mortgage originations in the matched sample, separately for households observed in treated and control country-wave cells. We distinguish four mortgage categories: any new mortgage, the first mortgage secured against the household main residence (1st HMR), the second and third mortgages secured against the HMR (2nd, 3rd HMR), and mortgages secured against other real estate. Our preferred outcome excludes refinanced loans.

Table 1: New Mortgages in Matched Sample

	Any new		1st HMR		2nd, 3rd HMR		Other Real Estate	
	Control	Treatment	Control	Treatment	Control	Treatment	Control	Treatment
Number of new mortgages	6651	4966	4411	3731	787	727	2299	1099
Of which								
Excl. refinanced	4597	3630	2681	2580	625	473	1784	899
Refinanced	2054	1336	1730	1151	162	254	515	200
Number of households	92190	92190	92190	92190	92190	92190	92190	92190
Share of HH with new mortgages (%)	7.21	5.39	4.78	4.05	0.85	0.79	2.49	1.19
Of which								
Excl. refinanced	4.99	3.94	2.91	2.8	0.68	0.51	1.94	0.98
Refinanced	2.23	1.45	1.88	1.25	0.18	0.28	0.56	0.22
Excl. Wave 4								
Number of new mortgages	6252	1884	4088	1462	767	271	2231	324
Of which								
Excl. refinanced	4595	1478	2679	1161	625	164	1784	261
Refinanced	1657	406	1409	301	142	107	447	63
Number of households	82011	44529	82011	44529	82011	44529	82011	44529
Share of HH with new mortgages (%)	7.62	4.23	4.98	3.28	0.94	0.61	2.72	0.73
Of which								
Excl. refinanced	5.6	3.32	3.27	2.61	0.76	0.37	2.18	0.59
Refinanced	2.02	0.91	1.72	0.68	0.17	0.24	0.55	0.14

Note: The table reports the number and share of new mortgage originations in the matched sample for BBM tightening actions, separately for treated and control households. The upper panel covers all four HFCS waves; the lower panel excludes wave 4, corresponding to the baseline sample used in the outcome analysis. Four loan categories are distinguished: any new mortgage (Any new), the first mortgage secured against the household main residence (1st HMR), the second and third mortgage secured against the HMR (2nd, 3rd HMR), and mortgages secured against other real estate (Other Real Estate). Within each category, originations are further decomposed into new originations excluding refinanced loans and refinanced loans. The number of households reflects the total matched sample size, not the number of borrowing households. Shares are computed as the number of mortgages divided by the total number of households in the respective subsample. Summary statistics are computed using the first HFCS implicate; the remaining four implicates yield materially identical statistics, as summary measures of socio-demographic and loan origination variables are not sensitive to the imputation of financial wealth and income values across implicates.

In the baseline sample covering waves 1–3, 4.23% of households in treated cells and 7.62% of households in control cells have any new mortgage. First HMR mortgages account for the largest share of originations in both groups, at 3.28% and 4.98%, respectively. These figures refer to recent originations identified using the windows described in Section 3.1, not to overall participation in mortgage debt.[9] When refinanced loans are excluded, the corresponding shares for any new

[9] According to HFCN (2023b), the overall participation rate in mortgage debt in 2023 was 23.7% for euro area countries and 13.7% for non-euro area countries.

mortgage are 3.32% in treated cells and 5.60% in control cells. Mortgage origination rates are descriptively lower in treated cells across all loan categories.

The upper panel of Table 1 includes all four HFCS waves. The lower panel excludes wave 4 and corresponds to the baseline outcome sample. The gap between treated and control cells remains visible in both panels. For any new mortgage, the shares are 5.39% and 7.21% in the full sample, compared with 4.23% and 7.62% after excluding wave 4. The number of households in treated cells falls from 92,190 in the full matched sample to 44,529 in the baseline sample. This reflects the concentration of BBM tightening actions in later waves and reinforces the need to treat wave 4 separately.

Table 2 reports mortgage origination shares by income decile. Mortgage origination rises with income across all four loan categories. For any new mortgage excluding refinancing, the share increases from 1.17% in the bottom income decile to 8.54% in the top decile. The same pattern appears for first HMR mortgages, where the share rises from 0.74% to 4.15%, and for second and third HMR mortgages, where it rises from 0.13% to 0.90%. The gradient is particularly steep for mortgages on other real estate, with shares increasing from 0.40% to 4.12%. Including refinanced loans does not change the overall pattern. Table A5 in the appendix reports the corresponding figures for the full four-wave sample.

The income gradient in mortgage origination is important for the analysis below. Households in the lowest income deciles rarely obtain new mortgages, while origination is much more common towards the top of the distribution. The next sections examine whether BBM tightening changes this gradient.

Table 2: New Mortgages in Matched Sample: Breakdown by Income Deciles

	Households with new mortgages (% share)							
	Excl. Refinanced				Incl. Refinanced			
	Any new	1st HMR	2nd, 3rd HMR	Other RE	Any new	1st HMR	2nd, 3rd HMR	Other RE
Full Sample	4.80	3.03	0.62	1.62	6.43	4.39	0.82	2.02
Income Deciles								
1	1.17	0.74	0.13	0.40	1.57	1.04	0.21	0.46
2	1.54	1.04	0.21	0.40	1.95	1.38	0.25	0.47
3	2.32	1.67	0.31	0.53	3.14	2.35	0.37	0.70
4	2.98	2.31	0.48	0.61	3.98	3.19	0.59	0.71
5	4.28	3.09	0.62	1.10	5.70	4.37	0.79	1.31
6	5.34	3.74	0.83	1.34	7.14	5.33	1.04	1.69
7	6.21	4.09	0.90	1.89	8.41	6.15	1.13	2.29
8	7.00	4.41	0.93	2.34	9.77	6.75	1.23	3.07
9	8.49	5.03	0.91	3.37	11.56	7.39	1.27	4.39
10	8.54	4.15	0.90	4.12	10.90	5.78	1.30	5.04

Note: The table reports the share of households with new mortgage originations in the matched sample, broken down by income decile. Statistics are reported for the baseline subsample excluding wave 4, separately for new originations excluding refinanced loans (left panel) and including refinanced loans (right panel). Full sample statistics in the first row combine treated and control households from Table 1, lower panel. Income deciles are computed separately for each country. Corresponding statistics for the full four-wave matched sample are reported in Table A5 in the appendix. Summary statistics are based on the first HFCS implicate; results are materially identical across all five implicates.

4. Empirical Framework

4.1 Baseline Specification

To examine whether the relationship between BBM tightening and new mortgage origination differs across the income distribution, we estimate the following linear probability model:

$$Y_{ict}^{(l)} = \alpha + \sum_{d=1}^{9} \gamma_d \mathbf{1}\{D_{ict} = d\} + \sum_{d=1}^{9} \beta_d \left(BBM_{ct} \times \mathbf{1}\{D_{ict} = d\}\right) + X_{ict}'\theta + \lambda_{ct} + \varepsilon_{ict}^{(l)} \quad (1)$$

The indices i, c, t, and l refer to household, country, survey wave, and loan type. The dependent variable $Y_{ict}^{(l)}$ equals one if household i obtains a new mortgage of type l within the wave t identification window, and zero otherwise. The identification windows are described in Section 3.3 and illustrated in Figure 1. We distinguish four mortgage categories: the first mortgage secured against the household main residence (1st HMR), the second and third mortgages secured against the HMR (2nd, 3rd HMR), mortgages secured against other real estate (Other Real Estate), and all three categories combined (Any new). Our preferred outcome excludes refinanced loans. Results including refinanced loans are reported alongside the baseline.

The variable BBM_{ct} equals one if at least one LTV or DSTI tightening measure took effect in country c within the wave t identification window, and zero otherwise. The variable D_{ict} denotes the position of household i in the within-country distribution of gross household income. Income decile 10 is the omitted reference category. The coefficients β_d capture how the association between BBM tightening and new mortgage origination differs for households in income decile d relative to households in the top income decile. We use decile 10 as the reference group because mortgage origination rates are very low in the bottom deciles, making them a noisy benchmark (Table 2), and because top-income households are more likely to be able to adjust to tighter borrowing limits, for example by increasing their down payment or reducing the loan amount relative to income. A negative coefficient β_d does not necessarily imply an absolute decline in mortgage origination for households in decile d. It means that the association with BBM tightening is more negative, or less positive, for that group than for households in decile 10. We also report a joint test of equality across deciles: $H_0 : \beta_1 = \beta_2 = \cdots = \beta_9$.

The vector X_{ict} includes household-level controls: wealth deciles and characteristics of the household reference person: gender, age and its square, education, employment status, and household type. Detailed definitions and the corresponding HFCS codes are provided in Table A3 in the appendix. The specification also includes country $\times$ wave fixed effects λ_{ct}. These absorb all observed and unobserved factors common to households within a given country-wave cell, including the main effect of BBM_{ct}.

Since BBM_{ct} varies only at the country-wave level, the coefficients β_d are identified from differences in the income gradient of mortgage origination between country-wave cells with and without BBM tightening. The baseline estimates should therefore be read as relative differences across the income distribution.

4.2 Estimation and Weighting

We estimate equation (1) using a linear probability model. This has two practical advantages. First, the interaction coefficients can be read directly as percentage-point differences relative to decile 10. Second, the model accommodates country $\times$ wave fixed effects in a straightforward way. Linear probability models are commonly used for binary outcomes with high-dimensional fixed effects and provide consistent estimates of average partial effects under standard assumptions (Angrist and Pischke, 2009; Wooldridge, 2010). As a diagnostic, each regression table reports the share of fitted values outside the interval $[-0.05, 1.05]$. This share is small across the specifications. We also re-estimate the baseline model using a logit specification and report average marginal effects in Section 5.3.

The baseline regressions are estimated on the matched sample described in Section 3.4, without survey weights. Matching balances treated and control households on observable characteristics. The country $\times$ wave fixed effects absorb differences across country-wave cells, including differences in national sampling schemes that affect all income groups within a cell in the same way. To assess whether the results are sensitive to weighting, we also estimate the baseline model using rescaled survey weights. For household i in country c and wave t, the rescaled weight is defined as:

$$w^*_{ict} = w_{ict} \cdot f_{ct}, \qquad f_{ct} = \frac{\sum_{j \in \mathscr{S}_{ct}} w_{jct}}{\sum_{j \in \mathscr{M}_{ct}} w_{jct}} \tag{2}$$

where $\mathscr{S}_{ct}$ denotes the full original sample, $\mathscr{M}_{ct}$ denotes the matched subsample, and w_{ict} is the original HFCS household weight `hw0010`. The rescaling preserves the total weight mass within each country-wave cell after matching. The weighted results are reported as a robustness check in Section 5.3.

The HFCS data are multiply imputed.[10] We combine estimates across all five implicates using Rubin's rules (Rubin, 1987). Point estimates are pooled as simple averages, and the standard errors account for both within- and between-implicate variation.

4.3 Complementary Specification

The country $\times$ wave fixed effects in equation (1) absorb the main effect of BBM_{ct}. The baseline model therefore does not identify the association between BBM tightening and mortgage origination for households in decile 10. To recover this association, we estimate a complementary specification with separate country and wave fixed effects:

$$\begin{aligned} Y^{(l)}_{ict} = \alpha + \delta BBM_{ct} &+ \sum_{d=1}^{9} \gamma_d \mathbf{1}\{D_{ict} = d\} \\ &+ \sum_{d=1}^{9} \beta_d \left(BBM_{ct} \times \mathbf{1}\{D_{ict} = d\}\right) + X'_{ict}\theta + Z'_{ct}\phi + \mu_c + \tau_t + \varepsilon^{(l)}_{ict} \end{aligned} \tag{3}$$

The coefficient δ captures the association between BBM tightening and new mortgage origination for households in income decile 10. For deciles $d = 1, \ldots, 9$, the corresponding association is given by $\delta + \beta_d$. The vector Z_{ct} contains three country-level controls aggregated over the relevant wave window: average real GDP growth, a real house price index, and the credit-to-GDP gap. All three variables are sourced from the BIS Statistical Warehouse. These controls account for macroeconomic conditions that vary across country-wave cells and may be related to both BBM tightening and household mortgage borrowing.

[10] See, for example, HFCN (2023a) for further information on multiple imputation in population surveys.

Equation (3) does not absorb all country-wave-specific factors. We therefore use it only as a complementary specification to illustrate the broad pattern of the estimated associations across all income deciles. Our main inference continues to rely on equation (1).

5. Results

5.1 Probability of Obtaining a New Mortgage

We first examine the average association between BBM tightening and new mortgage origination. Table 3 reports estimates without interactions between the BBM indicator and income deciles. For the baseline sample covering waves 1–3, the coefficients are small and statistically insignificant for most mortgage categories. The only exception is a marginally significant positive coefficient for all new mortgages. The picture changes when refinanced loans are included (Table B1 in the appendix). In that case, BBM tightening is associated with a reduction of 2.5 percentage points for all new mortgages and 3.0 percentage points for first HMR mortgages. Refinancing therefore accounts for part of the aggregate difference observed around tightening episodes.

Table 3: BBM Tightening and Loan Origination

Dependent Variable:	$\mathbf{1}\{NewMortgage = 1\}$							
Loan type:	All new		1st HMR		2nd, 3rd HMR		Other RE	
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
BBM	0.0127*	0.0062	0.004	0.0019	0.0019	-0.0007	0.0095	0.0062
	(0.0073)	(0.0074)	(0.0058)	(0.0061)	(0.0018)	(0.0013)	(0.0063)	(0.005)
$BBM \times W_4$		0.073***		0.0557***		0.009**		0.0127**
		(0.0163)		(0.015)		(0.0039)		(0.0051)
Obs.	126543	184378	126543	184378	126543	184378	126543	184378
Adj. R_2	0.12	0.12	0.08	0.08	0.02	0.02	0.06	0.05
Share_outside	4.21	4.1	1.14	0.99	0	0	0	0
HH Controls	Y	Y	Y	Y	Y	Y	Y	Y
Ctry Controls	Y	Y	Y	Y	Y	Y	Y	Y
Cntry FEs	Y	Y	Y	Y	Y	Y	Y	Y
Wave FEs	Y	Y	Y	Y	Y	Y	Y	Y

Note: The table reports regression results for a variant of equation (1) in which BBM_{ct} enters without interactions with income decile dummies. Income decile dummies are included as controls, with decile 10 as the omitted reference category. Country and wave fixed effects replace the country × wave fixed effects of the baseline, and three country-level controls aggregated over the wave window are added: real GDP growth, a real house price index, and the credit-to-GDP gap (all sourced from the BIS Statistical Warehouse). Columns (1), (3), (5), and (7) are estimated on the waves 1–3 subsample; columns (2), (4), (6), and (8) extend the sample to all four waves and add an interaction between BBM_{ct} and a wave 4 dummy. Results are reported for new originations excluding refinanced loans. *Share_outside* reports the share of fitted values outside $[-0.05, 1.05]$; see Section 4 for discussion. Estimates are combined across all five HFCS implicates using Rubin's rules (Rubin, 1987). Auxiliary statistics (*Share_outside*, *Adj.* R^2, and observation counts) are reported for the fifth implicate and are materially identical across all five implicates. Standard errors in parentheses are HC1 heteroskedasticity-robust, clustered at the country level. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

The interaction with the wave 4 dummy in columns 2, 4, 6, and 8 is positive and statistically significant across all mortgage categories. This indicates that the relationship between BBM tightening and mortgage origination was different during the period covered by wave 4. The wave overlaps with the COVID-19 pandemic and with exceptional policy measures, including loan moratoria, fiscal transfers, and credit guarantees. We therefore exclude it from the baseline analysis. The average coefficients may still conceal important differences across income groups: a tighter borrowing limit may have little effect on a household that can increase its down payment, but matter substantially for a household that was already close to the limit.

Table 4 presents the baseline results across income deciles. The omitted category is decile 10. The coefficients show how the association between BBM tightening and mortgage origination differs for each income decile relative to households at the top of the income distribution. Odd-numbered columns exclude refinanced loans and correspond to our preferred outcome; even-numbered columns include them. For all new mortgages, the interaction coefficients are small and mostly insignificant. This broad category combines mortgage types with different patterns.

Table 4: Extensive Margin: Baseline Results

Dependent Variable:	$\mathbf{1}\{NewMortgage = 1\}$							
Loan type:	All new		1st HMR		2nd, 3rd HMR		Other RE	
Model:	(1)	(2) incl. ref.	(3)	(4) incl. ref.	(5)	(6) incl. ref.	(7)	(8) incl. ref.
$BBM \times \mathbf{1}\{D=1\}$	0.0223	0.0281	−0.0074	−0.0062	0.0008	−0.0016	0.0309	0.0396
	(0.0278)	(0.0394)	(0.0131)	(0.0196)	(0.0033)	(0.0049)	(0.02)	(0.0268)
$BBM \times \mathbf{1}\{D=2\}$	0.0179	0.0222	−0.012	−0.012	−0.0004	−0.0035	0.0318	0.0402
	(0.0254)	(0.0361)	(0.0116)	(0.0168)	(0.0032)	(0.0051)	(0.0199)	(0.0265)
$BBM \times \mathbf{1}\{D=3\}$	0.0152	0.0152	−0.0152	−0.0191	−0.0022	−0.0055	0.0328*	0.0401
	(0.023)	(0.0305)	(0.0109)	(0.0147)	(0.003)	(0.0048)	(0.0199)	(0.0259)
$BBM \times \mathbf{1}\{D=4\}$	0.0063	0.0058	−0.0221*	−0.028*	−0.0026	−0.0051	0.0299	0.038
	(0.019)	(0.0253)	(0.0127)	(0.0157)	(0.0034)	(0.005)	(0.0191)	(0.0252)
$BBM \times \mathbf{1}\{D=5\}$	0.0043	−0.0044	−0.0216*	−0.0351**	−0.0051	−0.009	0.0287	0.0363
	(0.0162)	(0.0214)	(0.0118)	(0.0168)	(0.004)	(0.006)	(0.0178)	(0.0234)
$BBM \times \mathbf{1}\{D=6\}$	−0.0028	−0.0112	−0.0233*	−0.0367**	−0.0056	−0.009	0.0227	0.0292
	(0.0124)	(0.0167)	(0.0128)	(0.018)	(0.0044)	(0.0059)	(0.014)	(0.0187)
$BBM \times \mathbf{1}\{D=7\}$	−0.0063	−0.0208	−0.0235**	−0.0431**	−0.0085*	−0.0131**	0.0223*	0.0272*
	(0.0111)	(0.0161)	(0.012)	(0.0204)	(0.0048)	(0.0066)	(0.0127)	(0.0163)
$BBM \times \mathbf{1}\{D=8\}$	−0.0044	−0.0254*	−0.0159*	−0.0393**	−0.0044	−0.0077	0.0129*	0.013
	(0.0084)	(0.015)	(0.0091)	(0.0189)	(0.0038)	(0.0057)	(0.0078)	(0.0099)
$BBM \times \mathbf{1}\{D=9\}$	−0.006	−0.0195	−0.0083	−0.023*	−0.0016	−0.0029	0.0034	0.0016
	(0.0086)	(0.0127)	(0.0074)	(0.0129)	(0.0031)	(0.0035)	(0.0039)	(0.0047)
Obs.	126543	126543	126543	126543	126543	126543	126543	126543
Adj. R_2	0.12	0.17	0.08	0.13	0.02	0.03	0.06	0.07
Share_outside	4.38	7.87	0.88	3.87	0	0	0	0
pval_equal_betas	0.2514	0.8771	0.0312	0.6903	0.6478	0.7523	0.5193	0.7918
HH Controls	Y	Y	Y	Y	Y	Y	Y	Y
Ctry × Wave FEs	Y	Y	Y	Y	Y	Y	Y	Y

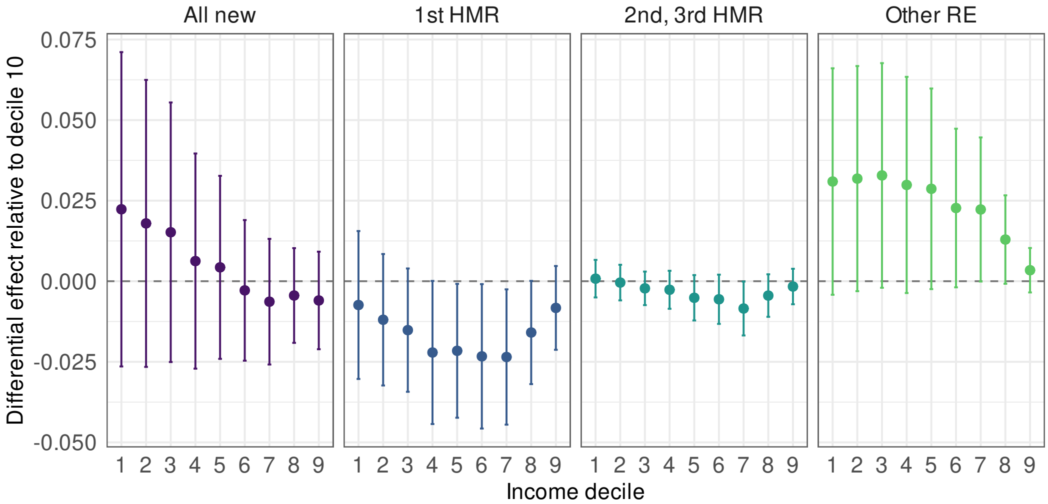
Note: The table reports regression results for the model specified in equation (1) for all four loan types: any new mortgage (All new), the first mortgage secured against the household main residence (1st HMR), the second and third mortgage on the HMR (2nd, 3rd HMR), and mortgages secured against other real estate (Other RE). All specifications are estimated on the waves 1–3 subsample of the matched sample, excluding wave 4 for the reasons discussed in Section 3.4. The variable D_{ict} denotes the decile position of household i in the within-country distribution of gross household income. The omitted income category is decile 10. Odd-numbered columns report results for new originations excluding refinanced loans (preferred specification); even-numbered columns include refinanced loans. *Share_outside* reports the share of fitted values outside $[-0.05, 1.05]$; see Section 4 for discussion. *p-val. equal* βs reports the p-value of a Wald test of the null hypothesis $H_0 : \beta_1 = \beta_2 = \cdots = \beta_9$. Estimates are combined across all five HFCS implicates using Rubin's rules (Rubin, 1987). Survey weights are not used; see Section 4 for discussion. Auxiliary statistics (*Share_outside*, *Adj.* R^2, and observation counts) are reported for the fifth implicate and are materially identical across all five implicates. Standard errors in parentheses are HC1 heteroskedasticity-robust, clustered at the country level. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

The clearest result appears for first HMR mortgages. The coefficients are negative across all income deciles relative to decile 10. In the preferred specification, the differences are statistically significant for deciles 4 to 8 and amount to approximately 2 percentage points. The Wald test rejects equality of the coefficients across income deciles. The estimates for the lowest three deciles are also negative, but not statistically significant. Mortgage origination rates are low in these deciles overall, leaving limited scope for a further decline. When refinanced loans are included, the estimated differences are larger and more precisely estimated.

The remaining mortgage categories show no comparable pattern. For second and third HMR mortgages, the coefficients are small and mostly insignificant. These loans are relatively rare, and we do not find a clear income gradient. Mortgages on other real estate follow a different pattern: the coefficients are positive relative to the top income decile and marginally significant for some middle-income groups. This category covers a broad range of properties, including secondary residences, garages, farms, commercial premises, and warehouses. These properties are not necessarily subject to the same borrowing limits as mortgages on the household main residence. We therefore treat these estimates as descriptive and do not interpret them further.

Figure 2 summarises the baseline estimates. The negative income gradient is concentrated in first HMR mortgages. Table B2 in the appendix reports estimates for all four waves. The results for waves 1–3 remain broadly similar, while the interactions with wave 4 confirm that the pandemic period differs materially from the baseline period.

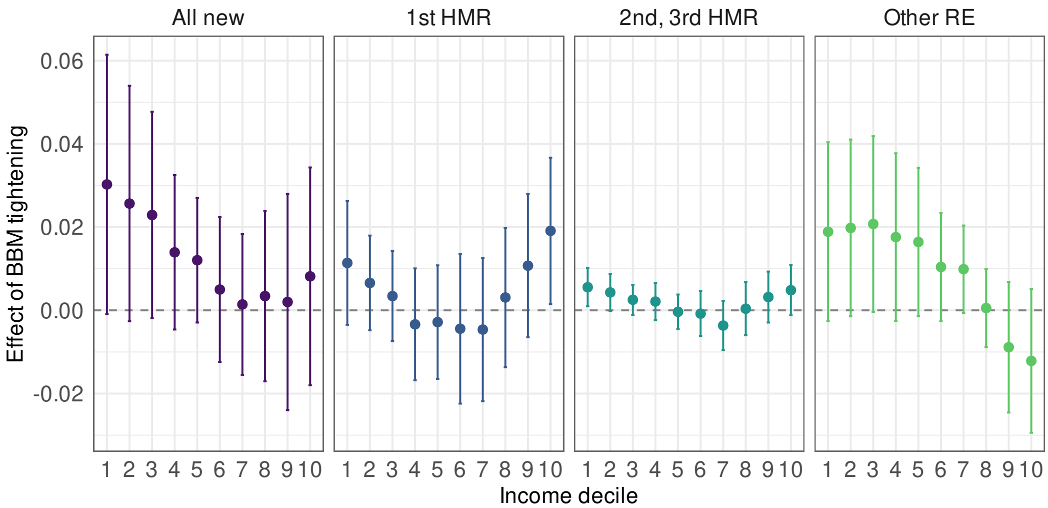
Figure 2: Estimated Differential Effects of BBM Tightening by Loan Type: Income Deciles



Note: The figure plots the estimated β coefficients from equation 1 using linear probability model, corresponding to the specifications reported in columns (1), (3), (5), and (7) of Table 4. Coefficient estimates are shown together with 90% confidence intervals. Each panel reports the estimates separately for an individual loan type.

The baseline model identifies differences relative to decile 10. It does not identify the association between BBM tightening and mortgage origination for top-income households because the country $\times$ wave fixed effects absorb the main BBM coefficient. Figure 3 therefore reports results from the complementary specification in equation (3), which replaces country $\times$ wave fixed effects with separate country and wave fixed effects and adds country-level controls. For first HMR mortgages, the estimated association is positive for households in the top income decile and lower for middle-income households. The positive coefficient for decile 10 is marginally significant. This result should be interpreted with caution because the complementary specification does not absorb all country-wave-specific factors that may coincide with BBM tightening. We therefore use it only to illustrate the broad pattern of the estimated associations. The baseline specification remains the basis for our main inference.

Figure 3: Estimated Effects of BBM Tightening by Loan Type: Income Deciles (Including Base Effect of Decile 10)



Note: The figure plots the estimated effects of BBM tightening on the probability of new mortgage origination across household income deciles, based on equation (3) and corresponding to columns (1), (3), (5), and (7) of Table B3 in the appendix. The reported effect for decile 10 corresponds to the coefficient $\hat{\delta}$, which captures average association between BBM tightening and new mortgage origination for top-income households. The reported effects for deciles $d = 1, \ldots, 9$ correspond to the linear combinations $\hat{\delta} + \hat{\beta}_d$, computed using the cluster-robust variance-covariance matrix as $\mathrm{Var}(\hat{\delta} + \hat{\beta}_d) = \mathrm{Var}(\hat{\delta}) + \mathrm{Var}(\hat{\beta}_d) + 2\,\mathrm{Cov}(\hat{\delta}, \hat{\beta}_d)$. Each panel reports estimates separately for one loan type. The sample excludes wave 4 for the reasons discussed in Section 3.4. New originations excluding refinanced loans are used throughout, consistent with the preferred specification. Vertical bars denote 90% confidence intervals based on HC1 heteroskedasticity-robust standard errors clustered at the country level.

5.2 Who Is Most Affected and Why?

We next examine four aspects of the baseline result: the role of LTV and DSTI tightening, differences across household groups, the number of policy actions, and household indebtedness.

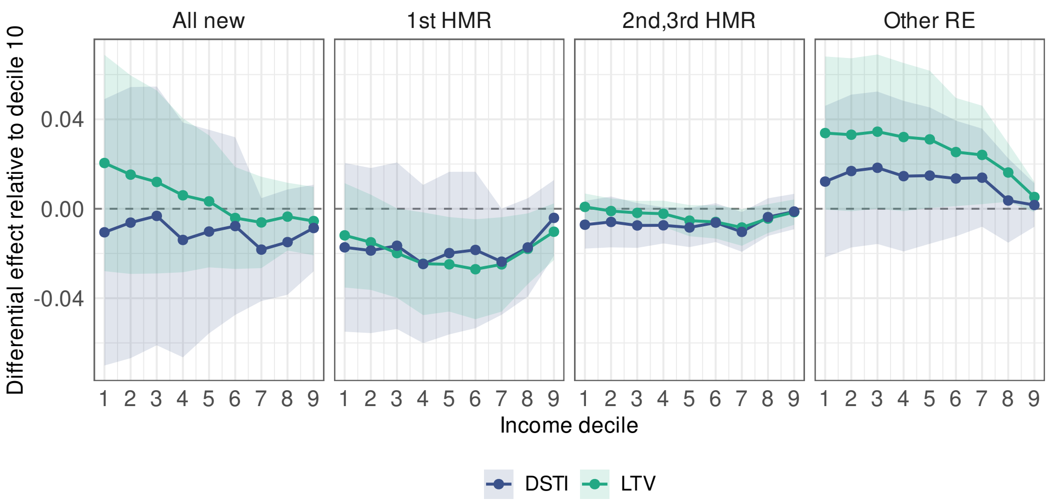
Figure 4 separates LTV and DSTI tightening. The income gradient for first HMR mortgages is driven mainly by LTV measures. The coefficients are negative and statistically significant for deciles 3 to 8, closely matching the baseline pattern. The estimates for DSTI tightening generally point in the same direction, but are less precise. This may partly reflect the smaller number of DSTI actions in the sample; their distribution across countries and waves is reported in Table A2. Mortgages on other real estate again differ from first HMR mortgages. In this category, DSTI tightening is associated with negative coefficients for some upper-middle-income deciles relative to the top. Given the broad range of properties included in this category, we do not interpret this pattern further.

We then examine whether the income gradient differs across household groups. Figure 5 focuses on first HMR mortgages and distinguishes households by age, the presence of dependent children, education, and gender of the reference person.[11] The clearest difference appears for young

[11] The estimates come from variants of the baseline model that include triple interactions between BBM tightening, income deciles, and the selected household characteristic. The triple-interaction coefficients capture whether the income gradient differs between the two groups.

households, defined as households whose reference person is below the age of 36. For deciles 6 and 7, the differential effect is more negative than for older households at the same income level. Younger households typically have less accumulated savings and housing equity, which may make tighter borrowing limits harder to meet. This interpretation is consistent with the results, although the HFCS does not allow us to identify first-time buyers directly. For households with dependent children, the estimates provide some indication of a smaller income gradient at the bottom of the distribution, but the pattern is not strong. We find no clear additional differences by education or gender of the household reference person.

Figure 4: Differential Effects of LTV vs. DSTI Tightening by Loan Type



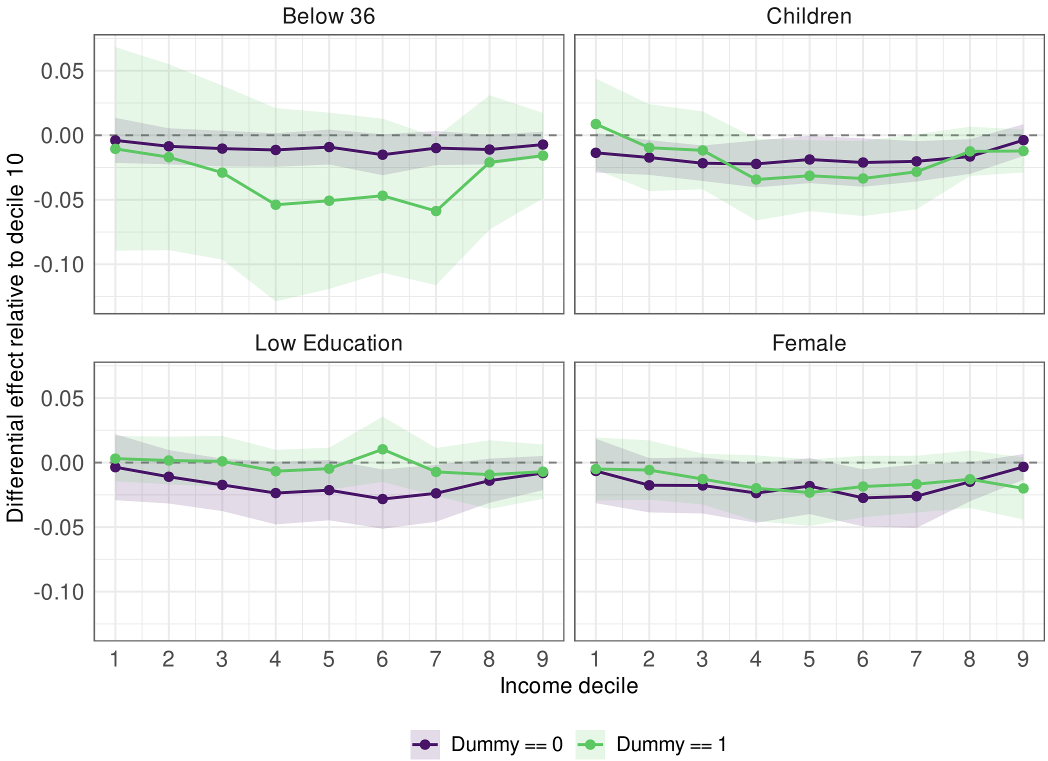
Note: The figure plots the estimated $\hat{\beta}_d$ coefficients from equation (1), separately for LTV tightening (Table B7, columns (1), (3), (5), and (7)) and DSTI tightening (Table B8, columns (1), (3), (5), and (7)), corresponding to new originations excluding refinanced loans. Each panel reports estimates for one loan type; within each panel, separate series are shown for LTV and DSTI tightening indicators. All other details follow the baseline Figure 2.

We next replace the binary BBM indicator with alternative measures of policy intensity. Table B10 uses the number of tightening actions within a wave. Table B11 uses the cumulative number of tightening actions up to the current wave. Table B12 captures the net direction of policy, assigning $+1$ to net tightening, -1 to net loosening, and zero otherwise. The cumulative measure produces more negative coefficients for middle-income households than the within-wave count. This is consistent with the possibility that successive tightening actions reinforce the constraints faced by some households over time.[12] The estimates based on the net policy direction are also negative for first HMR mortgages, but less precise. Loosening actions are relatively rare in the sample, so the results do not allow for a separate analysis of easing episodes.

Finally, Table B13 groups households by debt-to-income (DTI) deciles instead of income deciles. The coefficients are negative across DTI groups relative to the least indebted households and become more negative towards the top of the DTI distribution. Although the estimates are not statistically significant, the pattern is consistent with tighter borrowing limits being more relevant for highly leveraged households. This last exercise is only a directional check. DTI is a stock variable that reflects earlier borrowing decisions and may itself have been affected by past macroprudential measures.

[12] The coefficients should not be read as the causal effect of adding one more policy action. Tightening measures differ in size, design, and timing, and the cumulative count does not capture these differences.

Figure 5: Heterogeneous Effects of BBM Tightening Across Income Deciles



Note: The figure plots the estimated differential effects of borrower-based macroprudential tightening across household income deciles relative to decile 10, based on the variant of equation 1 augmented with triple interactions between the BBM tightening dummy, income decile dummies, and dummy variables for selected household-level characteristics, corresponding to columns (1), (3), (5) and (7) of Table B9. Each panel reports estimates separately for households with and without the indicated characteristic. All other details follow the baseline Figure 2.

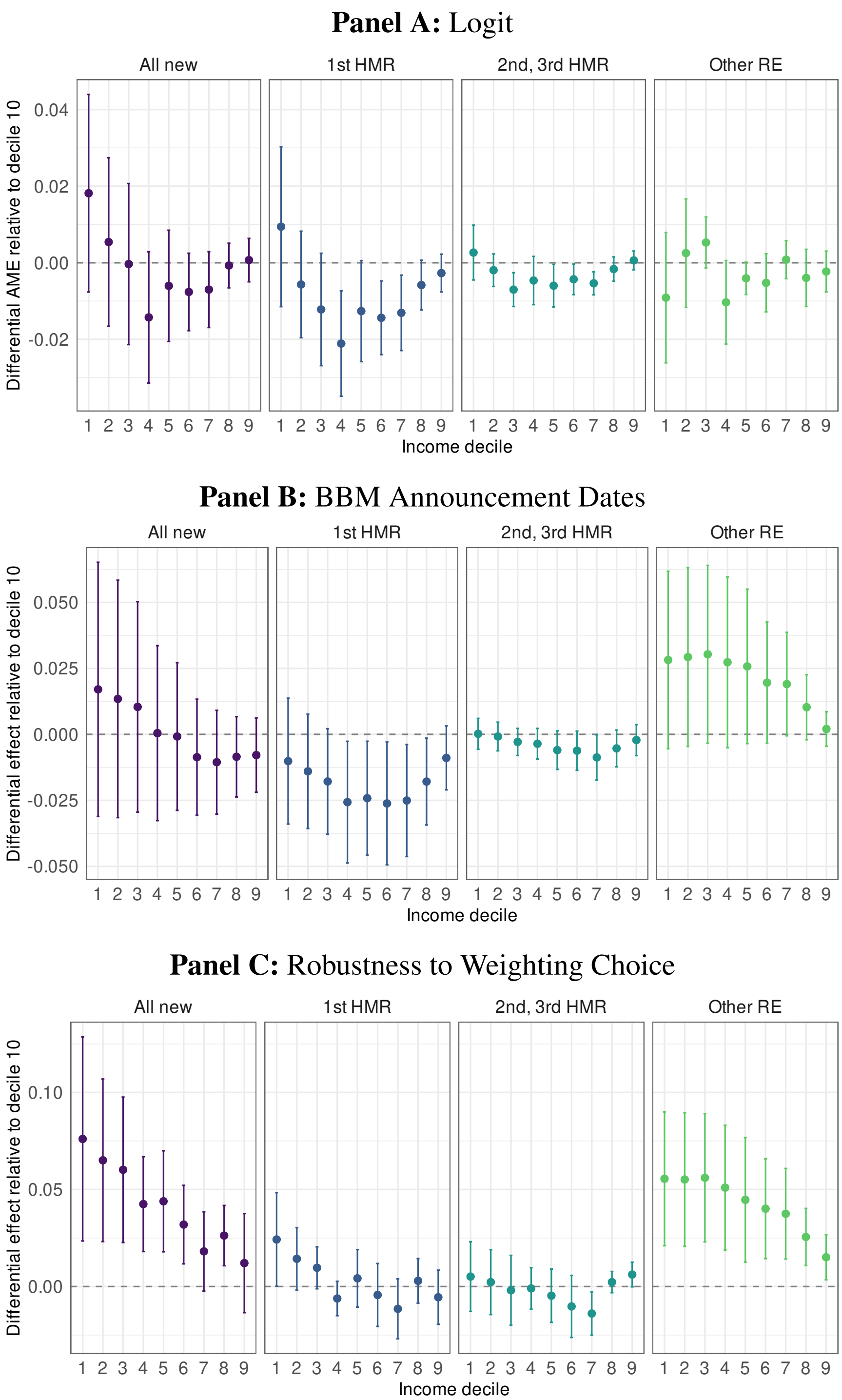
5.3 Robustness Checks

We examine whether the baseline results are sensitive to three choices: the use of a linear probability model, the timing used to code policy actions, and the treatment of survey weights. Figure 6 summarises the results.

Panel A reports average marginal effects from a logit model.[13] The pattern is close to the baseline estimates. For first HMR mortgages, the coefficients are negative for middle-income households and statistically significant for deciles 4 to 7. The estimated differences range from approximately 1.3 to 2 percentage points relative to the top income decile. The main result is therefore not driven by the linear probability specification.

[13] The average marginal effects are computed by averaging the marginal effect of the interaction term $BBM_{ct} \times \mathbf{1}D = d$ across all observations. They can therefore be read as percentage-point differences in the probability of obtaining a new mortgage for households in decile d relative to decile 10, and are directly comparable to the coefficients from the linear probability model.

Figure 6: Estimated Differential Effects of BBM Tightening across Income Deciles: Robustness



Note: All panels plot estimated differential effects of BBM tightening on the probability of new mortgage origination across income deciles relative to decile 10, corresponding to odd-numbered columns of the respective tables. Coefficient estimates are shown together with 90% confidence intervals based on standard errors clustered at the country level. The sample excludes wave 4 throughout. Panel A reports average marginal effects from the logit counterpart of equation (1) (Table B4). Panel B reports $\hat{\beta}_d$ coefficients from equation (1) estimated using announcement-date rather than effective-date BBM indicators (Table B5). Panel C reports $\hat{\beta}_d$ coefficients from equation (1) estimated with rescaled survey weights w^*_{ict} as defined in equation (2) (Table B6). All other details follow the baseline Figure 2.

Panel B uses policy announcement dates instead of effective dates.[14] The estimates remain similar to the baseline. The negative coefficients for first HMR mortgages are again concentrated in the middle of the income distribution. No equally clear pattern appears for the other mortgage categories.

Panel C reports estimates using rescaled survey weights.[15] The shape of the estimates is similar, although the coefficients are less precise. For first HMR mortgages, the estimates remain negative for middle- and upper-middle-income households relative to the top decile. The coefficients for second and third HMR mortgages remain small and mostly insignificant. Mortgages on other real estate retain the positive pattern discussed above.

6. Conclusions

This paper studies how the relationship between BBM tightening and new mortgage origination differs across the household income distribution. The main result is concentrated in first mortgages secured against the household main residence. Following BBM tightening, middle-income households are approximately 2 percentage points less likely to obtain such a mortgage relative to households in the top income decile. The pattern is driven mainly by LTV tightening. Estimates for DSTI tightening point in a similar direction, but are less precise. Among middle-income households, the differential effect is stronger for younger households.

These results suggest that the distributional effects of BBMs deserve attention alongside their financial stability benefits. An LTV limit can be easier to meet for a household that can increase its down payment than for one with limited savings. This may be particularly relevant for younger households, which typically have less accumulated wealth and housing equity. Our data do not allow us to identify first-time buyers directly or to estimate the longer-term effects on homeownership and wealth accumulation. The results nevertheless show that tightening does not affect all households in the same way. They also suggest that the choice between LTV and DSTI limits matters for the distribution of the effects.

An open question is whether the income gradient changes with housing market conditions. Tighter LTV limits may bind more strongly when house prices have already risen faster than household incomes. The effects may also depend on the interest rate environment. Studying these interactions would help clarify when the distributional consequences of BBM tightening are likely to be strongest.

[14] The baseline indicator assigns a tightening action to the month in which the new limit becomes effective. The alternative indicator assigns it to the month of announcement and therefore allows for the possibility that households adjust their decisions before implementation. Announcement dates may, however, understate the policy environment in later periods when a measure is announced in one wave but becomes binding only in the next.

[15] The baseline regressions are unweighted because the original HFCS survey weights were calibrated for the full survey sample rather than for the matched subsample. As a robustness check, we use rescaled weights w^*_{ict} defined in equation (2). The rescaling preserves the total weight mass within each country-wave cell after matching.

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Appendix A: Additional Information on Data and Methods

A.1 Household Finance and Consumption Survey Data

Table A1: Overview of HFCS Waves

Wave	Fieldwork Period	Households	Countries	New Countries
1	Nov 2008 – Aug 2011	38,276	15	AT, BE, CY, DE, ES, FI, FR, GR, IT, LU, MT, NL, PT, SI, SK
2	Nov 2011 – Jun 2015	61,097	20	+ EE, HU, IE, LV, PL
3	Sep 2016 – Jan 2019	77,695	22	+ HR, LT
4	Jan 2020 – Apr 2022	66,686	22	+ CZ; − PL

Note: The table summarises the four waves of the Household Finance and Consumption Survey (HFCS) coordinated by the European Central Bank. *Fieldwork Period* reports the earliest start and latest end of fieldwork across all participating countries. *Households* refers to the total number of interviewed households in the raw public-use microdata, prior to any sample restrictions applied in this study. *Countries* is the total number of participating countries per wave. *New Countries* lists changes in country composition relative to the preceding wave, with + denoting countries joining and − denoting countries exiting. The baseline analysis uses Waves 1–3 only; Wave 4, conducted during the COVID-19 pandemic, is used for robustness checks exclusively. The analytical sample is further restricted to countries with at least one borrower-based macroprudential policy action within the sample period; see Section 3.2.

A.2 Borrower-Based Macroprudential Policy Indicators

Table A2: BBM Policy Actions by Country and Wave

Panel A: Effective Dates

	Any BBM				LTV				DSTI			
Country	W1	W2	W3	W4	W1	W2	W3	W4	W1	W2	W3	W4
BE	0	0	0	1	0	0	0	1	0	0	0	0
CY	0	1	1	1	0	0	0	1	0	1	1	1
CZ	—	—	—	1	—	—	—	0	—	—	—	1
EE	—	0	1	0	—	0	1	0	—	0	1	0
FI	0	0	1	1	0	0	1	1	0	0	0	0
FR	0	0	0	1	0	0	0	0	0	0	0	1
HU	—	0	1	1	—	0	1	0	—	0	1	1
IE	—	0	1	0	—	0	1	0	—	0	0	0
LT	—	—	0	1	—	—	0	1	—	—	0	0
LU	0	0	0	1	0	0	0	1	0	0	0	0
LV	—	0	1	1	—	0	1	1	—	0	0	1
MT	0	0	0	1	0	0	0	1	0	0	0	1
NL	0	1	1	1	0	1	1	1	0	1	1	1
PL	—	1	1	—	—	1	1	—	—	0	0	—
PT	0	0	0	1	0	0	0	1	0	0	0	1
SI	0	0	1	1	0	0	1	0	0	0	1	1
SK	0	0	1	1	0	0	1	1	0	0	0	1

Panel B: Announcement Dates

	Any BBM				LTV				DSTI			
Country	W1	W2	W3	W4	W1	W2	W3	W4	W1	W2	W3	W4
BE	0	0	0	1	0	0	0	1	0	0	0	0
CY	0	1	1	1	0	0	0	1	0	1	1	1
CZ	—	—	—	1	—	—	—	1	—	—	—	1
EE	—	0	1	0	—	0	1	0	—	0	1	0
FI	0	0	1	1	0	0	1	1	0	0	0	0
FR	0	0	0	1	0	0	0	0	0	0	0	1
HU	—	1	1	1	—	1	1	0	—	1	1	1
IE	—	0	1	0	—	0	1	0	—	0	0	0
LT	—	—	1	1	—	—	1	1	—	—	0	0
LU	0	0	0	1	0	0	0	1	0	0	0	0
LV	—	0	1	1	—	0	1	1	—	0	0	1
MT	0	0	0	1	0	0	0	1	0	0	0	1
NL	0	1	1	1	0	1	1	1	0	1	1	1
PL	—	1	1	—	—	1	1	—	—	0	0	—
PT	0	0	0	1	0	0	0	1	0	0	0	1
SI	0	0	1	1	0	0	1	0	0	0	1	1
SK	0	0	1	1	0	0	1	1	0	0	1	1

Note: The table reports borrower-based macroprudential (BBM) policy actions by country and HFCS wave. Panel A is based on policy effective dates; Panel B is based on policy announcement dates. Entries take value 1 if at least one tightening of the respective instrument occurred in the given country during the wave identification window, and 0 otherwise. — denotes country–wave combinations for which the HFCS is not available. Countries with no BBM activity across all waves (AT, DE, ES, GR, IT, HR) are excluded from the analytical sample and are not reported here.

A.3 Propensity Score Matching and Summary Statistics

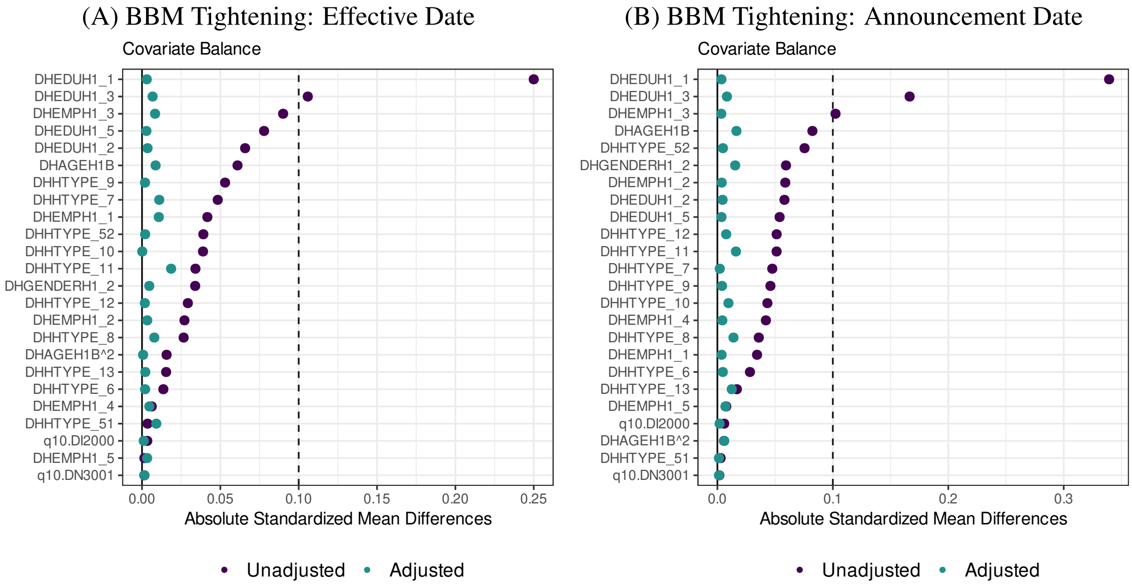
Table A3: Covariates used in Matching Procedures

Code	Name	Description and Categories
q10.DI2000	Gross income deciles	Household total gross income, divided into deciles computed separately for each country.
q10.DN3001	Net wealth deciles	Household net wealth (total assets excluding public and occupational pension minus total liabilities), divided into deciles computed separately for each country.
DHAGEH1B	Age	Age of the household reference person, recorded as a 5-year interval (e.g. 16–20, 20–25, . . .), capped at 85. Entered in the matching formula as a centred continuous variable and its square to account for non-linear age effects.
DHGENDERH1	Gender	Gender of the reference person. Categories: • 1 = Male • 2 = Female
DHEDUH1	Education	Highest level of education completed by the reference person. Categories (based on ISCED-2011): • 1 = Primary education or no formal education • 2 = Lower secondary or second stage of basic education • 3 = Upper secondary or post-secondary • 5 = Short-cycle tertiary education or Bachelor or Master or Doctoral degrees, or their equivalents
DHEMPH1	Main labor status	Main labor market status of the reference person. Categories: • 1 = Employed • 2 = Self-employed • 3 = Unemployed • 4 = Retired • 5 = Other
DHHTYPE	Household type	Household composition and structure. Categories: • 51 = One adult, younger than 64 years • 52 = One adult, older than 65 years • 6 = Two adults younger than 65 years • 7 = Two adults, at least one aged 65 years and over • 8 = Three or more adults • 9 = Single parent with dependent children • 10 = Two adults with one dependent child • 11 = Two adults with two dependent children • 12 = Two adults with three or more dependent children • 13 = Three or more adults with dependent children

Covariate balance. Covariate balance before and after matching is assessed using the absolute standardized mean difference (SMD) for each covariate, defined as the difference in group means divided by the pooled standard deviation of the treated group. The SMD is scale-free and does not depend on sample size. The conventional threshold for adequate balance is $|\text{SMD}| < 0.1$. For continuous covariates we additionally report variance ratios; a ratio of 1 indicates identical dispersion across groups.

Table A4 reports means and balance statistics for each covariate before and after matching, and Figure A1 (Panel A) displays the corresponding love plot. Prior to matching, most covariates are already well balanced between treated and control households, reflecting the fact that, after restricting the sample to countries with active BBM policy, both groups are drawn from broadly similar national populations. The main exceptions are two education categories: households with primary or no formal education exhibit a pre-matching SMD of -0.250, and households with upper secondary education exhibit an SMD of 0.106, indicating that country-wave cells with tightening actions contain a lower share of low-education households and a higher share of upper-secondary households relative to control cells. Age and unemployment status show moderate pre-matching imbalances (SMDs of 0.061 and -0.090, respectively), both within the 0.1 threshold. Income and wealth decile ranks are already closely aligned before matching (SMDs of 0.003 and -0.002), confirming that the country restriction is the primary source of comparability.

Figure A1: Covariate Balance Before and After Matching

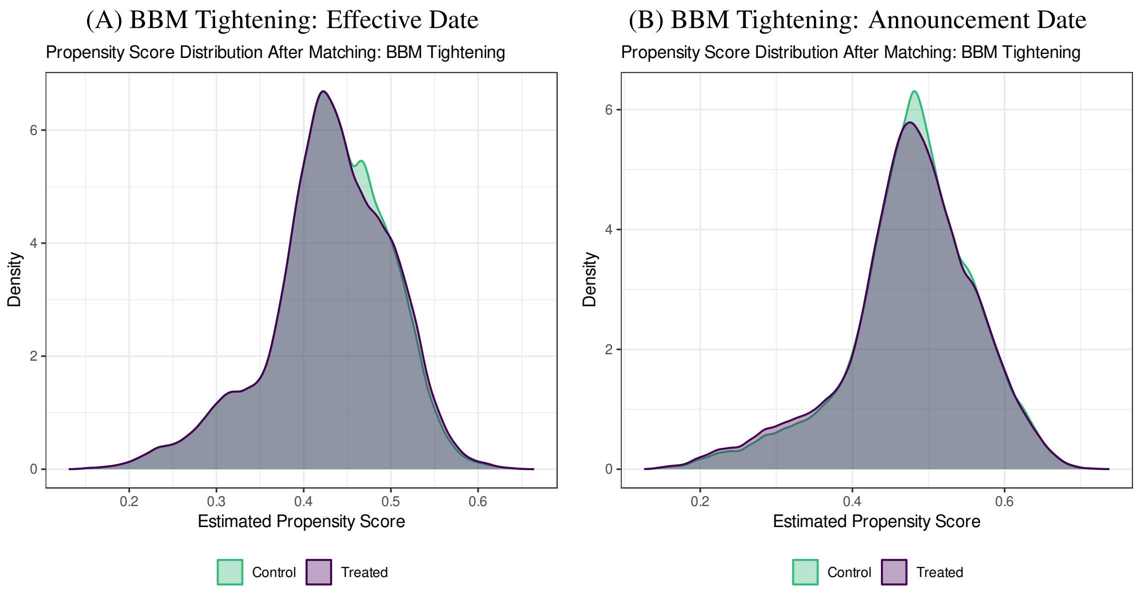


Note: The figure shows the absolute standardized mean differences (SMDs) for each covariate between treated and control households before (unadjusted) and after (adjusted) nearest-neighbour propensity score matching (1:1 ratio, caliper 0.05). Panel A corresponds to matching based on BBM tightening effective dates; Panel B corresponds to matching based on BBM tightening announcement dates. The vertical dashed line at 0.1 marks the conventional threshold for adequate balance. Covariates are ordered by their unadjusted SMDs. For binary and multi-category variables, SMDs are standardized using the standard deviation of the treated group, following Austin (2011). Countries without any BBM action (AT, DE, ES, GR, IT, HR) are excluded prior to matching. Results are reported for the first implicate.

Matching effectively removes all residual imbalances. After matching, every covariate falls below an absolute SMD of 0.02 — well within the conventional adequacy threshold — and variance ratios for continuous covariates are close to 1 in all cases (Table A4). The two education categories that showed the largest pre-matching imbalances are reduced to SMDs of –0.003 and 0.007, respectively. Figure A2 (Panel A) shows the distribution of estimated propensity scores for treated and control households in the matched sample. The two distributions overlap substantially across the 0.2–0.6 range, confirming that the caliper restriction (±0.05) successfully confines matching to a region of common support and that no extrapolation is required.

Panel B of both figures repeats the diagnostics for the announcement-date robustness specification. The pattern is qualitatively identical: all post-matching SMDs again fall below 0.02 and propensity score overlap is similarly broad, lending confidence that the effective-date baseline is not sensitive to the choice of treatment date definition.

Figure A2: Propensity Score Overlap Plots



Note: The figure shows the distribution of estimated propensity scores for treated and control households in the matched sample. Panel A corresponds to matching based on BBM tightening effective dates; Panel B corresponds to matching based on BBM tightening announcement dates. Propensity scores are estimated via logistic regression on the covariates listed in Table A3. Countries without any BBM action (AT, DE, ES, GR, IT, HR) are excluded prior to matching. Results are reported for the first implicate.

Table A4: Covariate Balance Before and After Matching: BBM Tightening, Effective Dates

Covariate	Mean Treated	Mean Control Before	Mean Control After	SMD Before	SMD After	Var. Ratio Before	Var. Ratio After
Continuous covariates							
q10.DI2000	5.498	5.488	5.514	0.003	-0.001	1.001	1.002
q10.DN3001	5.499	5.504	5.515	-0.002	-0.001	1.001	1.003
DHAGEH1B	-0.540	-1.516	-0.787	0.061	0.009	0.990	1.002
DHAGEH1B^2	256.577	261.089	256.028	-0.016	0.001	0.974	0.995
Gender							
DHGENDERH1 = 2 (Female)	0.407	0.390	0.403	0.034	0.005		
Education (DHEDUH1)							
DHEDUH1 = 1 (Primary)	0.084	0.153	0.085	-0.250*	-0.003		
DHEDUH1 = 2 (Lower sec.)	0.112	0.133	0.114	-0.066	-0.004		
DHEDUH1 = 3 (Upper sec.)	0.413	0.361	0.408	0.106*	0.007		
DHEDUH1 = 5 (Tertiary)	0.390	0.352	0.392	0.078	-0.003		
Labour status (DHEMPH1)							
DHEMPH1 = 1 (Employed)	0.504	0.483	0.510	0.042	-0.011		
DHEMPH1 = 2 (Self-empl.)	0.097	0.105	0.096	-0.027	0.003		
DHEMPH1 = 3 (Unemployed)	0.033	0.049	0.032	-0.090	0.008		
DHEMPH1 = 4 (Retired)	0.316	0.313	0.313	0.006	0.005		
DHEMPH1 = 5 (Other)	0.051	0.050	0.050	0.002	0.003		
Household type (DHHTYPE)							
DHHTYPE = 6	0.158	0.163	0.158	-0.014	0.002		
DHHTYPE = 7	0.182	0.163	0.175	0.048	0.011		
DHHTYPE = 8	0.071	0.065	0.069	0.027	0.008		
DHHTYPE = 9	0.041	0.052	0.041	-0.053	0.002		
DHHTYPE = 10	0.086	0.097	0.087	-0.039	0.000		
DHHTYPE = 11	0.101	0.111	0.107	-0.034	-0.019		
DHHTYPE = 12	0.046	0.052	0.046	-0.029	0.002		
DHHTYPE = 13	0.046	0.043	0.046	0.015	0.002		
DHHTYPE = 51	0.144	0.143	0.148	0.004	-0.009		
DHHTYPE = 52	0.124	0.111	0.122	0.039	0.002		

Note: The table reports covariate balance between treated and control groups before and after nearest-neighbour propensity score matching (1:1 ratio, caliper 0.05) for BBM tightening actions. The treated group consists of households surveyed in a wave where a tightening BBM action was effective; the control group consists of households in waves without a tightening action. SMD denotes the standardized mean difference; values below 0.1 in absolute terms indicate adequate balance. Variance ratios are reported for continuous covariates only; a value of 1 indicates identical dispersion across groups. For binary and multi-category factor variables, SMDs are standardized to ensure comparability across all covariates; balance statistics are reported for all categories. * denotes pre-matching SMD exceeding the 0.1 threshold in absolute terms. Results are reported for the first implicate. Countries without any BBM action (AT, DE, ES, GR, IT, HR) are excluded prior to matching.

Table A5: New Mortgages in the Full Matched Sample: Breakdown by Income Deciles

	Households with new mortgages (% share)							
	Excl. Refinanced				Incl. Refinanced			
	Any new	1st HMR	2nd, 3rd HMR	Other RE	Any new	1st HMR	2nd, 3rd HMR	Other RE
Full Sample	4.46	2.85	0.60	1.46	6.30	4.42	0.82	1.84
Income Deciles								
1	1.04	0.67	0.14	0.31	1.50	1.06	0.22	0.37
2	1.43	1.02	0.21	0.31	1.95	1.48	0.24	0.38
3	2.09	1.58	0.27	0.43	2.94	2.31	0.34	0.55
4	2.80	2.18	0.45	0.54	3.98	3.27	0.59	0.66
5	4.00	2.94	0.53	0.98	5.69	4.49	0.76	1.18
6	5.05	3.59	0.75	1.26	7.09	5.40	1.01	1.58
7	5.90	3.92	0.89	1.74	8.41	6.25	1.22	2.10
8	6.61	4.19	0.91	2.18	9.49	6.64	1.19	2.88
9	7.68	4.55	0.90	2.96	11	7.20	1.30	3.92
10	7.90	3.84	0.89	3.79	10.81	5.97	1.32	4.76

Note: The table reports the share of households with new mortgage originations in the matched sample, broken down by income decile. Statistics are reported for the full matched sample including all four HFCS waves, separately for new originations excluding refinanced loans (left panel) and including refinanced loans (right panel). Full sample statistics in the first row combine treated and control households from Table 1, upper panel. Income deciles are computed separately for each country. Summary statistics are based on the first HFCS implicate; results are materially identical across all five implicates.

Appendix B: Additional Regression Results

Table B1: BBM Tightening and Loan Incidence (Including Refinanced Loans)

Dependent Variable:	$\mathbf{1}\{NewMortgage = 1\}$							
Loan type:	All new		1st HMR		2nd, 3rd HMR		Other RE	
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
BBM	-0.0246**	-0.0371**	-0.0299**	-0.0378**	0.0013	-0.0041	-0.0006	-0.0031*
	(0.0119)	(0.0162)	(0.015)	(0.0173)	(0.0016)	(0.0026)	(0.0028)	(0.0018)
$BBM \times W_4$		0.0841***		0.0691***		0.0163**		0.0145**
		(0.0276)		(0.0248)		(0.007)		(0.0057)
Obs.	126543	184378	126543	184378	126543	184378	126543	184378
Adj. R_2	0.17	0.16	0.12	0.12	0.02	0.03	0.07	0.07
Share_outside	7.61	7.64	3.78	4.04	0	0	0	0
HH Controls	Y	Y	Y	Y	Y	Y	Y	Y
Ctry Controls	Y	Y	Y	Y	Y	Y	Y	Y
Country FEs	Y	Y	Y	Y	Y	Y	Y	Y
Wave FEs	Y	Y	Y	Y	Y	Y	Y	Y

Note: The table reports regression results for a variant of equation (1) in which BBM_{ct} enters without interactions with income decile dummies. Income decile dummies are included as controls, with decile 10 as the omitted reference category. Country and wave fixed effects replace the country $\times$ wave fixed effects of the baseline, and three country-level controls aggregated over the wave window are added: real GDP growth, a real house price index, and the credit-to-GDP gap (all sourced from the BIS Statistical Warehouse). Columns (1), (3), (5), and (7) are estimated on the waves 1–3 subsample; columns (2), (4), (6), and (8) extend the sample to all four waves and add an interaction between BBM_{ct} and a wave 4 dummy. Results are reported for new originations including refinanced loans. *Share_outside* reports the share of fitted values outside $[-0.05, 1.05]$; see Section 4 for discussion. Estimates are combined across all five HFCS implicates using Rubin's rules (Rubin, 1987). Auxiliary statistics (*Share_outside*, *Adj.* R^2, and observation counts) are reported for the fifth implicate and are materially identical across all five implicates. Standard errors in parentheses are HC1 heteroskedasticity-robust, clustered at the country level. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table B2: Baseline Results: Robustness to Inclusion of Wave 4

Dependent Variable:	$\mathbf{1}\{NewMortgage = 1\}$							
Loan type:	All new		1st HMR		2nd, 3rd HMR		Other RE	
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$BBM \times \mathbf{1}\{D = 1\}$	0.0042	0.0227	−0.01	−0.0071	−0.0016	0.0008	0.0155	0.0311
	(0.0193)	(0.0279)	(0.0097)	(0.0132)	(0.0031)	(0.0033)	(0.0125)	(0.02)
$BBM \times \mathbf{1}\{D = 2\}$	0.0036	0.0184	−0.0108	−0.0117	−0.0022	−0.0004	0.0162	0.032
	(0.0185)	(0.0255)	(0.0085)	(0.0117)	(0.0029)	(0.0031)	(0.0123)	(0.0199)
$BBM \times \mathbf{1}\{D = 3\}$	0.0015	0.0155	−0.0128*	−0.015	−0.0042	−0.0022	0.017	0.033*
	(0.0173)	(0.0231)	(0.0074)	(0.0111)	(0.0028)	(0.003)	(0.0129)	(0.0199)
$BBM \times \mathbf{1}\{D = 4\}$	−0.0013	0.0066	−0.0161**	−0.022*	−0.0033	−0.0027	0.0162	0.03
	(0.015)	(0.0192)	(0.0079)	(0.0127)	(0.0028)	(0.0034)	(0.0127)	(0.0192)
$BBM \times \mathbf{1}\{D = 5\}$	−0.001	0.0046	−0.0139**	−0.0215*	−0.0058**	−0.0051	0.0158	0.0288
	(0.0126)	(0.0163)	(0.0059)	(0.0119)	(0.0028)	(0.004)	(0.0116)	(0.0178)
$BBM \times \mathbf{1}\{D = 6\}$	−0.0041	−0.0026	−0.0145**	−0.0232*	−0.0057*	−0.0056	0.0129	0.0229
	(0.009)	(0.0125)	(0.0066)	(0.0128)	(0.003)	(0.0044)	(0.0101)	(0.0141)
$BBM \times \mathbf{1}\{D = 7\}$	−0.0039	−0.0061	−0.0137**	−0.0235**	−0.0055*	−0.0084*	0.0129	0.0224*
	(0.0088)	(0.0111)	(0.0065)	(0.0119)	(0.003)	(0.0048)	(0.0098)	(0.0128)
$BBM \times \mathbf{1}\{D = 8\}$	−0.0015	−0.0044	−0.0083	−0.0159*	−0.0034	−0.0045	0.0078	0.013*
	(0.0064)	(0.0084)	(0.0057)	(0.0092)	(0.0026)	(0.0038)	(0.0066)	(0.0078)
$BBM \times \mathbf{1}\{D = 9\}$	−0.0077	−0.006	−0.0072	−0.0083	−0.0014	−0.0016	−0.0006	0.0034
	(0.008)	(0.0087)	(0.0069)	(0.0075)	(0.0028)	(0.0032)	(0.0035)	(0.0039)
$BBM \times \mathbf{1}\{D = 1\} \times W_4$		−0.1139**		−0.0415*		−0.0127**		−0.0711**
		(0.0527)		(0.0228)		(0.0051)		(0.035)
$BBM \times \mathbf{1}\{D = 2\} \times W_4$		−0.0977**		−0.0266		−0.01**		−0.0705**
		(0.0452)		(0.0178)		(0.0049)		(0.0345)
$BBM \times \mathbf{1}\{D = 3\} \times W_4$		−0.0885**		−0.0167		−0.0088*		−0.0709**
		(0.0393)		(0.0151)		(0.0046)		(0.0334)
$BBM \times \mathbf{1}\{D = 4\} \times W_4$		−0.0717**		−0.0049		−0.0055		−0.0661**
		(0.0332)		(0.0165)		(0.0053)		(0.0323)
$BBM \times \mathbf{1}\{D = 5\} \times W_4$		−0.0544**		0.0065		−0.0032		−0.0606**
		(0.0273)		(0.0167)		(0.0065)		(0.03)
$BBM \times \mathbf{1}\{D = 6\} \times W_4$		−0.0333*		0.0167		0.0003		−0.0497**
		(0.0188)		(0.0169)		(0.0066)		(0.0224)
$BBM \times \mathbf{1}\{D = 7\} \times W_4$		−0.019		0.021		0.0075		−0.045**
		(0.013)		(0.0153)		(0.0066)		(0.0186)
$BBM \times \mathbf{1}\{D = 8\} \times W_4$		−0.0108		0.0178		0.0033		−0.0298***
		(0.0094)		(0.0112)		(0.005)		(0.0107)
$BBM \times \mathbf{1}\{D = 9\} \times W_4$		−0.0075		0.0075		0.0009		−0.0169***
		(0.0081)		(0.0073)		(0.003)		(0.0055)
Obs.	184378	184378	184378	184378	184378	184378	184378	184378
Adj. R_2	0.12	0.12	0.08	0.08	0.02	0.02	0.06	0.06
Share_outside	4.35	4.18	0.75	0.82	0	0	0	0
pval_equal_betas	0.7591	-	0.2257	-	0.3321	-	0.8745	-
HH Controls	Y	Y	Y	Y	Y	Y	Y	Y
Ctry × Wave FEs	Y	Y	Y	Y	Y	Y	Y	Y

Note: The table reports regression results for an extended version of equation (1) estimated on the full four-wave sample. All specifications report results for new originations excluding refinanced loans. The omitted income category is decile 10. Even-numbered columns additionally include triple interaction terms $BBM \times \mathbf{1}\{D = d\} \times W_4$, where W_4 is a dummy equal to one for observations from wave 4 and zero otherwise. The triple interaction coefficients measure the extent to which the differential effect of BBM tightening on households in decile d relative to decile 10 was attenuated or amplified during the COVID-19 pandemic period covered by wave 4. The p-value of the Wald test $H_0 : \beta_1 = \cdots = \beta_9$ is reported for odd-numbered columns only, as the presence of triple interactions renders the test uninformative for even-numbered columns. Estimates are combined across all five HFCS implicates using Rubin's rules (Rubin, 1987). Auxiliary statistics (*Share_outside*, *Adj.* R^2, and observation counts) are reported for the fifth implicate and are materially identical across all five implicates. Survey weights are not used; see Section 4 for discussion. *Share_outside* reports the share of fitted values outside $[-0.05, 1.05]$; see Section 4 for discussion. Standard errors in parentheses are HC1 heteroskedasticity-robust, clustered at the country level. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

B.1 Supplementary Results with the Base Effect

Table B3: Supplementary Results with the Base Effect

Dependent Variable:	$\mathbf{1}\{NewMortgage = 1\}$							
Loan type:	All new		1st HMR		2nd, 3rd HMR		Other RE	
Model:	(1)	(2) incl. ref.	(3)	(4) incl. ref.	(5)	(6) incl. ref.	(7)	(8) incl. ref.
BBM	0.0082	-0.0239	0.0191*	-0.0057	0.0049	0.0071	-0.0121	-0.0274*
	(0.0149)	(0.0251)	(0.01)	(0.0156)	(0.0034)	(0.0046)	(0.0098)	(0.0162)
$BBM \times \mathbf{1}\{D = 1\}$	0.0221	0.0277	-0.0077	-0.0066	0.0007	-0.0017	0.031	0.0396
	(0.0278)	(0.0393)	(0.013)	(0.0194)	(0.0033)	(0.0049)	(0.0201)	(0.0268)
$BBM \times \mathbf{1}\{D = 2\}$	0.0175	0.0217	-0.0125	-0.0126	-0.0005	-0.0036	0.032	0.0403
	(0.0254)	(0.036)	(0.0116)	(0.0167)	(0.0031)	(0.0051)	(0.02)	(0.0265)
$BBM \times \mathbf{1}\{D = 3\}$	0.0147	0.0147	-0.0157	-0.0196	-0.0023	-0.0056	0.0329*	0.0401
	(0.023)	(0.0305)	(0.0109)	(0.0146)	(0.003)	(0.0048)	(0.0199)	(0.026)
$BBM \times \mathbf{1}\{D = 4\}$	0.0058	0.0056	-0.0225*	-0.0281*	-0.0027	-0.0052	0.0298	0.038
	(0.0191)	(0.0253)	(0.0126)	(0.0157)	(0.0034)	(0.005)	(0.0192)	(0.0252)
$BBM \times \mathbf{1}\{D = 5\}$	0.0039	-0.0046	-0.0219*	-0.0353**	-0.0052	-0.009	0.0286	0.0363
	(0.0162)	(0.0214)	(0.0118)	(0.0168)	(0.004)	(0.006)	(0.0178)	(0.0234)
$BBM \times \mathbf{1}\{D = 6\}$	-0.0032	-0.0112	-0.0235*	-0.0366**	-0.0056	-0.009	0.0226	0.0292
	(0.0124)	(0.0167)	(0.0127)	(0.0179)	(0.0043)	(0.0058)	(0.014)	(0.0187)
$BBM \times \mathbf{1}\{D = 7\}$	-0.0067	-0.0207	-0.0237**	-0.043**	-0.0085*	-0.0131**	0.0221*	0.0271*
	(0.0111)	(0.016)	(0.0119)	(0.0203)	(0.0048)	(0.0065)	(0.0127)	(0.0163)
$BBM \times \mathbf{1}\{D = 8\}$	-0.0047	-0.0253*	-0.016*	-0.039**	-0.0045	-0.0077	0.0127	0.0129
	(0.0084)	(0.015)	(0.0091)	(0.0188)	(0.0038)	(0.0057)	(0.0078)	(0.0099)
$BBM \times \mathbf{1}\{D = 9\}$	-0.0062	-0.0194	-0.0084	-0.0229*	-0.0016	-0.0028	0.0033	0.0016
	(0.0086)	(0.0127)	(0.0074)	(0.0128)	(0.0031)	(0.0035)	(0.0039)	(0.0047)
Obs.	126543	126543	126543	126543	126543	126543	126543	126543
Share_outside	4.21	7.6	1.15	3.86	0	0	0	0
Adj. R_2	0.12	0.17	0.08	0.12	0.02	0.02	0.06	0.07
pval_equal_betas	0.882	0.873	0.5082	0.6264	0.7765	0.7515	0.7553	0.8483
HH Controls	Y	Y	Y	Y	Y	Y	Y	Y
Ctry Controls	Y	Y	Y	Y	Y	Y	Y	Y
Ctry FEs	Y	Y	Y	Y	Y	Y	Y	Y
Wave FEs	Y	Y	Y	Y	Y	Y	Y	Y

Note: The table reports regression results for the model specified in equation (3) for all four loan types: any new mortgage (All new), the first mortgage secured against the household main residence (1st HMR), the second and third mortgage on the HMR (2nd, 3rd HMR), and mortgages secured against other real estate (Other RE). In contrast to the baseline specification in equation (1), this model replaces country $\times$ wave fixed effects with separate country and wave fixed effects, which allows the main effect of BBM_{ct} to be identified. All specifications are estimated on the waves 1–3 subsample of the matched sample. The omitted income category is decile 10. Odd-numbered columns report results for new originations excluding refinanced loans (preferred specification); even-numbered columns include refinanced loans. Estimates are combined across all five HFCS implicates using Rubin's rules (Rubin, 1987). Auxiliary statistics (*Share_outside*, *Adj.* R^2, and observation counts) are reported for the fifth implicate and are materially identical across all five implicates. Survey weights are not used; see Section 4 for discussion. *Share_outside* reports the share of fitted values outside $[-0.05, 1.05]$; see Section 4 for discussion. *p-val. equal* βs reports the p-value of a Wald test of the null hypothesis $H_0 : \beta_1 = \beta_2 = \cdots = \beta_9$. Standard errors in parentheses are HC1 heteroskedasticity-robust, clustered at the country level. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

B.2 Robustness of Baseline

Table B4: Robustness to Baseline Results: Logit

Dependent Variable:	$\mathbf{1}\{NewMortgage = 1\}$							
Loan type:	All new		1st HMR		2nd, 3rd HMR		Other RE	
Model:	(1)	(2) incl. ref.	(3)	(4) incl. ref.	(5)	(6) incl. ref.	(7)	(8) incl. ref.
$BBM \times \mathbf{1}\{D = 1\}$	0.0182	0.0277	0.0094	0.015	0.0027	0.0025	-0.0091	-0.0032
	(0.0147)	(0.0183)	(0.0119)	(0.0165)	(0.0041)	(0.0035)	(0.0097)	(0.0062)
$BBM \times \mathbf{1}\{D = 2\}$	0.0054	0.0125	-0.0057	-0.0008	-0.0019	-0.0034	0.0025	0.0035
	(0.0126)	(0.0158)	(0.0079)	(0.0109)	(0.0024)	(0.0026)	(0.0081)	(0.0099)
$BBM \times \mathbf{1}\{D = 3\}$	-0.0003	-0.0038	-0.0122	-0.0188	-0.007**	-0.009***	0.0053	0.006
	(0.012)	(0.0143)	(0.0084)	(0.011)	(0.0025)	(0.0026)	(0.0038)	(0.0053)
$BBM \times \mathbf{1}\{D = 4\}$	-0.0143	-0.014	-0.0211**	-0.0268**	-0.0046	-0.0056	-0.0103	-0.005
	(0.0098)	(0.0137)	(0.0079)	(0.0112)	(0.0036)	(0.0035)	(0.0062)	(0.0061)
$BBM \times \mathbf{1}\{D = 5\}$	-0.006	-0.0168	-0.0126	-0.0252**	-0.006*	-0.0098**	-0.0041	-0.001
	(0.0083)	(0.0098)	(0.0075)	(0.0098)	(0.0032)	(0.0038)	(0.0024)	(0.0022)
$BBM \times \mathbf{1}\{D = 6\}$	-0.0076	-0.0126	-0.0144**	-0.0228***	-0.0043*	-0.0066**	-0.0052	-0.0027
	(0.0058)	(0.0085)	(0.0055)	(0.0076)	(0.0023)	(0.0026)	(0.0043)	(0.0043)
$BBM \times \mathbf{1}\{D = 7\}$	-0.007	-0.0179**	-0.0131**	-0.0266***	-0.0054***	-0.009***	0.0008	0.0012
	(0.0057)	(0.0077)	(0.0056)	(0.0081)	(0.0017)	(0.0024)	(0.0028)	(0.0032)
$BBM \times \mathbf{1}\{D = 8\}$	-0.0007	-0.0136**	-0.0058	-0.0196***	-0.0016	-0.0039	-0.004	-0.0071
	(0.0033)	(0.005)	(0.0037)	(0.0056)	(0.0018)	(0.0029)	(0.0043)	(0.0049)
$BBM \times \mathbf{1}\{D = 9\}$	0.0007	-0.0054	-0.0027	-0.0107**	0.0006	-0.0004	-0.0023	-0.0025
	(0.0032)	(0.0038)	(0.0028)	(0.0041)	(0.0014)	(0.0012)	(0.003)	(0.0035)
Obs.	126540	126540	126540	126540	126540	126540	126540	126540
Pseudo_R2	0.2475	0.2789	0.2344	0.2679	0.2064	0.2009	0.2625	0.2777
HH Controls	Y	Y	Y	Y	Y	Y	Y	Y
Ctry × Wave FEs	Y	Y	Y	Y	Y	Y	Y	Y

Note: The table reports average marginal effects (AMEs) for the logit counterpart of the model specified in equation 1. All models are estimated using only the first three waves. Odd-numbered columns report results for new originations excluding refinanced loans; even-numbered columns include refinanced loans. Estimates employ only the first HFCS implicate. Survey weights are not used. AMEs are computed as the average marginal effect of the interaction term $BBM_{ct} \times \mathbf{1}\{D = d\}$ averaged over all observations, and capture the differential change in the probability of obtaining a new mortgage for households in income decile d relative to the top income decile (decile 10). The main effect of BBM tightening is not reported as it is absorbed by country × wave fixed effects. Standard errors, reported in parentheses, are HC1 heteroskedasticity-robust standard errors clustered at the country level. McFadden's pseudo-R^2 is computed relative to an intercept-only null model. Significance levels are denoted by *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

Table B5: Robustness of Baseline Results: Announcement Dates

Dependent Variable:	$\mathbf{1}\{NewMortgage = 1\}$							
Loan type:	All new		1st HMR		2nd, 3rd HMR		Other RE	
Model:	(1)	(2) incl. ref.	(3)	(4) incl. ref.	(5)	(6) incl. ref.	(7)	(8) incl. ref.
$BBM \times \mathbf{1}\{D=1\}$	0.017	0.0219	-0.0101	-0.0092	0.0002	-0.0023	0.0282	0.0358
	(0.0275)	(0.0391)	(0.0136)	(0.0204)	(0.0033)	(0.0049)	(0.0192)	(0.0253)
$BBM \times \mathbf{1}\{D=2\}$	0.0134	0.0163	-0.014	-0.0147	-0.0008	-0.004	0.0293	0.0366
	(0.0256)	(0.0367)	(0.0124)	(0.0182)	(0.0031)	(0.005)	(0.0193)	(0.0252)
$BBM \times \mathbf{1}\{D=3\}$	0.0104	0.0087	-0.0178	-0.0225	-0.0029	-0.0064	0.0303	0.0365
	(0.0227)	(0.0302)	(0.0114)	(0.0154)	(0.0029)	(0.0047)	(0.0192)	(0.0247)
$BBM \times \mathbf{1}\{D=4\}$	0.0005	-0.0012	-0.0257*	-0.032*	-0.0035	-0.0062	0.0273	0.0342
	(0.0189)	(0.0255)	(0.0131)	(0.0164)	(0.0033)	(0.0047)	(0.0184)	(0.0237)
$BBM \times \mathbf{1}\{D=5\}$	-0.0008	-0.0102	-0.0242**	-0.0379**	-0.006	-0.0098	0.0258	0.0324
	(0.016)	(0.0218)	(0.0123)	(0.017)	(0.0042)	(0.0061)	(0.0167)	(0.0217)
$BBM \times \mathbf{1}\{D=6\}$	-0.0086	-0.0175	-0.0262**	-0.0395**	-0.0062	-0.0096	0.0196	0.0253
	(0.0125)	(0.0176)	(0.0133)	(0.0182)	(0.0042)	(0.0058)	(0.0131)	(0.0171)
$BBM \times \mathbf{1}\{D=7\}$	-0.0106	-0.0246	-0.0251**	-0.0436**	-0.0087*	-0.0136**	0.019*	0.0233
	(0.0112)	(0.0164)	(0.0121)	(0.0193)	(0.0049)	(0.0067)	(0.0112)	(0.0145)
$BBM \times \mathbf{1}\{D=8\}$	-0.0085	-0.0291*	-0.0179*	-0.0406**	-0.0053	-0.0086	0.0103	0.0102
	(0.0087)	(0.015)	(0.0094)	(0.0177)	(0.004)	(0.0059)	(0.007)	(0.0088)
$BBM \times \mathbf{1}\{D=9\}$	-0.0078	-0.0206*	-0.0089	-0.023**	-0.0022	-0.0034	0.002	0.0004
	(0.008)	(0.0118)	(0.0069)	(0.0116)	(0.0034)	(0.0039)	(0.0037)	(0.0046)
Obs.	137425	137425	137425	137425	137425	137425	137425	137425
Adj. R_2	0.13	0.17	0.08	0.13	0.02	0.03	0.06	0.08
Share_outside	4.88	8.07	1.2	4.21	0	0	0	0.01
pval_equal_betas	0.2333	0.6874	0.0093	0.5969	0.8385	0.7758	0.5576	0.6632
HH Controls	Y	Y	Y	Y	Y	Y	Y	Y
Ctry × Wave FEs	Y	Y	Y	Y	Y	Y	Y	Y

Note: The table reports regression results for the same specification as Table 4; see that table for full details on the estimation approach, sample, and reported statistics. The only difference is that the BBM tightening indicator BBM_{ct} is constructed using announcement dates rather than effective dates of policy actions. Specifically, a country-wave cell is assigned a value of one if at least one BBM tightening action was publicly announced within the relevant wave window, regardless of when the measure became effective; see Section 3.2 for discussion. The matching procedure is also based on announcement dates; see Section 3.4 for discussion. Standard errors in parentheses are HC1 heteroskedasticity-robust, clustered at the country level. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table B6: Robustness of Baseline Results: Weighting Choice

Dependent Variable:	$\mathbf{1}\{NewMortgage = 1\}$							
Loan type:	All new		1st HMR		2nd, 3rd HMR		Other Real Estate	
Model:	(1)	(2) incl. ref.	(3)	(4) incl. ref.	(5)	(6) incl. ref.	(7)	(8) incl. ref.
$BBM \times \mathbf{1}\{D = 1\}$	0.076**	0.1022**	0.0243*	0.0418*	0.0051	0.0052	0.0555***	0.0673***
	(0.03)	(0.0429)	(0.0138)	(0.0229)	(0.0103)	(0.0135)	(0.0197)	(0.026)
$BBM \times \mathbf{1}\{D = 2\}$	0.065***	0.0886**	0.0143	0.0299	0.0023	0.0015	0.0552***	0.0663***
	(0.0239)	(0.0368)	(0.0092)	(0.0185)	(0.0095)	(0.014)	(0.0196)	(0.0256)
$BBM \times \mathbf{1}\{D = 3\}$	0.0602***	0.0714**	0.0097	0.0136	-0.0019	-0.0036	0.056***	0.0652***
	(0.0214)	(0.0297)	(0.0062)	(0.0137)	(0.0103)	(0.0146)	(0.0189)	(0.024)
$BBM \times \mathbf{1}\{D = 4\}$	0.0425***	0.0559***	-0.0062	-0.0017	-0.001	-0.0025	0.051***	0.0625***
	(0.0139)	(0.0208)	(0.005)	(0.0084)	(0.0061)	(0.0104)	(0.0183)	(0.024)
$BBM \times \mathbf{1}\{D = 5\}$	0.0439***	0.0462**	0.0042	-0.002	-0.0047	-0.008	0.0447**	0.0543**
	(0.0148)	(0.0217)	(0.0084)	(0.0124)	(0.0078)	(0.0119)	(0.0183)	(0.0236)
$BBM \times \mathbf{1}\{D = 6\}$	0.0319***	0.0278*	-0.0043	-0.0135	-0.0103	-0.0129	0.0401***	0.0449**
	(0.0115)	(0.0149)	(0.0092)	(0.0104)	(0.0091)	(0.0124)	(0.0147)	(0.018)
$BBM \times \mathbf{1}\{D = 7\}$	0.0181	0.0079	-0.0115	-0.0297**	-0.0139**	-0.0176*	0.0375***	0.0423**
	(0.0116)	(0.0165)	(0.0088)	(0.0139)	(0.0064)	(0.0096)	(0.0133)	(0.0168)
$BBM \times \mathbf{1}\{D = 8\}$	0.0263***	0.0181	0.0029	-0.0117	0.0023	0.003	0.0255***	0.0258**
	(0.0088)	(0.0126)	(0.0065)	(0.0091)	(0.0031)	(0.0053)	(0.0084)	(0.0109)
$BBM \times \mathbf{1}\{D = 9\}$	0.0121	-0.0016	-0.0055	-0.0215***	0.0062*	0.004**	0.0151**	0.015**
	(0.0146)	(0.0118)	(0.008)	(0.0052)	(0.0036)	(0.002)	(0.0066)	(0.0076)
Obs.	126543	126543	126543	126543	126543	126543	126543	126543
Adj. R_2	0.14	0.19	0.1	0.15	0.03	0.03	0.06	0.07
Share_outside	8.41	11.52	4.1	8.66	0	0	0	0.1
HH Controls	Y	Y	Y	Y	Y	Y	Y	Y
Ctry × Wave FEs	Y	Y	Y	Y	Y	Y	Y	Y

Note: The table reports regression results for the same specification as Table 4; see that table for full details on the estimation approach, sample, and reported statistics. The only difference is that rescaled survey weights w^*_{ict}, as defined in equation (2), are used in the regression in place of the unweighted baseline. Standard errors in parentheses are HC1 heteroskedasticity-robust, clustered at the country level. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

B.3 Extensions of Baseline

Table B7: Extension of Baseline: LTV Tightening

Dependent Variable:	$\mathbf{1}\{NewMortgage = 1\}$							
Loan type:	All new		1st HMR		2nd, 3rd HMR		Other RE	
Model:	(1)	(2) incl. ref.	(3)	(4) incl. ref.	(5)	(6) incl. ref.	(7)	(8) incl. ref.
$LTV \times \mathbf{1}\{D=1\}$	0.0205	0.0247	-0.0119	-0.0123	0.0008	-0.001	0.0338*	0.0423
	(0.0276)	(0.039)	(0.0133)	(0.0197)	(0.0034)	(0.0051)	(0.0195)	(0.0261)
$LTV \times \mathbf{1}\{D=2\}$	0.0153	0.0188	-0.015	-0.0162	-0.001	-0.0035	0.0331*	0.0414
	(0.0253)	(0.0359)	(0.0121)	(0.0173)	(0.0032)	(0.0053)	(0.0195)	(0.0259)
$LTV \times \mathbf{1}\{D=3\}$	0.012	0.0114	-0.0198*	-0.0246	-0.0018	-0.0041	0.0345*	0.0416
	(0.0233)	(0.0312)	(0.0114)	(0.0154)	(0.0031)	(0.0049)	(0.0197)	(0.0257)
$LTV \times \mathbf{1}\{D=4\}$	0.006	0.0041	-0.0246*	-0.0312*	-0.0022	-0.0049	0.0321*	0.0402
	(0.0196)	(0.0262)	(0.0131)	(0.0163)	(0.0033)	(0.0049)	(0.0189)	(0.0249)
$LTV \times \mathbf{1}\{D=5\}$	0.0033	-0.0078	-0.0249**	-0.0396**	-0.0053	-0.0099	0.031*	0.038
	(0.0168)	(0.0223)	(0.0121)	(0.017)	(0.004)	(0.006)	(0.0175)	(0.0231)
$LTV \times \mathbf{1}\{D=6\}$	-0.0041	-0.0139	-0.027**	-0.0408**	-0.0059	-0.009	0.0254*	0.0306*
	(0.013)	(0.0175)	(0.0127)	(0.018)	(0.0042)	(0.0058)	(0.0138)	(0.0184)
$LTV \times \mathbf{1}\{D=7\}$	-0.0061	-0.0217	-0.0249**	-0.0452**	-0.0084*	-0.0128**	0.0241*	0.0285*
	(0.0117)	(0.0168)	(0.012)	(0.0202)	(0.0047)	(0.0065)	(0.0126)	(0.0161)
$LTV \times \mathbf{1}\{D=8\}$	-0.0035	-0.0245	-0.0179**	-0.0413**	-0.0044	-0.0069	0.0162**	0.0165*
	(0.0086)	(0.0154)	(0.009)	(0.0187)	(0.0037)	(0.0058)	(0.0075)	(0.0095)
$LTV \times \mathbf{1}\{D=9\}$	-0.0055	-0.0213*	-0.0103	-0.0273**	-0.0015	-0.0025	0.0053	0.0035
	(0.0087)	(0.0125)	(0.0072)	(0.0123)	(0.0032)	(0.0035)	(0.0038)	(0.0048)
Obs.	126560	126560	126560	126560	126560	126560	126560	126560
Adj. R^2	0.12	0.17	0.08	0.13	0.02	0.03	0.06	0.07
Share_outside	4.40	7.83	0.92	3.85	0	0	0	0
p-val. equal βs	0.131	0.127	0.049	0.000	0.280	0.050	0.454	0.015
HH Controls	Y	Y	Y	Y	Y	Y	Y	Y
Ctry × Wave FEs	Y	Y	Y	Y	Y	Y	Y	Y

Note: The table reports regression results for the same specification as Table 4; see that table for full details on the estimation approach, sample, and reported statistics. The only difference is that the BBM_{ct} indicator is replaced by LTV_{ct}, a binary variable equal to one if at least one LTV tightening action occurred in country c within the wave t identification window, and zero otherwise. Standard errors in parentheses are HC1 heteroskedasticity-robust, clustered at the country level. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table B8: Extension of Baseline: DSTI Tightening

Dependent Variable:	$\mathbf{1}\{NewMortgage = 1\}$							
Loan type:	All new		1st HMR		2nd, 3rd HMR		Other RE	
Model:	(1)	(2) incl. ref.	(3)	(4) incl. ref.	(5)	(6) incl. ref.	(7)	(8) incl. ref.
$DSTI \times \mathbf{1}\{D=1\}$	−0.0105	−0.0004	−0.0173	−0.0133	−0.0071	−0.0074	0.0121	0.0184
	(0.034)	(0.0424)	(0.0215)	(0.0261)	(0.0061)	(0.0071)	(0.0193)	(0.0242)
$DSTI \times \mathbf{1}\{D=2\}$	−0.0062	0.0003	−0.0187	−0.0171	−0.0059	−0.0084	0.0169	0.023
	(0.0346)	(0.0429)	(0.0211)	(0.0248)	(0.0065)	(0.009)	(0.0195)	(0.0246)
$DSTI \times \mathbf{1}\{D=3\}$	−0.0032	0.0017	−0.0165	−0.0165	−0.0075	−0.0107	0.0183	0.024
	(0.033)	(0.0384)	(0.0212)	(0.0238)	(0.0057)	(0.0083)	(0.0194)	(0.0239)
$DSTI \times \mathbf{1}\{D=4\}$	−0.0139	−0.0073	−0.0247	−0.0248	−0.0074	−0.0082	0.0146	0.0209
	(0.0299)	(0.0346)	(0.0202)	(0.0226)	(0.0046)	(0.0068)	(0.0192)	(0.0238)
$DSTI \times \mathbf{1}\{D=5\}$	−0.0102	−0.0122	−0.0198	−0.0279	-0.0084^{*}	−0.01	0.0148	0.0211
	(0.026)	(0.0292)	(0.0207)	(0.0231)	(0.005)	(0.008)	(0.0174)	(0.0215)
$DSTI \times \mathbf{1}\{D=6\}$	−0.0077	−0.0096	−0.0184	−0.0262	−0.0062	−0.0082	0.0135	0.0198
	(0.0227)	(0.0253)	(0.0199)	(0.0229)	(0.005)	(0.0068)	(0.0148)	(0.0175)
$DSTI \times \mathbf{1}\{D=7\}$	−0.0183	−0.0257	-0.0237^{*}	-0.0373^{*}	-0.0103^{**}	-0.0132^{*}	0.0139	0.0183
	(0.0131)	(0.0174)	(0.0135)	(0.0202)	(0.0051)	(0.0073)	(0.0125)	(0.0151)
$DSTI \times \mathbf{1}\{D=8\}$	−0.0149	−0.0247	−0.0173	-0.0318^{*}	−0.0037	−0.0044	0.0037	0.0043
	(0.0134)	(0.0166)	(0.0125)	(0.0191)	(0.0048)	(0.0066)	(0.0108)	(0.0118)
$DSTI \times \mathbf{1}\{D=9\}$	−0.0086	−0.015	−0.0041	−0.0101	−0.0012	−0.0017	0.0017	−0.0007
	(0.011)	(0.0137)	(0.0096)	(0.015)	(0.0045)	(0.0059)	(0.0055)	(0.0059)
Obs.	126560	126560	126560	126560	126560	126560	126560	126560
Share_ones	4.79	6.44	3.02	4.38	0.61	0.81	1.63	2.03
Adj. R_2	0.12	0.17	0.08	0.12	0.02	0.03	0.06	0.07
Share_outside	4.33	7.74	0.84	3.73	0	0	0	0
p-val. equal βs	0.2086	0.1312	0.035	0.0642	0.0861	0.7788	0.0095	0.0408
HH Controls	Y	Y	Y	Y	Y	Y	Y	Y
Ctry × Wave FEs	Y	Y	Y	Y	Y	Y	Y	Y

Note: The table reports regression results for the same specification as Table 4; see that table for full details on the estimation approach, sample, and reported statistics. The only difference is that the BBM_{ct} indicator is replaced by $DSTI_{ct}$, a binary variable equal to one if at least one DSTI tightening action occurred in country c within the wave t identification window, and zero otherwise. Standard errors in parentheses are HC1 heteroskedasticity-robust, clustered at the country level. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table B9: Extension of Baseline: Heterogeneous Effects

Dependent Variable:	$\mathbf{1}\{NewMortgage = 1\}$							
Loan type:	1st HMR							
Variable	Below 36		Children		Low Educ.		Female	
Model:	(1)	(2) incl. ref.	(3)	(4) incl. ref.	(5)	(6) incl. ref.	(7)	(8) incl. ref.
$BBM \times \mathbf{1}\{D=1\}$	−0.0040	−0.0063	−0.0136	−0.0218**	−0.0036	−0.0014	−0.0065	−0.0073
	(0.0100)	(0.0159)	(0.0087)	(0.0098)	(0.0146)	(0.0214)	(0.0142)	(0.0207)
$BBM \times \mathbf{1}\{D=2\}$	−0.0086	−0.0106	−0.0172**	−0.0259***	−0.0110	−0.0094	−0.0176	−0.0197
	(0.0080)	(0.0132)	(0.0077)	(0.0091)	(0.0118)	(0.0166)	(0.0120)	(0.0175)
$BBM \times \mathbf{1}\{D=3\}$	−0.0103	−0.0146	−0.0217***	−0.0348***	−0.0173	−0.0231	−0.0177	−0.0231
	(0.0079)	(0.0121)	(0.0078)	(0.0118)	(0.0116)	(0.0153)	(0.0124)	(0.0164)
$BBM \times \mathbf{1}\{D=4\}$	−0.0114	−0.0152	−0.0222**	−0.0332**	−0.0236*	−0.0293*	−0.0236*	−0.0310*
	(0.0074)	(0.0106)	(0.0104)	(0.0146)	(0.0139)	(0.0169)	(0.0131)	(0.0168)
$BBM \times \mathbf{1}\{D=5\}$	−0.0091	−0.0193	−0.0188*	−0.0346**	−0.0214	−0.0348*	−0.0182	−0.0341*
	(0.0077)	(0.0119)	(0.0105)	(0.0153)	(0.0133)	(0.0178)	(0.0124)	(0.0176)
$BBM \times \mathbf{1}\{D=6\}$	−0.0151*	−0.0222*	−0.0211**	−0.0355**	−0.0282**	−0.0420**	−0.0274**	−0.0386**
	(0.0091)	(0.0126)	(0.0107)	(0.0167)	(0.0131)	(0.0186)	(0.0126)	(0.0169)
$BBM \times \mathbf{1}\{D=7\}$	−0.0099	−0.0267*	−0.0202**	−0.0363**	−0.0238*	−0.0457**	−0.0260*	−0.0484**
	(0.0075)	(0.0143)	(0.0089)	(0.0143)	(0.0126)	(0.0216)	(0.0140)	(0.0227)
$BBM \times \mathbf{1}\{D=8\}$	−0.0111*	−0.0320**	−0.0165**	−0.0350**	−0.0140	−0.0384*	−0.0149*	−0.0437**
	(0.0066)	(0.0141)	(0.0077)	(0.0153)	(0.0098)	(0.0198)	(0.0086)	(0.0197)
$BBM \times \mathbf{1}\{D=9\}$	−0.0072	−0.0212**	−0.0038	−0.0133	−0.0081	−0.0252*	−0.0033	−0.0209*
	(0.0057)	(0.0106)	(0.0070)	(0.0092)	(0.0076)	(0.0132)	(0.0057)	(0.0111)
$BBM \times \mathbf{1}\{D=1\} \times V$	−0.0066	0.0121	0.0223*	0.0419*	0.0066	0.0024	0.0015	0.0082
	(0.0380)	(0.0426)	(0.0130)	(0.0245)	(0.0152)	(0.0199)	(0.0071)	(0.0078)
$BBM \times \mathbf{1}\{D=2\} \times V$	−0.0084	0.0115	0.0076	0.0314	0.0126	0.0106	0.0118	0.0210**
	(0.0351)	(0.0394)	(0.0146)	(0.0282)	(0.0150)	(0.0185)	(0.0091)	(0.0095)
$BBM \times \mathbf{1}\{D=3\} \times V$	−0.0186	−0.0167	0.0100	0.0248	0.0183	0.0213	0.0050	0.0094
	(0.0331)	(0.0342)	(0.0134)	(0.0267)	(0.0170)	(0.0212)	(0.0082)	(0.0097)
$BBM \times \mathbf{1}\{D=4\} \times V$	−0.0425	−0.0454	−0.0121	−0.0078	0.0169	0.0169	0.0037	0.0106
	(0.0382)	(0.0382)	(0.0111)	(0.0194)	(0.0177)	(0.0224)	(0.0103)	(0.0090)
$BBM \times \mathbf{1}\{D=5\} \times V$	−0.0416	−0.0490	−0.0126	−0.0151	0.0167	0.0179	−0.0051	0.0043
	(0.0342)	(0.0361)	(0.0095)	(0.0161)	(0.0164)	(0.0230)	(0.0106)	(0.0098)
$BBM \times \mathbf{1}\{D=6\} \times V$	−0.0318	−0.0513	−0.0124	−0.0144	0.0385**	0.0438**	0.0088	0.0058
	(0.0301)	(0.0344)	(0.0114)	(0.0164)	(0.0196)	(0.0217)	(0.0080)	(0.0072)
$BBM \times \mathbf{1}\{D=7\} \times V$	−0.0488*	−0.0561*	−0.0081	−0.0202	0.0166	0.0324	0.0094	0.0178
	(0.0276)	(0.0295)	(0.0106)	(0.0182)	(0.0164)	(0.0241)	(0.0130)	(0.0137)
$BBM \times \mathbf{1}\{D=8\} \times V$	−0.0099	−0.0158	0.0040	−0.0071	0.0047	0.0149	0.0020	0.0197*
	(0.0277)	(0.0308)	(0.0076)	(0.0100)	(0.0205)	(0.0286)	(0.0100)	(0.0114)
$BBM \times \mathbf{1}\{D=9\} \times V$	−0.0086	−0.0160	−0.0084	−0.0217	0.0011	0.0092	−0.0167	−0.0125
	(0.0156)	(0.0192)	(0.0093)	(0.0138)	(0.0146)	(0.0177)	(0.0115)	(0.0083)
Obs.	126540	126540	126540	126540	126540	126540	126540	126540
Adj. R^2	0.09	0.13	0.08	0.13	0.08	0.13	0.08	0.13
Share_outside	0.18	2.53	0.77	3.39	0.92	3.69	0.91	3.87
HH Controls	Y	Y	Y	Y	Y	Y	Y	Y
Ctry × Wave FEs	Y	Y	Y	Y	Y	Y	Y	Y

Note: The table reports regression results for the same specification as Table 4, restricted to first HMR mortgages; see that table for full details on the estimation approach, sample, and reported statistics. The specification is augmented with triple interaction terms $BBM_{ct} \times \mathbf{1}\{D=d\} \times V_i$, where V_i is a binary household-level indicator for a socio-demographic characteristic. Four characteristics are examined: *Below 36*, equal to one if the household reference person is younger than 36 years; *Children*, equal to one if the household includes at least one dependent child; *Low Educ.*, equal to one if the reference person has at most lower secondary education (DHEDUH1 ≤ 2); and *Female*, equal to one if the reference person is female. The double interaction coefficients $BBM \times \mathbf{1}\{D=d\}$ capture the differential effect of BBM tightening for households in decile d relative to decile 10 among households *not* exhibiting the indicated characteristic ($V_i = 0$). The triple interaction coefficients $BBM \times \mathbf{1}\{D=d\} \times V$ measure the additional differential effect for households that do exhibit the characteristic ($V_i = 1$). Odd-numbered columns report results for new originations excluding refinanced loans (preferred specification); even-numbered columns include refinanced loans. Results are based on the first HFCS implicate only. Standard errors in parentheses are HC1 heteroskedasticity-robust, clustered at the country level. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table B10: Extension of Baseline: Intensity of BBM Tightening

Dependent Variable:	$\mathbf{1}\{NewMortgage = 1\}$							
Loan type:	All new		1st HMR		2nd, 3rd HMR		Other RE	
Model:	(1)	(2) incl. ref.	(3)	(4) incl. ref.	(5)	(6) incl. ref.	(7)	(8) incl. ref.
$BBM\text{-}freq \times \mathbf{1}\{D=1\}$	0.0118	0.0152	−0.0008	0.0003	−0.0002	−0.0016	0.0135	0.0176
	(0.0129)	(0.0183)	(0.0063)	(0.0099)	(0.0036)	(0.0049)	(0.0092)	(0.0122)
$BBM\text{-}freq \times \mathbf{1}\{D=2\}$	0.0077	0.0106	−0.0037	−0.0031	−0.0018	−0.0033	0.0133	0.0172
	(0.0114)	(0.0165)	(0.0051)	(0.0084)	(0.003)	(0.0044)	(0.0095)	(0.0124)
$BBM\text{-}freq \times \mathbf{1}\{D=3\}$	0.0081	0.0084	−0.0044	−0.0062	−0.0021	−0.0039	0.0138	0.0173
	(0.0099)	(0.0132)	(0.0046)	(0.007)	(0.0025)	(0.0041)	(0.0092)	(0.0118)
$BBM\text{-}freq \times \mathbf{1}\{D=4\}$	0.0038	0.0055	−0.0079*	−0.0087	−0.0022	−0.0034	0.0126	0.0167
	(0.0074)	(0.01)	(0.0048)	(0.0061)	(0.0018)	(0.0031)	(0.0088)	(0.0115)
$BBM\text{-}freq \times \mathbf{1}\{D=5\}$	0.0056	0.0023	−0.0042	−0.0092	−0.0028	−0.0052	0.0111	0.0146
	(0.0068)	(0.009)	(0.0052)	(0.0073)	(0.0021)	(0.0038)	(0.0078)	(0.0103)
$BBM\text{-}freq \times \mathbf{1}\{D=6\}$	0.0011	−0.0014	−0.0071	−0.0119*	−0.0034	−0.0047	0.0096	0.0125
	(0.0048)	(0.0059)	(0.005)	(0.0069)	(0.0028)	(0.0038)	(0.0066)	(0.0086)
$BBM\text{-}freq \times \mathbf{1}\{D=7\}$	0.0000	−0.0066	−0.0058	−0.0143	−0.0035*	−0.0058	0.0082	0.0104
	(0.0046)	(0.0071)	(0.0057)	(0.0094)	(0.002)	(0.0036)	(0.0056)	(0.0071)
$BBM\text{-}freq \times \mathbf{1}\{D=8\}$	0.0019	−0.0069	−0.0031	−0.0126	−0.0005	−0.002	0.0053*	0.0051
	(0.0032)	(0.0063)	(0.0038)	(0.0085)	(0.0014)	(0.0021)	(0.0028)	(0.0033)
$BBM\text{-}freq \times \mathbf{1}\{D=9\}$	0.002	−0.0054	−0.0003	−0.0083	0.0004	−0.0005	0.0011	0.0004
	(0.0044)	(0.0066)	(0.0035)	(0.0062)	(0.001)	(0.001)	(0.0015)	(0.0018)
Obs.	126540	126540	126540	126540	126540	126540	126540	126540
Adj. R^2	0.13	0.17	0.09	0.13	0.02	0.03	0.06	0.07
Share_outside	5.07	7.71	2.26	5.33	0	0	0	0
HH Controls	Y	Y	Y	Y	Y	Y	Y	Y
Ctry × Wave FEs	Y	Y	Y	Y	Y	Y	Y	Y

Note: The table reports regression results for the same specification as Table 4; see that table for full details on the estimation approach, sample, and reported statistics. The only difference is that the binary BBM_{ct} indicator is replaced by a count variable $BBM\text{-}freq_{ct}$, equal to the number of BBM tightening actions that occurred in country c within the wave t identification window, and zero if no tightening occurred. The interaction coefficients therefore capture the differential association between the *intensity* of BBM tightening and new mortgage origination for households in decile d relative to decile 10, with a one-unit increase corresponding to one additional tightening action within the wave window. Results are based on the first HFCS implicate only. Standard errors in parentheses are HC1 heteroskedasticity-robust, clustered at the country level. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table B11: Extension of Baseline: Cumulative Intensity of BBM Tightening

Dependent Variable:	$\mathbf{1}\{NewMortgage = 1\}$							
Loan type:	All new		1st HMR		2nd, 3rd HMR		Other RE	
Model:	(1)	(2) incl. ref.	(3)	(4) incl. ref.	(5)	(6) incl. ref.	(7)	(8) incl. ref.
$BBM\text{-}cum \times \mathbf{1}\{D = 1\}$	0.0193	0.0242	0.0003	0.0017	0.002	0.0002	0.0194	0.0251
	(0.0187)	(0.0266)	(0.0093)	(0.0143)	(0.0028)	(0.0042)	(0.0133)	(0.0178)
$BBM\text{-}cum \times \mathbf{1}\{D = 2\}$	0.015	0.019	−0.0035	−0.0022	0.0003	−0.0024	0.0198	0.0253
	(0.0168)	(0.0242)	(0.0077)	(0.0118)	(0.0022)	(0.0042)	(0.0136)	(0.018)
$BBM\text{-}cum \times \mathbf{1}\{D = 3\}$	0.0122	0.0124	−0.0066	−0.0094	−0.0013	−0.0039	0.0204	0.0251
	(0.0151)	(0.0199)	(0.0073)	(0.0103)	(0.0022)	(0.0041)	(0.0131)	(0.017)
$BBM\text{-}cum \times \mathbf{1}\{D = 4\}$	0.0069	0.0084	−0.0107	−0.0129	−0.0012	−0.0034	0.0179	0.0234
	(0.0116)	(0.0156)	(0.0075)	(0.0095)	(0.0018)	(0.0032)	(0.0125)	(0.0166)
$BBM\text{-}cum \times \mathbf{1}\{D = 5\}$	0.0081	0.0036	−0.0064	−0.0143	−0.0022	−0.0058	0.016	0.0213
	(0.011)	(0.0139)	(0.0088)	(0.0109)	(0.0023)	(0.004)	(0.0111)	(0.0148)
$BBM\text{-}cum \times \mathbf{1}\{D = 6\}$	0.001	−0.0029	−0.0114	−0.0188*	−0.0027	−0.0056	0.0134	0.0175
	(0.0077)	(0.0099)	(0.0074)	(0.0101)	(0.0027)	(0.004)	(0.0093)	(0.0122)
$BBM\text{-}cum \times \mathbf{1}\{D = 7\}$	0.0006	−0.0093	−0.0089	−0.0218*	−0.0037	−0.0072*	0.0122	0.0149
	(0.0068)	(0.0096)	(0.0081)	(0.0127)	(0.0024)	(0.0039)	(0.008)	(0.0103)
$BBM\text{-}cum \times \mathbf{1}\{D = 8\}$	−0.0002	−0.0132	−0.006	−0.0207*	−0.0014	−0.0033	0.0071	0.0062
	(0.0049)	(0.0093)	(0.0057)	(0.0116)	(0.002)	(0.0034)	(0.0044)	(0.0055)
$BBM\text{-}cum \times \mathbf{1}\{D = 9\}$	−0.0007	−0.0108	−0.0019	−0.0133	0.0004	−0.0007	0.0011	−0.0003
	(0.0066)	(0.0094)	(0.0053)	(0.0087)	(0.0015)	(0.0014)	(0.0025)	(0.003)
Obs.	126540	126540	126540	126540	126540	126540	126540	126540
Adj. R^2	0.13	0.17	0.09	0.13	0.02	0.03	0.06	0.07
Share_outside	5.10	7.69	2.25	5.35	0	0	0	0
HH Controls	Y	Y	Y	Y	Y	Y	Y	Y
Ctry × Wave FEs	Y	Y	Y	Y	Y	Y	Y	Y

Note: The table reports regression results for the same specification as Table 4; see that table for full details on the estimation approach, sample, and reported statistics. The only difference is that the binary BBM_{ct} indicator is replaced by a cumulative count variable $BBM\text{-}cum_{ct}$, equal to the number of HFCS waves up to and including wave t in which at least one BBM tightening action occurred in country c. This variable therefore captures the cumulative exposure of households to macroprudential tightening across successive waves, ranging from zero (no tightening in any preceding or current wave) to four (tightening in all four waves). The interaction coefficients capture the differential association between cumulative BBM tightening exposure and new mortgage origination for households in decile d relative to decile 10, with a one-unit increase corresponding to one additional wave of tightening. Results are based on the first HFCS implicate only. Standard errors in parentheses are HC1 heteroskedasticity-robust, clustered at the country level. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table B12: Extension of Baseline: Direction of BBM Policy Actions

Dependent Variable:	$\mathbf{1}\{NewMortgage = 1\}$							
Loan type:	All new		1st HMR		2nd, 3rd HMR		Other RE	
Model:	(1)	(2) incl. ref.	(3)	(4) incl. ref.	(5)	(6) incl. ref.	(7)	(8) incl. ref.
$BBM\text{-}dir \times \mathbf{1}\{D = 1\}$	0.035	0.0488	0.0071	0.0137	0.0024	0.0036	0.0286	0.0383
	(0.0252)	(0.0342)	(0.0124)	(0.0177)	(0.0038)	(0.0047)	(0.0179)	(0.0236)
$BBM\text{-}dir \times \mathbf{1}\{D = 2\}$	0.0297	0.0423	0.002	0.008	0.0013	0.0016	0.0292	0.0388
	(0.0233)	(0.0317)	(0.011)	(0.0152)	(0.0033)	(0.0048)	(0.0181)	(0.0237)
$BBM\text{-}dir \times \mathbf{1}\{D = 3\}$	0.0272	0.0354	−0.0006	0.0009	−0.0007	−0.0009	0.0299*	0.0388*
	(0.0207)	(0.0258)	(0.0108)	(0.0134)	(0.0032)	(0.005)	(0.0172)	(0.0222)
$BBM\text{-}dir \times \mathbf{1}\{D = 4\}$	0.0197	0.0293	−0.0059	−0.0041	−0.001	−0.0002	0.0263	0.036*
	(0.0165)	(0.0208)	(0.0113)	(0.0133)	(0.0029)	(0.0043)	(0.0165)	(0.0216)
$BBM\text{-}dir \times \mathbf{1}\{D = 5\}$	0.0155	0.0166	−0.0059	−0.0115	−0.0029	−0.0036	0.0235	0.0322*
	(0.015)	(0.0179)	(0.0118)	(0.0141)	(0.0034)	(0.0053)	(0.0145)	(0.0191)
$BBM\text{-}dir \times \mathbf{1}\{D = 6\}$	0.0087	0.0101	−0.011	−0.0163	−0.0035	−0.004	0.0214*	0.0295*
	(0.0115)	(0.0139)	(0.0112)	(0.0144)	(0.004)	(0.0052)	(0.0119)	(0.0155)
$BBM\text{-}dir \times \mathbf{1}\{D = 7\}$	0.0058	−0.0001	−0.0089	−0.0217	−0.0049	−0.0064	0.0188*	0.0252*
	(0.0082)	(0.0118)	(0.0101)	(0.0166)	(0.0034)	(0.0051)	(0.0103)	(0.0129)
$BBM\text{-}dir \times \mathbf{1}\{D = 8\}$	0.0031	−0.0097	−0.0068	−0.0234	−0.0011	−0.001	0.0112*	0.0121*
	(0.0072)	(0.0117)	(0.0078)	(0.0151)	(0.0028)	(0.0045)	(0.0063)	(0.0074)
$BBM\text{-}dir \times \mathbf{1}\{D = 9\}$	0.0022	−0.0073	−0.0004	−0.012	−0.0002	−0.0009	0.0041	0.0043
	(0.0087)	(0.0128)	(0.0076)	(0.0121)	(0.002)	(0.002)	(0.0032)	(0.004)
Obs.	126540	126540	126540	126540	126540	126540	126540	126540
Adj. R^2	0.13	0.17	0.09	0.13	0.02	0.03	0.06	0.07
Share_outside	5.04	7.70	2.26	5.42	0	0	0	0
HH Controls	Y	Y	Y	Y	Y	Y	Y	Y
Ctry × Wave FEs	Y	Y	Y	Y	Y	Y	Y	Y

Note: The table reports regression results for the same specification as Table 4; see that table for full details on the estimation approach, sample, and reported statistics. The only difference is that the binary BBM_{ct} indicator is replaced by a ternary direction variable $BBM\text{-}dir_{ct}$, equal to $+1$ if the net balance of BBM policy actions in country c within the wave t identification window was tightening, -1 if it was loosening, and 0 if there was no net action. This variable therefore captures both the direction and the net stance of macroprudential policy within each country-wave cell, allowing the effects of tightening and loosening to be estimated symmetrically within a single specification. The interaction coefficients capture the differential association between the net policy direction and new mortgage origination for households in decile d relative to decile 10. Results are based on the first HFCS implicate only. Standard errors in parentheses are HC1 heteroskedasticity-robust, clustered at the country level. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table B13: Extension of Baseline: Effect of BBM Tightening Across DTI Deciles

Dependent Variable:	$\mathbf{1}\{NewMortgage = 1\}$							
Loan type:	All new		1st HMR		2nd, 3rd HMR		Other RE	
Model:	(1)	(2) incl. ref.	(3)	(4) incl. ref.	(5)	(6) incl. ref.	(7)	(8) incl. ref.
$BBM \times \mathbf{1}\{DTI = 2\}$	−0.0065	−0.0055	0.0022	0.0041	0.0012	0.001	−0.0092	−0.0097
	(0.0075)	(0.007)	(0.0032)	(0.0044)	(0.001)	(0.0009)	(0.0073)	(0.0075)
$BBM \times \mathbf{1}\{DTI = 3\}$	−0.0052	−0.002	0.002	0.008	0.001	0.0027	−0.0077	−0.0093
	(0.0066)	(0.0072)	(0.004)	(0.0066)	(0.0034)	(0.0043)	(0.0064)	(0.0078)
$BBM \times \mathbf{1}\{DTI = 4\}$	−0.0115	−0.0144	0.0072	0.008	−0.0016	−0.0018	−0.0168	−0.0188
	(0.0151)	(0.0185)	(0.0048)	(0.0072)	(0.0025)	(0.0033)	(0.0133)	(0.0148)
$BBM \times \mathbf{1}\{DTI = 5\}$	−0.0184	−0.0309	0.0049	0.0002	−0.0006	0.001	−0.0228	−0.0306
	(0.0208)	(0.0295)	(0.0067)	(0.0106)	(0.0035)	(0.0045)	(0.0166)	(0.021)
$BBM \times \mathbf{1}\{DTI = 6\}$	−0.0368	−0.0648	0.0005	−0.0206	0.0004	0.0011	−0.0368*	−0.0485*
	(0.0323)	(0.0542)	(0.0144)	(0.0292)	(0.0061)	(0.0069)	(0.0195)	(0.0276)
$BBM \times \mathbf{1}\{DTI = 7\}$	−0.0362	−0.0693	0.0008	−0.028	−0.0043	−0.0011	−0.0364	−0.049
	(0.0418)	(0.0726)	(0.0208)	(0.0436)	(0.0074)	(0.009)	(0.0238)	(0.0325)
$BBM \times \mathbf{1}\{DTI = 8\}$	−0.0356	−0.0783	0.0038	−0.035	−0.0123	−0.0122	−0.042	−0.0534
	(0.0553)	(0.0855)	(0.033)	(0.0589)	(0.0107)	(0.0135)	(0.027)	(0.034)
$BBM \times \mathbf{1}\{DTI = 9\}$	−0.0974	−0.1287	−0.043	−0.0867	−0.0358*	−0.0332	−0.046	−0.0534
	(0.0811)	(0.1113)	(0.0537)	(0.0854)	(0.0207)	(0.0232)	(0.0304)	(0.0363)
$BBM \times \mathbf{1}\{DTI = 10\}$	−0.1134	−0.1335	−0.0509	−0.0803	−0.0211	−0.0174	−0.0665	−0.0811
	(0.0874)	(0.1004)	(0.0486)	(0.0626)	(0.0157)	(0.0175)	(0.0447)	(0.0557)
Obs.	63025	63025	63025	63025	63025	63025	63025	63025
Adj. R^2	0.24	0.32	0.17	0.25	0.04	0.05	0.11	0.14
Share_outside	11.20	13.34	8.22	11.18	0	0	2.18	4.51
HH Controls	Y	Y	Y	Y	Y	Y	Y	Y
Ctry × Wave FEs	Y	Y	Y	Y	Y	Y	Y	Y

Note: The table reports regression results for the same specification as Table 4; see that table for full details on the estimation approach, sample, and reported statistics. The key difference is that income decile dummies $\mathbf{1}\{D = d\}$ are replaced by debt-to-income (DTI) decile dummies $\mathbf{1}\{DTI = d\}$, with DTI decile 1 serving as the omitted reference category. DTI deciles are computed as the ratio of total household debt to gross household income, ranked within each country. Household income decile dummies are retained as additional controls. The interaction coefficients therefore capture the differential association between BBM tightening and new mortgage origination for households in DTI decile d relative to the lowest DTI decile, with higher deciles corresponding to more indebted households relative to their income. The sample is restricted to households with positive debt, which reduces the number of observations relative to the baseline. Results are based on the first HFCS implicate only. Standard errors in parentheses are HC1 heteroskedasticity-robust, clustered at the country level. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

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