Beyond the Aggregate: Heterogeneous Effects of Monetary Policy on Credit Allocation*

Sui-Jade Ho[1,2], Özer Karagedikli[1,3], and Samantha Ong[2]

[1]Asia School of Business
[2]Bank Negara Malaysia
[3]Centre for Applied Macroeconomic Analysis

January 6, 2025 – Version 1.0
Preliminary - NOT TO BE QUOTED

Abstract

How does monetary policy affect mortgage allocation across income groups? Using comprehensive credit registry data from Malaysia (2017-2023), we examine the distributional effects of monetary policy shocks on new mortgage demand, probability of approvals, value of new mortgage originations, maturity of new mortgages, and search activity. Exploiting high-frequency policy surprises and granular loan-level and borrower-level data, we find that monetary policy shocks disproportionately impact higher-income households. On average, a positive 100 basis point policy rate shock reduces the value of mortgage applications by 1.45 percentage points and new loan values by 8.5 percentage points. The marginal effects of a monetary policy shocks are larger and significant for the top four income deciles. Middle-income applicants face a modest decrease in approval probabilities, while lower-income groups remain largely unaffected. Policy tightening also increases multiple-bank applications (search activity) primarily among higher-income borrowers. Our results demonstrate substantial heterogeneity in the transmission of monetary policy through the mortgage market across the income distribution.

Keywords: Monetary policy, credit allocation, household finance, mortgage market, Malaysia
JEL Classification Codes: E52, D14, E58, G21

---

*The views expressed in this paper are the views of the authors and do not represent the views of the Bank Negara Malaysia, the central bank of Malaysia. We would like to thank the seminar participants at the Bank Negara Malaysia. We would also like to thank Andrew Coleman, Patrick Honohan, Fraziali Ismail, Anella Munro, Mohamad Hasni Sha'ari, Athanasios Orphanides, Dimitrije Ruzic and Maisy Wong for comments and suggestions. Correspondence: Ho: jade.ho@asb.edu.my, Karagedikli: ozer.karagedikli@asb.edu.my and Ong: samanthaong@bnm.gov.my

1. Introduction

Monetary policy affects output, employment, asset prices, inflation and interest rates. As households differ in their employment status, sectors of employment, financial asset holdings and so on, it is conceivable that monetary policy will have differential effects on different households. However, the transmission of monetary policy and its effects on the real economy that have long been central to macroeconomic research, traditionally focused on aggregate outcomes. Recent years have witnessed a growing interest in understanding the heterogeneous effects of monetary policy across different segments of society. This shift reflects the recognition that monetary policy may have differential effects on various socioeconomic groups and that existing inequalities might influence the efficacy of monetary policy transmission mechanisms (BIS (2021)).

This paper investigates the distributional impact of monetary policy on allocation of new mortgages in Malaysia, an upper-middle-income emerging market that provides a compelling setting to examine monetary policy and mortgage allocation dynamics. Specifically, we explore the following question: How do monetary policy shocks affect mortgage allocation across different income groups? Our analysis focuses on the following key dimensions of the mortgage market: (1) value of new mortgage applications, (2) probability of mortgage application approval, (3) amount of new mortgages originated, and (4) maturity of new mortgages. In addition, we also consider the impact on search behavior of prospective borrowers.

We leverage a rich and comprehensive credit registry data maintained by the central bank of Malaysia, Bank Negara Malaysia (BNM). This dataset allows us to examine the universe of new mortgage applications, and originations in Malaysia between 2017 and 2023. The dataset includes detailed information on application outcomes, new loan characteristics, and attributes of applicants and borrowers. In addition, the dataset maintains specific dates on every step of a loan process (i.e., date of application(s), the date of approval decision and the date of origination of the loan). These features of the Malaysian credit registry shares important similarities with the Spanish and Ugandan credit registries used in influential studies by Jiménez et al. (2012), Jiménez et al. (2014) and Abuka et al. (2019), allowing for comparably rich analysis of credit market dynamics.

We combine the credit registry data with a high-frequency measure of monetary policy surprises, following Kuttner (2001), taking into consideration central bank's information effects as detailed by Miranda-Agrippino and Ricco (2021). This approach allows us to identify exogenous variations in monetary policy and estimate their causal effects on mortgage credit allocation. Our empirical strategy involves a series of panel regressions that exploit the granularity of the credit registry data. For each of the five outcome variables mentioned above, we estimate differential effects of monetary policy shocks across income deciles. To address potential endogeneity concerns, we employ a variety of fixed effects and control variables. In particular, we include time $\times$ location (state) and time $\times$ bank fixed effects to account for time-varying local demand and bank characteristics. These fixed effects, that we introduce to our specifications progressively, are intended to absorb the time-varying, observed and unobserved bank specific and state specific heterogeneities that might come from a variety of channels.[1]

We find that a positive monetary policy shock has dampening effects on real values of mortgage application. A 100 basis points increase in the monetary policy surprise reduces mortgage demand by 1.45 percentage points. However, this overall effect hides a significant degree of heterogeneity across income distribution. We find that effects are mostly concentrated among higher-income households, more specifically in the top four income deciles. This suggests that credit demand from higher-income groups is more elastic with respect to monetary policy rate, possibly due to greater financial sophistication or access to alterna-

[1] Jiménez et al. (2014), in addition, uses individual (firm) $\times$ bank fixed effect. We cannot use that as we use a narrow window around monetary policy announcements and as a result it is not conceivable to have large enough number of individuals who apply for a mortgage before and after a monetary policy announcement.

tive financing options. In contrast, lower-income deciles show minimal sensitivity in loan applications, indicating relatively inelastic credit demand possibly driven by necessity-based borrowing or the influence of targeted homeownership initiatives.

In terms of probability of new mortgage approval, we find that lower-income borrowers appears largely unaffected, with negligible changes in likelihood of approval of their application. In contrast, middle-income applicants exhibit the most pronounced sensitivity, experiencing a statistically significant, albeit economically modest, decrease in approval probabilities of 3-4 percentage points following a 100 basis point policy rate increase. Higher-income borrowers display a slight negative response, though these effects are not statistically significant.

On the origination of new mortgages, we find that contractionary monetary policy reduces new loan values. A 100 basis point increase in the policy rate surprise is associated with an 8.5 percentage point decrease in the real value of new loans. Like in credit demand, we find that the contractionary effects are mostly concentrated among the top four income deciles.

We find no significant impact of monetary policy surprises on loan maturity across all income groups, suggesting that the primary channel of policy transmission operates through loan values rather than loan tenures. Combined, these results suggest that the mortgage market effects of monetary policy largely work through higher income households while the borrowers in the lower part of the income distribution remain largely unaffected as far as the value of new mortgages is concerned.

Our analysis of borrower search behavior provides additional insights into the credit market dynamics. We find that a 100 basis points contractionary monetary policy shock increases the likelihood of borrowers applying to multiple banks by about 4.5 percentage points. Notably, the impact of monetary policy shock on search activity is more pronounced for higher-income (above median) deciles. This increased search intensity among these borrowers may have important implications for market efficiency and the distribution of gains from trade in the mortgage market, given that search can be a source of price dispersion in credit markets (Agarwal et al. (2024).

Our paper contributes to several strands of credit allocation literature in macroeconomics and finance. First, we make a contribution to the growing body of research on the heterogeneous effects of monetary policy. Early studies in this area, such as Coibion et al. (2017), relied primarily on survey data and found that lower interest rates were associated with reduced inequality. More recent work has leveraged administrative data to provide more granular insights. Amberg et al. (2022) document a U-shaped effect of monetary policy shocks on income distribution in Sweden, while Leahy and Thapar (2022) find significant heterogeneity in the effects of monetary policy surprises across age groups in the US.

Second, our paper contributes to the more recent literature that uses credit registry data around the world to understand the heteregenous effects of the policy. This literature, the credit channel of monetary policy transmission builds on seminal work by Bernanke and Gertler (1995), and examines this channel at a disaggregated level. The seminal work by Jiménez et al. (2014) uses the Spanish credit registry to investigate the impact of monetary policy on banks' risk-taking behavior. They find that lower interest rates induce less capitalized banks to grant more loans to ex-ante riskier firms and to commit larger loan amounts with fewer collateral requirements to these firms. Their study highlights the importance of bank balance sheet strength in the transmission of monetary policy to credit supply. More recently, Jasova et al. (2021) use the Spanish credit registry data to analyze the effects of monetary policy through defaults, finding significant heterogeneity in how the path of monetary policy affects ex-post loan defaults. Our paper extends this line of inquiry to the household sector, focusing on how monetary policy affects mortgage credit allocation across the income distribution.

Third, our work relates to research on the role of housing in monetary policy transmission and wealth accumulation. Di et al. (2007) and Wainer and Zabel (2020) show that households build wealth through homeownership, with the amortizing nature of mortgage payments being one enabler. Cloyne et al. (2020) demonstrate that the response of household consumption to monetary policy shocks varies significantly between mortgagors, outright homeowners, and renters. More recently, Ringo (2023) examines how monetary policy affects home buying inequality in the United States, finding that expansionary monetary policy disproportionately benefits wealthy households in their home purchases, potentially exacerbating wealth inequality. Adding to this literature, Ligonniere and Ouerk (2024) investigate the impact of monetary policy surprises on credit volumes across the income distribution in France. They find that expansionary monetary policy surprises lead to increased mortgage credit exclusively for households in the top 20 percent income bracket, while having no impact on mortgage credit for the remaining 80 percent of households. Their study attributes these effects to individual demand factors, particularly related to rental investments and mechanisms of intertemporal substitution and affordability. Our paper extends this line of inquiry to the household sector in an emerging market context, focusing on how monetary policy affects mortgage credit allocation across the income distribution, which in turn can influence housing purchase decisions and the transmission of monetary policy to the real economy.

Finally, we contribute to the literature on search frictions in credit markets, building on work such as Agarwal et al. (2024) on sequential search in mortgage markets. Our findings on increased search activity following policy tightening provide new evidence on how monetary policy can affect market dynamics in the financial sector.

The remainder of the paper is structured as follows: Section 2 discusses potential channels and hypotheses the paper proposes and investigates. Section

3 describes our key datasets and institutional background. Section 4 outlines our empirical strategy as well as the identification assumptions. Section 5 highlights some key stylised facts from the mortgage dataset in Malaysia. Section 6 presents the results along five dimensions we mentioned earlier for the mortgage applications and new loans while Section 7 describes the results from the additional analysis on search activity. Section 8 outlines our robustness checks and finally, Section 9 concludes and discusses potential policy implications and future directions.

2. Hypothesis Development

The effects of monetary policy on credit allocation may vary across the income distribution for several reasons. On the demand side, we expect a sharper decline in loan applications among higher-income groups. For lower-income households, one major constraint in accessing the housing market is the down payment, which is unlikely to be immediately affected by short-term changes in monetary policy. In contrast, higher-income households are more sensitive to rising interest rates, especially when applying for mortgages to purchase additional properties. These households tend to have greater flexibility in their borrowing decisions and are more likely to invest in larger, more expensive homes beyond their first property. As a result, rising interest rates are expected to disproportionately impact high-income households. Additionally, as interest rates increase, the attractiveness of housing as an investment may decline relative to other assets, further reducing mortgage applications from high-income households.

On the supply side, similar dynamics may affect the total loans approved for high-income households. High levels of debt repayment, combined with the negative effects of rising interest rates on house prices, may lead to a greater reduction in the volume of new mortgages extended to higher-income borrowers compared to other groups. As a result, we anticipate a larger contraction in mortgage lending to high-income individuals following interest rate hikes, relative to lower-income households. For instance, Ringo (2023) finds that contractionary monetary policy is associated with a reduction in mortgage lending in higher-income areas, suggesting that leverage plays a significant role in credit allocation. Similarly, Ligonniere and Ouerk (2024) show that in France, higher-income households experience a more pronounced decline in mortgage lending after interest rate increases. This supports our argument that leverage and rising interest rates, or their combination, affect different segments of the income distribution in varying ways.

We do not predict significant changes in the average maturity of new mortgages following monetary policy shocks. Mortgage contracts in Malaysia, as in many other jurisdictions, are standardized, with terms typically lasting 35 years or until the borrower reaches the age of 70. While the maturity of existing mortgages may be adjusted in response to interest rate fluctuations, we do not expect a significant shift in the maturity of new loans.[2]

Finally, we anticipate an increase in search activity among borrowers. Search frictions have been shown to contribute to price (interest rate) dispersion in various markets. Although the Malaysian credit registry data does not currently include complete interest rate information, we can investigate whether households engage in additional search activity following a monetary policy shock. In terms of search behavior, households at the lower end of the income distribution, who are often younger and first-time buyers, may be more concerned about securing loan approval. In contrast, those at the higher end may focus on managing debt repayment, as they are likely to be more leveraged. Thus, both groups may increase their search efforts, albeit for different reasons. We will test this by examining the incidence of multiple mortgage applications for the same property across the income distribution.

[2] Existing mortgage holders may also switch banks through the search channel. However, in this paper we only focus on the new borrowers.

3. Data and Institutional Background

Our analysis draws on three primary sources of data: monetary policy indicators (section 3.1), the Malaysian Credit Registry (section 3.2) and household income (section 3.3). This section provides an overview of these data sources and the relevant institutional context of Malaysia's financial system.

3.1 Monetary policy indicators

Monetary policy decisions are made by the Monetary Policy Committee (MPC) of the central bank, which publishes its decisions on the Overnight Policy Rate (OPR) - the sole policy interest rate - in a statement on their website at 3:00 PM local time on scheduled announcement days. For the period in our sample, the Committee meets at least six times annually, as per statutory requirements.

To construct a series of monetary policy shocks for Malaysia, we adapt the methodology developed by Miranda-Agrippino and Ricco (2021) to the Malaysian context. This approach allows us to identify exogenous variations in monetary policy while accounting for the information set available to both policymakers and economic agents at the time of policy decisions.

Our primary source of monetary policy expectations is the Kuala Lumpur Interbank Offered Rate (KLIBOR) for the 1-month tenor. We chose KLIBOR 1m as it closely reflects short-term interest rate expectations in the Malaysian financial market.We gather daily KLIBOR 1m rates covering the period from January 2017 to December 2023. This timeframe emcompasses 42 monetary policy meetings, each followed by a same-day statement release detailing the policy decision. We define a narrow one-day window around each BNM monetary policy announcement. This tight window helps isolate the impact of monetary policy news from other economic developments.

For each event, we calculate the monetary policy surprise as the change in the KLIBOR 1m rate within the defined window. Formally, let $f_{t,d}$ denote the KLIBOR

1m rate on day d of month t. The monetary policy surprise mp_t for the policy announcement in month t is computed as:

$$mp_t = f_{t,d_{post}} - f_{t,d_{pre}} \tag{1}$$

where d_{pre} and d_{post} represent the day of and the day after the announcement, respectively.

To address the potential conflation of monetary policy shocks with the central bank's private information, we follow Miranda-Agrippino and Ricco (2021) in projecting these surprises onto a rich set of macroeconomic and financial variables available at the time of the policy decision. This step is crucial for separating the true policy shock from the response to the central bank's information advantage. Finally, we regress the surprise series on lagged and forecast values of GDP growth and inflation. The residuals from this regression constitute our series of monetary policy shocks, purged of anticipatory effects and the central bank's private information.

3.2 Credit registry

We utilize administrative data from the Central Credit Reference Information System (CCRIS), maintained by Bank Negara Malaysia (BNM), the Central Bank of Malaysia to analyze how monetary policy interacts with credit allocation across different income groups.

A key feature of Malaysia's institutional landscape is its long-standing commitment to promoting homeownership, particularly among lower- and middle-income households. This commitment is exemplified by programs such as the Primary Market Housing Development Program (PR1MA), launched in 2011, and others such as My First Home Scheme, MyHome, Rumah Selangorku and RUMAWIP. These housing initiatives may potentially affect the transmission of monetary policy by influencing credit access [and household responsiveness to interest rate changes] across the income distribution.

The Malaysian mortgage market exhibits characteristics that make it particularly suitable for this study. Most residential mortgages are floating rate mortgages in Malaysia that are linked to the OPR, creating a direct mechanism through which OPR changes can affect household finances. This prevalence of floating-rate loans, combined with government housing initiatives, potentially amplifies the transmission of monetary policy to household credit decisions while introducing heterogeneous effects across different income segments.

The credit registry encompasses information from licensed commercial, Islamic, investment, and development banks, as well as major non-bank financial institutions. The system imposes no reporting thresholds. Our analysis utilizes two comprehensive datasets from CCRIS. The first dataset, which we term the "Mortgage Origination Data," comprises about 1.4 million mortgage contracts initiated between 2017 and 2023. For each mortgage, we observe an extensive set of variables: borrower characteristics (age, gender, income, sector of employment etc), loan features (amount, term), property details (location, type, value), and the identity of the lending institution. Nominal mortgage values are deflated with the national house price index.

The second dataset, our "Mortgage Application Data," contains 3.4 million mortgage applications submitted between 2017 and 2023. Uniquely, this dataset includes both approved and rejected applications, a feature shared with only a few other credit registries, such as those in Spain (Jiménez et al. (2012) and Jiménez et al. (2014)) and Uganda (Abuka et al. (2019)). For each application, we observe the applicant's characteristics (age, gender, income, sector of employment etc), requested loan amount and intended property location. Critically, we also observe the number and timing of applications made by each applicant across all financial institutions, a feature that allows us to analyze search behavior.

This comprehensive data structure enables several methodological approaches particularly relevant to studying the impact of monetary policy on credit allocation:

- Observation of both successful and unsuccessful credit applications across income groups.

- Precise timing of loan events, facilitating accurate linking of credit outcomes to monetary policy shocks.

3.3 Household income

In this section, we detail our approach to constructing a reliable household income series using data from the credit registry, a task complicated by the absence of direct household income information. Our method combines credit registry data with official income thresholds to create a consistent and meaningful income distribution analysis.

Firstly, we utilize the “joint income” variable from the credit registry as a proxy for household income where available. This approach is based on the assumption that joint applicants for mortgages typically represent a household unit. For mortgages applied for individually, we use the ”individual income” data as a proxy for household income.

To ensure consistency with national standards and facilitate comparability, we align our income thresholds with those defined in the official statistics of Malaysia. The Department of Statistics of Malaysia conduct the Household Income and Expenditure Survey twice within any period of 5 years. From these surveys, the household income deciles are derived. For years between the surveys, we calculate the income decile thresholds by interpolating using the Compound Annual Growth Rate (CAGR) between the known values. This method assumes a smooth progression of income growth within each decile over time, allowing us to have consistent thresholds for each year in our study period. Table A1 in the Appendix presents the income decile thresholds across three years (2016, 2019, and 2022), derived from the periodic Households Income Surveys conducted by the Department of Statistics, Malaysia.[3]

By applying population thresholds to our constructed household income proxy within the credit registry data, we segment the data into income groups that correspond with nationally recognized categories. This approach enhances the relevance and interpretability of our subsequent analysis on the impact of monetary policy on income distribution through the credit channel in Malaysia. Similar to the mortgage value, we also deflated the income levels by the national consumer price index to obtain real income levels for our analysis.

It is important to acknowledge the limitations of this approach. The use of "joint income" and individual income as proxies may not capture the full complexity of household financial situations, particularly in cases where there are multiple income earners in a household who are not joint applicants on a mortgage. Additionally, our method may not account for informal or unreported income sources that could influence a household's true economic position. To address some of these limitations, we have conducted sensitivity analyses using alternative income cut-offs, which we discuss in detail in the section on robustness checks.

4. Empirical Strategy

Our empirical strategy leverages the rich features of the Malaysian credit registry data and high-frequency monetary policy surprises to examine the distributional effects of monetary policy across the income spectrum in Malaysia. Our sample spans from January 2017 to December 2023. Central to our identification strategy is the granular data on loan application submission and loan approval dates. This temporal precision allows us to delineate between applicants

[3]Notably, the income growth rates vary significantly across quintiles. Between 2016 and 2022, incomes in the bottom quintile increased by less than 15 percent, at an annual growth rate of approximately 2.5 percent. In contrast, the second-to-top quintile experienced a growth rate of around 20 percent, while the very top group saw a growth rate exceeding 20 percent. These official thresholds and growth rates inform our categorisation of households in the credit registry data.

who submitted before a monetary policy decision day and those who applied afterwards, as well as discriminate between loans that were approved before and after a policy decision date. The differential outcomes across these groups provide a measure of monetary policy's effect.

In our baseline specification, we employ a 28-calendar-day (20-working-day) window centered around each policy decision day to isolate the effect of monetary policy announcements. We compare outcomes of applicants within 14 calendar days (10 working days) after an announcement to those who applied within the same time frame prior to the meeting.

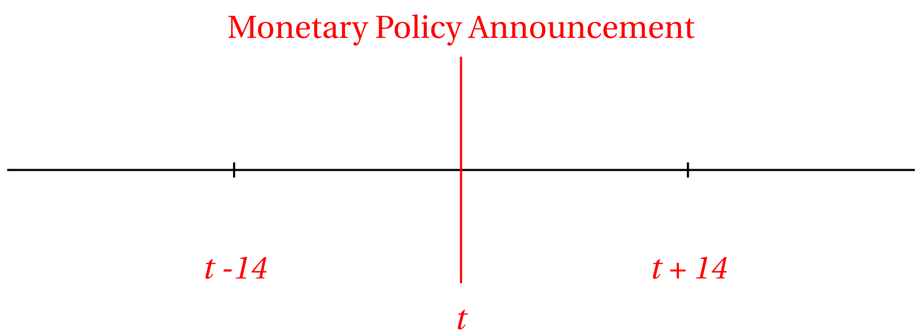


Figure 1: Timeline of Monetary Policy Announcement and Events Window

Figure 1 illustrates this estimation window around the monetary policy announcement (t). The choice of our window size is based on two primary considerations: First, we ensure that the windows do not overlap between consecutive policy meetings, maintaining the independence of each observation period. Second, we account for the regulatory context in Malaysia, where commercial banks are mandated to implement any change in the base rate (the main reference rate for mortgages) within seven working days following a policy rate change. Our 20-working-day window accommodates this regulatory timeframe.

By focusing on a narrow window around each announcement, we minimize the likelihood that observed changes in decisions are due to factors other than the monetary policy announcement. This methodology aligns with similar studies in the literature; for instance, Ringo (2023) uses a 6-weeks window around the monetary policy announcement in their analysis of monetary policy and home buying inequality.

There are well-known empirical challenges when dealing with loan outcomes given the interaction between credit demand and supply drivers. We use bank $\times$ time fixed effects to absorb time-varying bank-specific changes in credit supply. In our baseline regression, *time* is defined as the window around the monetary policy decision as discussed above.

On the demand side, while it is more standard to include a borrower $\times$ time fixed effects, it is rare for a borrower to purchase multiple properties within a narrow window. Instead, we control for various borrower demographics, including household income (our key variable of interest), age, employment sector, gender of the primary borrower, whether the borrower is a civil servant, and whether the loan is the first loan or the first housing loan of the borrower.[4] This approach, similar to that adopted by Ligonniere and Ouerk (2024), allows us to compare the same type of borrowers from the same bank before and after a monetary policy announcement.

To further strengthen our identification strategy, we incorporate state $\times$ time fixed effects to account for local demand shocks. This addition is crucial as it controls for time-varying, region-specific factors that may influence credit markets independently of monetary policy. For instance, these fixed effects capture localized economic fluctuations, changes in regional housing markets, or state-level policy interventions that could confound our estimates.

[4] We define "first loan" and "first housing loan" based on the available data in our credit registry, which begins in January 2017. A borrower is considered to have a "first loan" if they have no existing credit line (including credit cards) in any month from January 2017 until they take up the new mortgage loan under consideration. Similarly, a "first housing loan" refers to borrowers who have no record of a housing loan from January 2017 until the current loan application. These indicators serve as proxies for credit history, given that we do not directly observe credit scores. It is important to note that this classification may misidentify borrowers who had fully repaid their loans prior to 2017 as first-time borrowers. Despite this limitation, these variables provide valuable information about recent credit behavior and borrowing patterns within our observable timeframe.

Our main econometric specification is as follows:

$$\mathrm{Y}_{it} = \alpha + \beta_1 MP_t \times D_{it} + \sum_{k=1}^{K} \beta_{2k} IQ_{ik} \times MP_t \times D_{it} + \gamma \mathbf{X}_{it} + \nu_{m,t} + \psi_{s,t} + \varepsilon_{it} \quad (2)$$

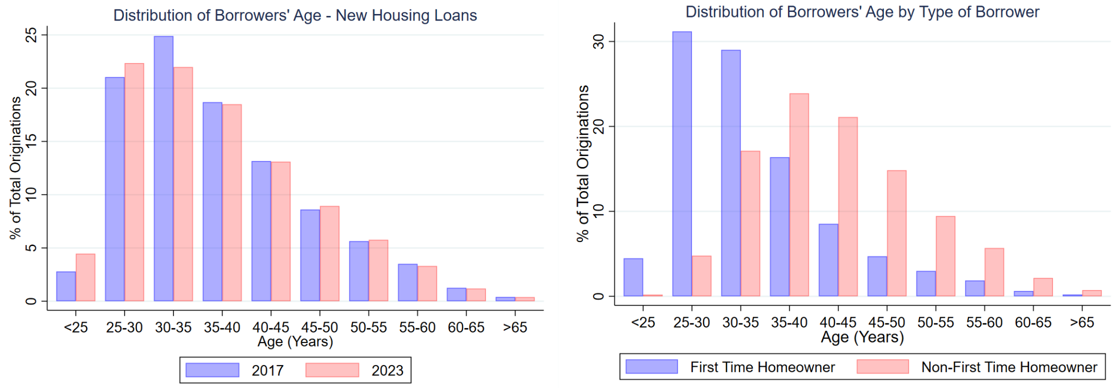
where, Y_{it} consists of value of loan applied, probability of the loan being approved, value of new mortgage loan originated and loan maturity. MP_t is the monetary policy shock at time t, D_t is an indicator variable for days after the monetary policy announcement day within the window, IQ_{ik} is an indicator variable for the income decile (k) of borrower i, $\mathbf{X}_{it}$ is a vector of other control variables for borrower i at time t (i.e., age, gender, civil servant indicator, sector of employment and whether the loan is the first loan or the first housing loan). We also have $\nu_{m,t}$ and $\psi_{s,t}$ as the bank $\times$ time and state $\times$ time fixed effects, respectively. Standard errors are clustered at the bank level.

5. Stylised Facts

In this section, we summarise some basic stylized facts about the distributional aspects of the new mortgage originations. We begin with the distribution of new mortgages across age. The left panel in figure 2 below shows the distributions in 2017 and 2023, beginning and the end of our sample respectively. Comparing 2017 and 2023, the age distributions of mortgage originations show slight variations among younger borrowers (under 35) but remain largely consistent across other age groups. The right panel shows the distribution of new mortgages across first-time homeowners while the right panel shows the distribution across first-time homeowners and non-first time homeowners over the entire sample (2017 - 2023) period. Over the sample, first-time home buyers tend to be young people with almost 75 percent of them between the age of 25 and 40.

Figure 3 shows the share of first-time homeowners as a proportion of total new mortgage originations in terms of numbers (left panel) and total nominal value

Figure 2: Distribution of Loans Across Age



In 2017 and 2023

Over the sample

of lending (right panel). The share of number of first-time homeowners as a proportion to total new borrowers was just over 60 percent in 2017 and steadily increased to 64 percent in 2022 before falling back a notch in 2023. In terms of the share of total value of lending that is extended to the first-time homeowners, the share stands around 55 percent of total new mortgages in value terms. These figures suggest that the first-time homeowners make a significant share of the total borrowing and to the extent they differ from other borrowers in terms of their constraints their response to monetary policy shocks might be different.

Figure 3: Borrower type - Share of first-time homeowners

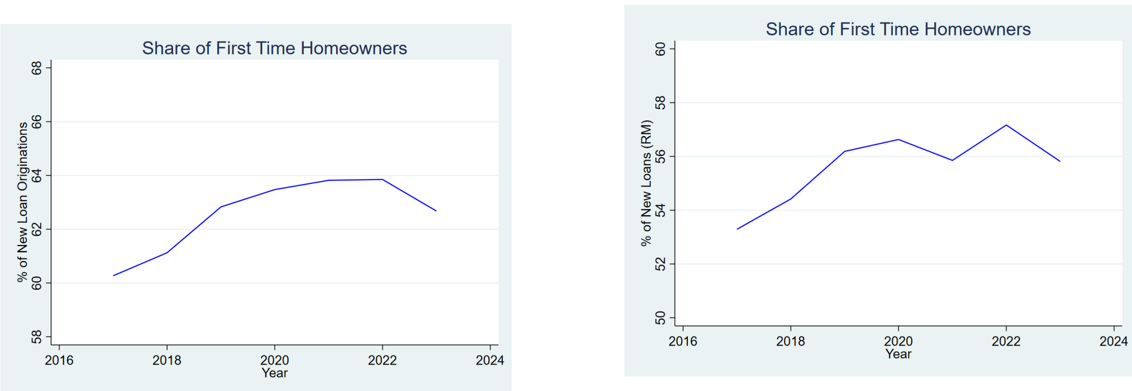
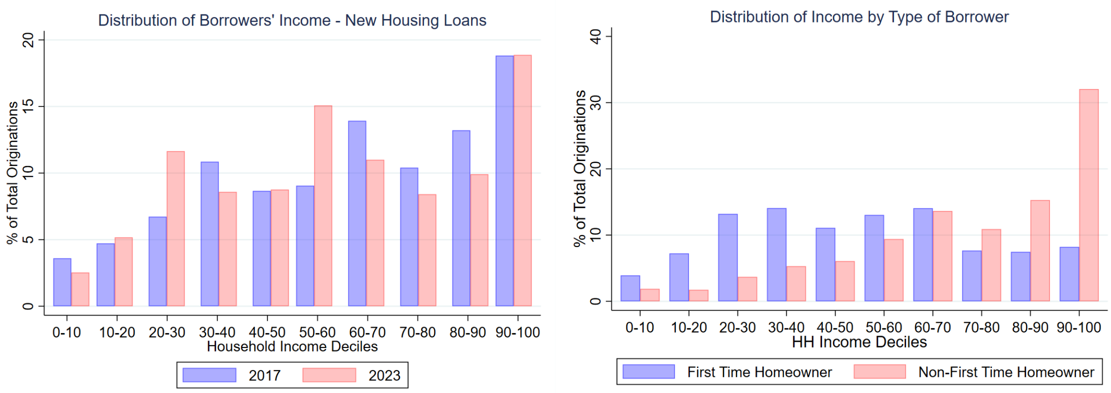


Figure 4 shows the distribution of new mortgage lending across income levels. The left panel compares this distribution in 2017 and 2023. In 2023, compared

Figure 4: Distribution of Loans Across Income



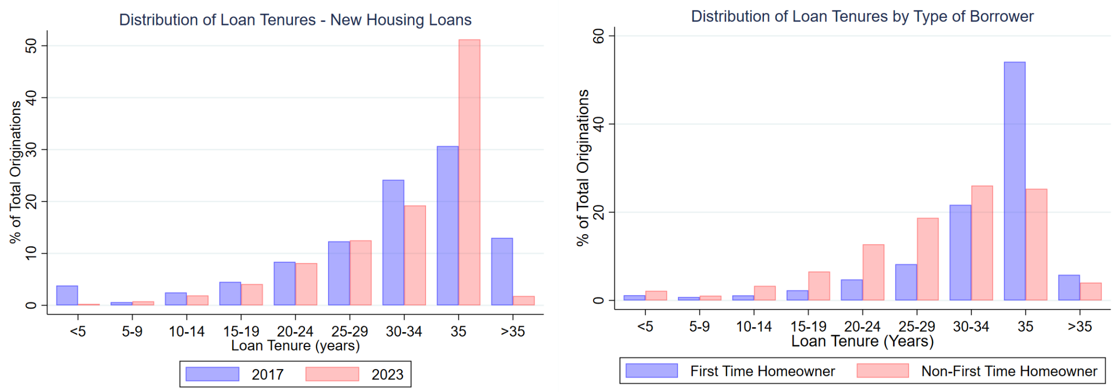
In 2017 and 2023

Over the sample

to 2017, there was a notable shift in lending patterns: the share of new mortgages extended to borrowers in the third and sixth income deciles increased sharply, while the first, seventh, eighth, and ninth deciles experienced a decline. The right panel presents the income distribution of borrowers, distinguishing between first-time homeowners and non-first-time homeowners over the entire sample period. This chart reveals significant disparities between these two groups. First-time homeowners are more heavily represented in the lower to middle-income deciles, with their highest concentration in the 20-30 and 30-40 income brackets. In contrast, non-first-time homeowners show a strong skew towards higher income levels, with a particularly pronounced presence in the highest income decile (90-100). This stark difference underscores the income gap between new entrants to the housing market and more established homeowners, highlighting potential implications for housing affordability and wealth accumulation across different segments of the population.

Finally, we present the distributions of tenures of new mortgages (figure 5). In 2023, a substantial majority—between 85 percent and 90 percent—of new mortgages had tenures ranging from 25 to 35 years. Notably, 35-year mortgages, which represent the maximum allowable tenure, alone accounted for over 50 percent of new originations. This concentration at the upper limit of available tenures reflects the impact of a policy directive that allowed banks to offer mortgage products with maturities up to 35 years. The prevalence of these maximum-length mortgages suggests that borrowers are leveraging the full extent of available tenure options, likely in an effort to reduce monthly payments and increase affordability.

Figure 5: Distribution of New Mortgage Tenure



In 2017 and 2023 | Over the sample

6. Main Results

This section presents evidence on the transmission of monetary policy to mortgage credit allocation in Malaysia using our baseline specification. Our empirical analysis reveals substantial heterogeneity in the transmission of monetary policy to mortgage credit allocation in Malaysia. We present our findings following the temporal sequence of the credit process, from loan applications to their approval as well as the impact on new mortgage loans originated. For each outcome variable, we present our regression results in tables, followed by a graphical plot of the relevant margins.

6.1 Loan Application Dynamics

Table 1 presents our results on the impact of monetary policy surprises on loan application behaviour. The dependent variable is the log of real loan value applied. We estimate six specifications, progressively adding fixed effects and income decile and other borrowers' characteristics as controls to address potential confounding factors.

Our key variable of interest, "Monetary Policy Surprise $\times$ Post" interaction, shows a consistently negative effect across all specifications, suggesting that contractionary monetary policy surprises reduce loan demand. The income decile coefficients, introduced in columns (4)-(6), reveal a strong positive relationship between household income and loan demand. These results are robust to the inclusion of a wide array of control variables, including income, age, gender, employment sector, civil servant status, and loan history. Relative to the lowest income decile (0-10 percentile), households in higher income deciles consistently apply for larger loans. This relationship is monotonic and highly significant, with the highest income decile (90-100 percentile) applying for loans that are 99.5 percent to 111.7 percent larger than the lowest decile, depending on the specification.

The inclusion of bank $\times$ time and state $\times$ time fixed effects in columns (5) and

(6) reduces the magnitude of the monetary policy surprise coefficient, suggesting that some of the effect is absorbed by time-varying bank-specific or state-specific factors. However, the effect remains statistically significant at the 5 percent and 10 percent levels, respectively. Our most comprehensive specification in column (6), which includes both bank $\times$ time and state $\times$ time fixed effects, indicates that a 100 basis points increase in the monetary policy surprise reduces loan demand by 1.45 percentage point, significant at the 10 percent level.

Next, our analysis reveals heterogeneous effects of monetary policy across income deciles. To capture this variation, we incorporated interaction terms between monetary policy surprises and income deciles in our model (full regression results in Table A2 in the Appendix). Figure 6 illustrates the average marginal effects of a 100 basis point increase in monetary policy shock on loan application values across income deciles. The top four deciles show a fall in application values, while the bottom six deciles show largely insignificant changes in application values. As such, the overall dampening effect is most pronounced in the top deciles of the income distribution. In other words, when we compare borrowers from the same income decile (controlling for other demographic observables) before and after a monetary policy announcement, we find that those in the higher income deciles had a larger percentage point decline in the amount of loan applied after the announcement.

Table 1: Effect on Log Real Loan Value Applied

Dependent variable	Log(Real Loan Value Applied)					
	(1)	(2)	(3)	(4)	(5)	(6)
Monetary Policy Surprise X Post	-0.0284**	-0.0122	-0.00949	-0.0218**	-0.0166**	-0.0145*
	(0.0119)	(0.0096)	(0.0097)	(0.0081)	(0.0080)	(0.0079)
10-20 percentile				-0.0162	-0.0020	-0.0057
				(0.0479)	(0.0447)	(0.0419)
20-30 percentile				0.200***	0.194***	0.169***
				(0.0628)	(0.0593)	(0.0578)
30-40 percentile				0.309***	0.294***	0.264***
				(0.0658)	(0.0621)	(0.0614)
40-50 percentile				0.422***	0.405***	0.377***
				(0.0676)	(0.0650)	(0.0641)
50-60 percentile				0.536***	0.505***	0.470***
				(0.0726)	(0.0697)	(0.0692)
60-70 percentile				0.661***	0.617***	0.570***
				(0.0756)	(0.0720)	(0.0715)
70-80 percentile				0.735***	0.693***	0.652***
				(0.0744)	(0.0719)	(0.0714)
80-90 percentile				0.862***	0.810***	0.761***
				(0.0773)	(0.0746)	(0.0740)
90-100 percentile				1.117***	1.057***	0.995***
				(0.0804)	(0.0773)	(0.0768)
Other control variables						
Age	No	No	No	Yes	Yes	Yes
Gender	No	No	No	Yes	Yes	Yes
Employment sector	No	No	No	Yes	Yes	Yes
Civil servant status	No	No	No	Yes	Yes	Yes
First loan status	No	No	No	Yes	Yes	Yes
First housing loan status	No	No	No	Yes	Yes	Yes
Fixed effects						
Time	Yes	No	No	Yes	No	No
Bank-Time	No	Yes	Yes	No	Yes	Yes
State-Time	No	No	Yes	No	No	Yes
Observations	1,481,069	1,481,024	1,481,024	1,448,493	1,448,448	1,448,448
R-squared	0.007	0.099	0.166	0.280	0.319	0.353

Note: Standard errors are clustered at the bank level in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

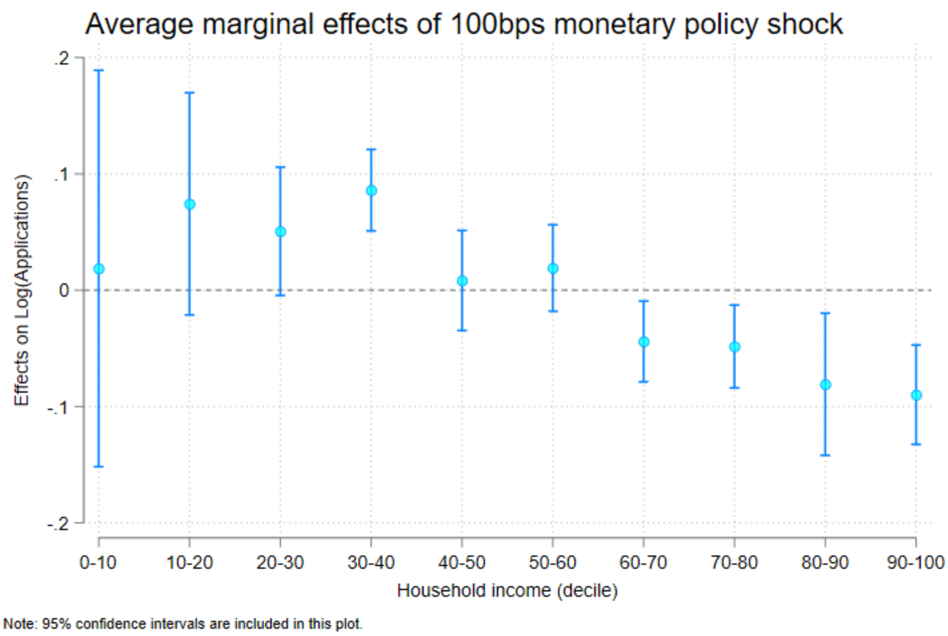


Figure 6: Values of Applications for New Mortgages

We interpret the impact on loan applications as direct evidence of the impact of monetary policy on mortgage credit demand. The heightened sensitivity of higher-income households to monetary policy shocks suggests that credit demand from this group is more elastic with respect to interest rates. This could be due to greater financial sophistication, with these borrowers more attuned to changes in the interest rate environment and quicker to adjust their borrowing plans accordingly. Additionally, higher-income households may have access to alternative financing options or liquid assets, allowing them to postpone borrowing when rates are unfavorable. The possibility that these households are more likely to borrow for discretionary purposes, such as second homes or investment properties, could also explain their greater sensitivity to the cost of credit.

Conversely, the minimal sensitivity in mortgage loan applications among lower-income deciles suggests that housing demand from this group is relatively inelastic to monetary policy changes. This relative inelasticity could stem from the nature of necessity-driven borrowing in the housing market. Lower-income households often apply for mortgages out of a pressing need for housing rather than as an investment choice, making their demand less responsive to interest rate fluctuations. Furthermore, these households typically face limited housing options, which constrains their ability to delay purchases or seek alternatives in response to changing interest rates. The lack of flexibility in housing choices reinforces the inelasticity of their mortgage demand. Adding to this, Malaysia's targeted homeownership initiatives play a crucial role in shaping this dynamic. Government interventions, such as affordable housing programs, may have shielded lower-income households from the full impact of monetary policy fluctuations.

6.2 Loan Approval and Uptake

Table 2 presents our analysis of loan approval probabilities. Notably, there is no significant impact on the probability of loan approval from a monetary policy surprise. Columns (1) to (3) shows the result from the specification without any borrower characteristics control but includes variations of time, bank $\times$ time and/or state $\times$ time fixed effects. A 100 basis point monetary policy surprise is associated with about 3 percentage points decrease in the probability of loan approval but it is not statistically significant. Columns (4) to (6) include controls in the form of borrower characteristics. Of note, compared to the base income group (bottom 10th percentile), higher income groups (above 20th percentile) have a significantly higher probability of obtaining approvals. Nonetheless, in these regressions, the impact of monetary policy surprise on the probability of loan approval remains not statistically significant.

Table 2: Effect on Loan Approval Probability

Dependent variable	Loan Approved					
	(1)	(2)	(3)	(4)	(5)	(6)
Monetary Policy Surprise X Post	-0.0242	-0.0294	-0.0297	-0.0224	-0.0284	-0.0287
	(0.0188)	(0.0186)	(0.0183)	(0.0180)	(0.0180)	(0.0177)
10-20 percentile				0.0058	0.0094	0.0097
				(0.0145)	(0.0082)	(0.0080)
20-30 percentile				0.0512**	0.0476***	0.0471***
				(0.0211)	(0.0115)	(0.0111)
30-40 percentile				0.0592**	0.0533***	0.0526***
				(0.0247)	(0.0162)	(0.0154)
40-50 percentile				0.0573*	0.0615***	0.0606***
				(0.0288)	(0.0197)	(0.0193)
50-60 percentile				0.0614**	0.0672***	0.0658***
				(0.0292)	(0.0172)	(0.0170)
60-70 percentile				0.0589*	0.0536***	0.0524***
				(0.0312)	(0.0165)	(0.0159)
70-80 percentile				0.0759**	0.0827***	0.0812***
				(0.0340)	(0.0205)	(0.0201)
80-90 percentile				0.0705**	0.0739***	0.0723***
				(0.0344)	(0.0195)	(0.0190)
90-100 percentile				0.0659*	0.0745***	0.0720***
				(0.0351)	(0.0199)	(0.0189)
Other control variables						
Age	No	No	No	Yes	Yes	Yes
Gender	No	No	No	Yes	Yes	Yes
Employment sector	No	No	No	Yes	Yes	Yes
Civil servant status	No	No	No	Yes	Yes	Yes
First loan status	No	No	No	Yes	Yes	Yes
First housing loan status	No	No	No	Yes	Yes	Yes
Fixed effects						
Time	Yes	No	No	Yes	No	No
Bank-Time	No	Yes	Yes	No	Yes	Yes
State-Time	No	No	Yes	No	No	Yes
Observations	1,440,954	1,440,911	1,440,911	1,409,549	1,409,506	1,409,506
R-squared	0.002	0.099	0.102	0.016	0.111	0.113

Note: Standard errors are clustered at the bank level in parentheses.
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Next, to further explore heterogeneous effects of approval, we interact the policy rate surprise with borrower income deciles (Table A3 in the Appendix). Figure 7 shows the average marginal effects of a 100 basis points monetary policy shock on the probability of approval across income deciles. Point estimates suggest heterogeneous effects across the income distribution, with lower income deciles exhibiting different responses compared to middle and higher income groups. At the lower end of the income spectrum, comprising the bottom three deciles, we observe minimal sensitivity to monetary policy shocks. The point estimates for these groups hover near zero, with wide confidence intervals spanning both positive and negative territories. This suggests that loan approval probabilities for lower-income borrowers remain largely unaffected by monetary tightening. Moving into the middle-income range, particularly the 40-50 and 50-60 deciles, we see a more pronounced effects with negative point estimates that are statistically significant. As we transition to the higher income deciles, the pattern becomes more varied, with largely negative point estimates but more imprecisely estimated.

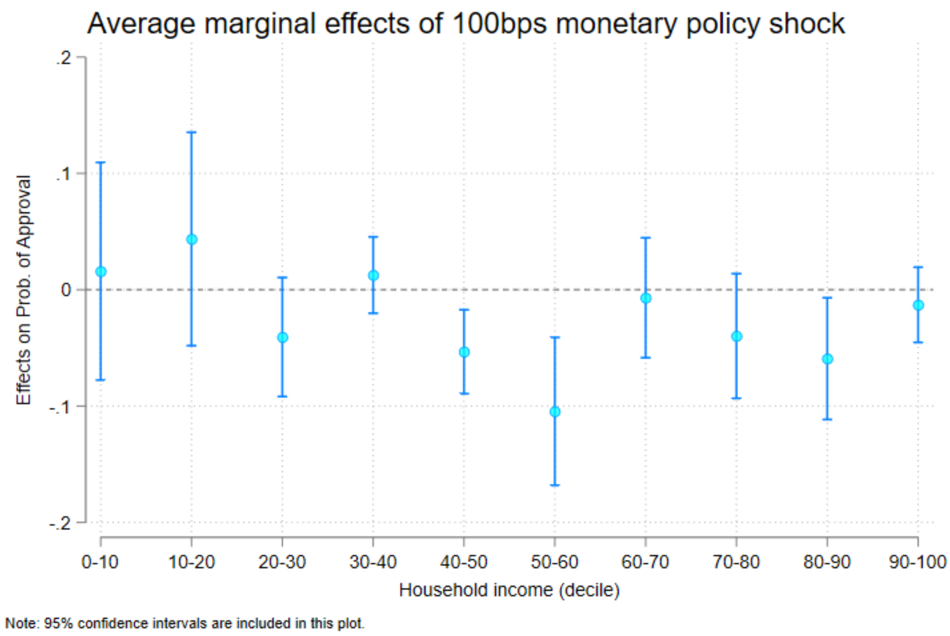


Figure 7: Probability of loan approvals

Our next key result is shown in Table 3 which presents estimates of the impact of monetary policy surprises on the real value of new loans. The coefficient on "Monetary Policy Surprise X Post" is consistently negative and statistically significant across all specifications, indicating that contractionary monetary policy reduces new loan originations. In our most comprehensive specification (column 6), a 100 basis point increase in the policy rate surprise is associated with a 8.5 percentage point decrease in the real value of new loans, significant at the 1 percent level. The coefficients on income percentile dummies reveal a strong, monotonic relationship between income and loan size. Relative to the lowest decile, borrowers in the 90-100 percentile obtain loans that are approximately 97 percentage points larger, ceteris paribus.

As before, to further explore heterogeneous effects of new mortgage loan value, we interact the policy rate surprise with borrower income deciles (Table A4 in the Appendix). Figure 8 shows the effects on the allocation of new mortgages across income groups of a 100 basis points unexpected increase in monetary policy. The estimates suggest a decline in the top 40 percentiles of the income distribution with the largest effect in the top 20 percent. The impact on the bottom 60th income deciles is statistically not significant.

The consistency between application values and realized loan amounts for higher-income groups suggests that the monetary policy shock primarily operates through a demand-side channel for these borrowers. Higher-income households appear to adjust their borrowing intentions downward in response to tightening monetary conditions, a behavior that translates directly into reduced loan sizes. This alignment indicates that for affluent borrowers, the equilibrium outcome is predominantly driven by their own borrowing decisions rather than supply-side constraints.

Table 3: Impact on Log(Real value of new loans)

Dependent variable	Log (Real value of new loans)					
	(1)	(2)	(3)	(4)	(5)	(6)
Monetary Policy Surprise X Post	-0.112**	-0.109**	-0.0968**	-0.0892**	-0.0955***	-0.0850***
	(0.0459)	(0.0416)	(0.0407)	(0.0339)	(0.0284)	(0.0272)
10-20 percentile				-0.0456	-0.0299	-0.0333
				(0.0472)	(0.0437)	(0.0404)
20-30 percentile				0.150**	0.147***	0.128**
				(0.0581)	(0.0527)	(0.0519)
30-40 percentile				0.268***	0.256***	0.233***
				(0.0618)	(0.0559)	(0.0567)
40-50 percentile				0.382***	0.369***	0.345***
				(0.0645)	(0.0589)	(0.0591)
50-60 percentile				0.496***	0.473***	0.443***
				(0.0698)	(0.0626)	(0.0631)
60-70 percentile				0.619***	0.582***	0.545***
				(0.0716)	(0.0638)	(0.0642)
70-80 percentile				0.715***	0.680***	0.645***
				(0.0720)	(0.0648)	(0.0649)
80-90 percentile				0.841***	0.795***	0.755***
				(0.0767)	(0.0694)	(0.0689)
90-100 percentile				1.074***	1.025***	0.970***
				(0.0791)	(0.0708)	(0.0704)
Other control variables						
Age	No	No	No	Yes	Yes	Yes
Gender	No	No	No	Yes	Yes	Yes
Employment sector	No	No	No	Yes	Yes	Yes
Civil servant status	No	No	No	Yes	Yes	Yes
First loan status	No	No	No	Yes	Yes	Yes
First housing loan status	No	No	No	Yes	Yes	Yes
Fixed effects						
Time	Yes	No	No	Yes	No	No
Bank-Time	No	Yes	Yes	No	Yes	Yes
State-Time	No	No	Yes	No	No	Yes
Observations	622,767	622,719	622,713	582,174	582,125	582,119
R-squared	0.006	0.104	0.146	0.195	0.258	0.282

Note: Standard errors are clustered at the bank level in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

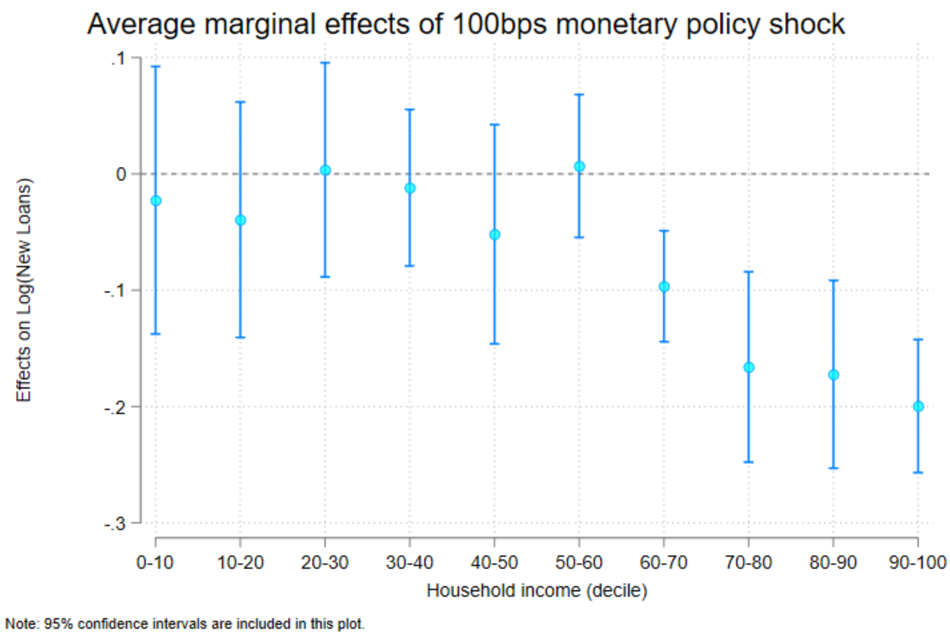


Figure 8: New mortgage loan

For lower-income groups, the minimal impact on both loan application values and realized new loan amounts reinforces the notion of inelastic demand, possibly driven by necessity-based borrowing. The stability in both metrics for this segment suggests that neither borrower behavior nor lender policies are significantly altered by the monetary shock, potentially due to the presence of government support programs or specialized lending criteria that insulate these borrowers from market fluctuations.

Finally, Table 4 documents the relationship between monetary policy surprises and loan maturity. Across all specifications, the impact of policy shocks on maturity appears muted. Even in our preferred specification (column 6), a 100 basis point tightening yields a statistically insignificant reduction in loan term.

There is also a non-monotonic pattern of maturity across income groups. Borrowers in the 30th to 80th percentiles secure substantially longer loan terms compared to the bottom decile, with the peak effect observed in the 70-80th percentile bracket. Of note, the highest earners (90-100th percentile) show no significant difference in loan duration relative to the lowest income group.

Figure 9 shows the average marginal effects of monetary policy surprises on the maturity of new mortgages along the incomes distribution. We do not find any significant impact on the maturities of new mortgages. This is probably because of the more structural nature of mortgage contracts and designs. Most mortgages in Malaysia are between 30 and 35 years of maturity and generally bounded by the maximum number of employment years remaining for the applicant.

Table 4: Effect on Loan Maturity

Dependent variable	Maturity					
	(1)	(2)	(3)	(4)	(5)	(6)
Monetary Policy Surprise X Post	-0.293	-0.490	-0.297	-0.135	-0.322	-0.127
	(0.289)	(0.359)	(0.288)	(0.228)	(0.281)	(0.221)
10-20 percentile				0.652***	0.727***	0.642***
				(0.143)	(0.189)	(0.137)
20-30 percentile				0.901***	0.974***	0.879***
				(0.164)	(0.195)	(0.158)
30-40 percentile				1.017***	1.217***	0.995***
				(0.168)	(0.189)	(0.163)
40-50 percentile				1.109***	1.164***	1.084***
				(0.177)	(0.227)	(0.172)
50-60 percentile				1.117***	1.192***	1.081***
				(0.192)	(0.243)	(0.193)
60-70 percentile				1.105***	1.299***	1.060***
				(0.208)	(0.249)	(0.208)
70-80 percentile				1.338***	1.390***	1.290***
				(0.191)	(0.259)	(0.192)
80-90 percentile				1.099***	1.228***	1.046***
				(0.221)	(0.279)	(0.223)
90-100 percentile				0.194	0.289	0.150
				(0.199)	(0.258)	(0.207)
Other control variables						
Age	No	No	No	Yes	Yes	Yes
Gender	No	No	No	Yes	Yes	Yes
Employment sector	No	No	No	Yes	Yes	Yes
Civil servant status	No	No	No	Yes	Yes	Yes
First loan status	No	No	No	Yes	Yes	Yes
First housing loan status	No	No	No	Yes	Yes	Yes
Fixed effects						
Time	Yes	No	No	Yes	No	No
Bank-Time	No	Yes	Yes	No	Yes	Yes
State-Time	No	No	Yes	No	No	Yes
Observations	620,338	620,386	620,332	580,253	580,302	580,247
R-squared	0.103	0.009	0.110	0.374	0.325	0.378

Note: Standard errors are clustered at the bank level in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

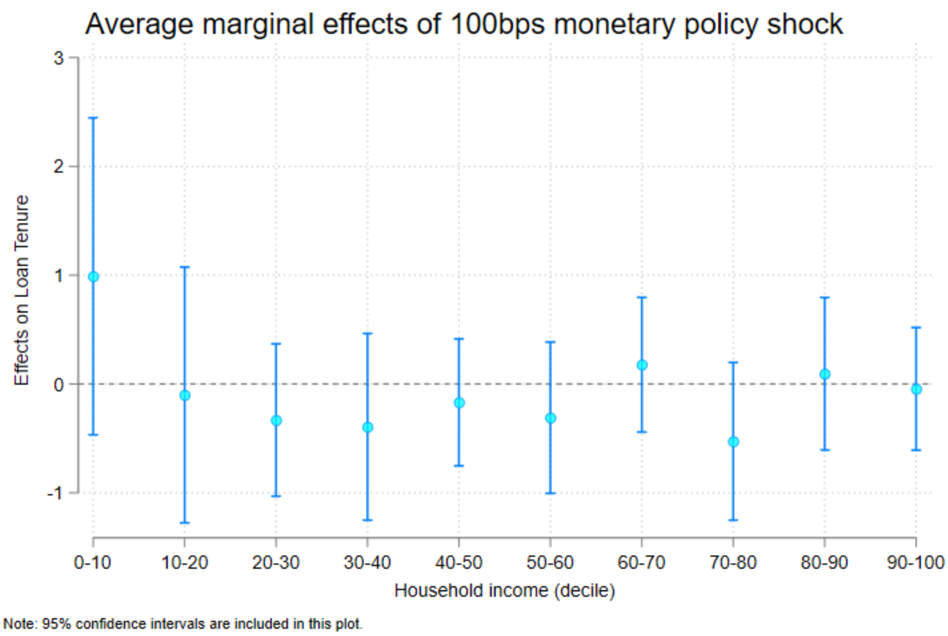


Figure 9: Loan tenure

7. Additional Findings

In addition to our baseline findings in the previous section, we also consider the impact of monetary policy on search behavior of prospective borrowers. We employ a linear probability model to estimate the impact of monetary policy on the likelihood of multi-bank applications. The dependent variable is binary, taking the value of one if a borrower applies to more than one bank and zero otherwise. The specification is as follows:

$$\mathrm{Y}_{it} = \alpha + \beta_1 MP_t \times D_{it} + \sum_{k=1}^{K} \beta_{2k} IQ_{ik} \times MP_t \times D_{it} + \gamma \mathbf{X}_{it} + \psi_{s,t} + \varepsilon_{it} \qquad (3)$$

where Y_{it} is a binary variable taking the value of 1 if borrower i applies to more than one bank at time t, and 0 otherwise. MP_t is the monetary policy shock at time t, D_{it} is an indicator variable for days after the monetary policy announcement day within the window, IQ_{ik} is an indicator variable for the income decile (k) of borrower i, and $\mathbf{X}_{it}$ is a vector of other control variables for borrower i

at time t (i.e., age, gender, civil servant indicator, sector of employment and whether the loan is the first loan or the first housing loan). We include $\psi_{s,t}$ as state-time fixed effects. Notably, we omit bank $\times$ time fixed effects in this specification, as the dependent variable captures behavior across multiple banks.

Table 5 shows the impact on the probability of multi-bank applications. Columns (1) and (2) present the results with time and state-time fixed effects, respectively. Unlike the analysis in our baseline results, we do not include bank-time fixed effects for this section. This is because the dependent variable is a binary variable of whether an applicant applies to one bank only vis-a-vis multiple banks. As such, it is not sensible to include bank fixed effects. We find that a 100 basis points contractionary monetary policy shock increases the likelihood of borrowers applying to multiple banks by about 4 to 4.3 percentage points. Once we control for borrowers' characteristics, we find that the level impact of monetary policy shock is similar in magnitude and remains statistical significance (Columns (3) and (4)). Of note, in Column (4), with state $\times$ time fixed effects, we find that the effect is more pronounced for higher-income deciles, with the highest income decile experiencing a 11.7 percentage point higher increase compared to the lowest decile.

Next, we estimate the average marginal effects of a positive monetary policy shock on the probability of applying to more than one bank by various income deciles (the full regression is presented in Table A6 in the Appendix). Figure 10 shows that search behavior is more pronounced among the those households with income above median. The greater search elasticity exhibited by these borrowers may reflect their lower search costs relative to the potential benefits. This could be due to higher financial literacy, lower opportunity costs of time spent searching, or larger loan amounts that make the potential savings from finding a better rate more substantial.

Table 5: Probability of Applying to Multiple Banks

Dependent variable	Probability of applying to multiple banks			
	(1)	(2)	(3)	(4)
Monetary Policy Surprise X Post	0.0405***	0.0434***	0.0433***	0.0452***
	(0.0068)	(0.0072)	(0.0072)	(0.0075)
10-20 percentile			0.0228***	0.0215***
			(0.0046)	(0.0046)
20-30 percentile			0.0521***	0.0450***
			(0.0044)	(0.0039)
30-40 percentile			0.0632***	0.0557***
			(0.0057)	(0.0051)
40-50 percentile			0.0652***	0.0591***
			(0.0066)	(0.0060)
50-60 percentile			0.0816***	0.0746***
			(0.0076)	(0.0070)
60-70 percentile			0.115***	0.103***
			(0.0076)	(0.0073)
70-80 percentile			0.100***	0.0921***
			(0.0097)	(0.0092)
80-90 percentile			0.124***	0.113***
			(0.0098)	(0.0093)
90-100 percentile			0.131***	0.117***
			(0.0097)	(0.0093)
Other Control Variables:				
Age	No	No	Yes	Yes
Gender	No	No	Yes	Yes
Employment sector	No	No	Yes	Yes
Civil servant status	No	No	Yes	Yes
First loan status	No	No	Yes	Yes
First housing loan status	No	No	Yes	Yes
Fixed Effects:				
Time	Yes	No	Yes	No
State-Time	No	Yes	No	Yes
Observations	1,186,901	1,186,901	1,160,089	1,160,089
R-squared	0.001	0.018	0.017	0.029

Note: Standard errors are clustered at the bank level in parentheses.

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

The heterogeneous response in search behavior has important implications for market efficiency and the distribution of gains from trade in the mortgage market. As Hortaçsu and Syverson (2004) demonstrate in the context of mutual funds, heterogeneous search intensities can lead to price dispersion and market segmentation. While our findings suggest potential heterogeneity in search across income groups upon monetary policy shocks, the absence of loan-level interest rate data in our dataset precludes a direct examination of price dispersion. Nevertheless, we can conjecture that the increased search activity among higher-income borrowers may enhance competition among lenders for this segment, potentially leading to more favorable terms and conditions for these borrowers.

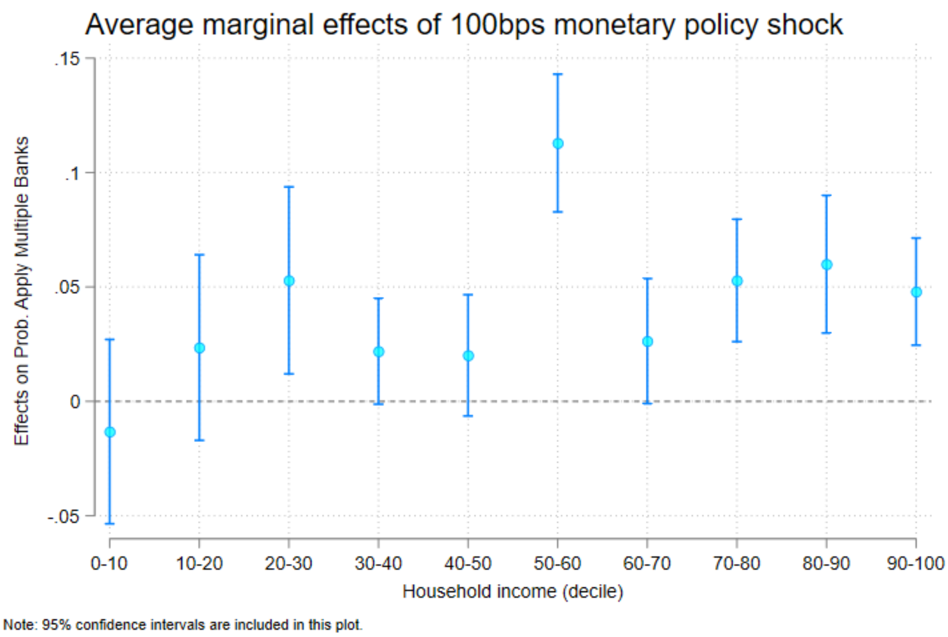


Figure 10: Probability of applying to more than one bank

8. Robustness Checks

To ensure the validity and reliability of our findings on the impact of monetary policy on income distribution in Malaysia, we conducted several robustness checks to address potential concerns regarding our methodology and strengthen the credibility of our results.

8.1 Alternative Size of Event Windows

In this section, we test the robustness of our results to the choice of window size by varying the duration of the windows around the monetary policy announcements. The maximum window size was constrained by the proximity of consecutive Monetary Policy Committee (MPC) meetings, typically those in January and March. On average, this allowed for a maximum window of plus and minus 21 calendar days, which is our alternative size of the event window.

Our results are robust to this extension. Across all key indicators—loan applications, approval rates, new loan originations and loan tenure, as well as, search behavior, the patterns and statistical significance remain consistent with our baseline findings. Figures A1-A4 in Section B of the appendix illustrate this.

8.2 Alternative Measures of Household Income and Income Cutoffs

To address potential concerns about the definition and measurement of income groups and to mitigate the sensitivity of our results to specific income cutoffs, we explore alternative approaches to categorizing household income groups. This analysis serves as a robustness of our main findings and to situate our work within the broader literature on income distribution and the middle class.

The definition and measurement of income groups, particularly the middle class, have been subjects of extensive debate in the economic literature. As noted by Atkinson and Brandolini (2019), there is no universally accepted definition of the middle class, and various approaches have been proposed to capture this elusive concept. Our robustness checks aim to address this challenge by employing multiple widely-recognized methods from the literature. We consider the following alternative approaches:

1. Alternative 1: Following Easterly (2001), we define the middle class as households with incomes between the 20th and 80th percentiles of the income distribution. This approach offers a broad definition of the middle class,and can potentially help to remove any noise and measurement errors inherent in too narrowly defined income groups.

2. Alternative 2: We follow Krueger (2012), and define the middle class as households with incomes between 50 percent and 150 percent of the median income. This approach provides a definition of the middle class that is relative to the central tendency of the income distribution. Households below 50 percent of the median income are classified as lower income, while those above 150 percent of the median are considered upper income.

3. Alternative 3: To account for the specific economic context of Malaysia, we utilize the locally recognized (and widely used) income group classifications: B40 (Bottom 40 percent), M40 (Middle 40 percent), and T20 (Top 20 percent). These categories are widely used in Malaysian policy discussions and analyses.

The figures A6 - A20 show the marginal impact of monetary policy surprises on our key variables of interest are presented in the Appendix (Section C). Our findings demonstrate that the main conclusions of our study remain robust across these alternative specifications, with some nuanced variations across different income group definitions.

For loan applications, we find a consistent pattern across all three alternative definitions. High-income households consistently exhibit a propensity to apply for smaller amount of loans following a positive monetary policy surprise. The estimated coefficients for this group are negative and statistically significant across all specifications. In contrast, the middle-income category shows no significant change in loan application behavior, with point estimates close to zero and confidence intervals including zero. For lower-income households, the results are less precise. While some estimates suggest a positive effect, standard errors are large.

Regarding loan approval rates, across all alternative income group definitions, we find no discernible impact on the lower-income group, with point estimates close to zero and confidence intervals consistently including zero. Middle-income borrowers consistently show the more pronounced negative response to a 100 basis point monetary policy shock, with a statistically significant decrease in loan approval probabilities. However, it is important to note that this effect, while statistically significant, remains economically small, with point estimates of a 3-4 percentage point reduction in approval probability. Higher-income applicants show a slight negative response, though often not statistically significant.

The patterns observed in new loan values mirror those seen in loan applications. High-income groups consistently show a negative and statistically significant response to monetary policy tightening across all alternative definitions. This suggests that the decrease in loan applications for this group translates into fewer new loans being originated. Lastly, our analysis of loan tenure reveals no significant changes across all income groups, regardless of the definition used.

Examining search behavior, we observe positive and statistically significant effects for both middle- and high-income groups across all alternative definitions. This suggests that these households increase their search efforts for loans in response to monetary policy tightening. The results for the lower-income group are less clear-cut, with inconsistent signs and statistical significance across specifications.

8.3 Alternative Measure of Monetary Policy

In our baseline model, we utilised monetary policy shocks as our primary measure, following the methodology of Miranda-Agrippino and Ricco (2021). However, to test the robustness of our results, we employed an alternative measure: the change in the Overnight Policy Rate (OPR) itself. This approach allows us to directly examine the effects of observed policy rate changes, potentially capturing both anticipated and unanticipated components of monetary policy actions.

Results as shown in Figures A21-A24 of section D in the appendix remain qualitatively consistent across both specifications. This reinforces the overall conclusions about the distributional effects of monetary policy on credit allocation. However, we observe an attenuation in the magnitude of effects on loan applications and new loan values when using the change in OPR as our monetary policy indicator.

This attenuation is expected and can be attributed to the feature that the OPR changes include both anticipated and unanticipated components of monetary policy that dates back to Kuttner (2001). Anticipated changes are likely already priced into market expectations and the decisions of household and the banks, leading to smaller observed effects in response to the overall change. In contrast, our baseline measure of monetary policy shocks aims to capture the unanticipated component of policy changes, which may more accurately reflect shifts in the true policy stance.

9. Conclusions

By using the universe of new mortgage applications, and originations from the Malaysian credit registry data, we investigate the distributional effects of high frequency monetary policy surprises on mortgage credit allocation with a specific focus on the effects across the distribution of income. Malaysian credit registry maintains arrays of rich information for every single mortgage applicant regardless of the approval status. These features of the data enables us to examine the effects of monetary policy on a number of dimensions: value of new mortgage applications, probability of approval, value of new mortgage originated, maturity of new mortgages, as well as the probability of prospective borrowers making applications to multiple banks (search).

We find that a positive monetary policy shock has significant dampening effects on mortgage credit allocation. However, this overall effect hides a rich degree of heterogeneity across income distribution. To a first approximation, our results show that monetary policy affects the top forty percent of the income distribution more than the bottom sixty percent. In terms of real value of mortgage applications and new loan originated, the top forty percent of the income distribution experience a significant fall in response to a higher interest rate. Bottom sixty percent does not show a significant change. The lack of response to monetary policy by households in the first sixty percent of the distribution is likely to be driven by large first home policy initiatives in Malaysia. However, this is only to a first approximation, and specifics of our findings can be summarised as below.

A contractionary monetary policy surprise leads to a statistically significant decline in the real value of mortgage applications. However, this effect is primarily driven by the top four income deciles, with little to no change observed in the bottom six deciles. Similar results are observed in the real value of mortgage approvals where the top four deciles observe a fall in the approvals of their real mortgages. The effects of monetary policy on the probability of mortgage approvals on the other hand is more a middle-income story: Probability of mortgage approvals fall for the middle two deciles, fifth and the sixth deciles and also for the eight deciles. Combined with the real value of loans approved, this results suggest that even though for some income groups the probability of approval remains the same, the amount of loans approved fall following a monetary policy tightening.

A novel finding we have is the change in the search behaviour in response to monetary policy: We find that a contractionary policy also leads to an increase in the probability of households applying to multiple banks following particularly among middle and high income households. Finally, on the maturity of new mortgage, we do not find any effect across any part of the income distribution.

Our paper, makes several contribution: First, we use the universe of credit registry data in an emerging market economy and show that the monetary policy effects are indeed heterogeneous. We provide clear evidence that the monetary policy in Malaysia works through the top of the incomes distribution as far as the specific part of the credit channel, new of mortgage credit allocation, we studied.

The heterogeneous response in search behavior suggests that the transmission of monetary policy through credit markets may be more complex than previously understood. Policymakers may need to consider how changes in policy rates affect not just the overall level of credit but also the distribution of bargaining power and information acquisition in credit markets. Future research could explore whether the increased search activity among higher-income borrowers ultimately leads to better loan terms, and whether this creates long-term disparities in credit access and cost across income groups.

Our results are robust across alternative monetary policy measures, event window sizes, and income group definitions. Despite these additional analyses, some limitations persist. For instance, by design our study does not fully account for potential long-term effects of monetary policy on income distribution that may manifest beyond our maximum event window. Additionally, while we have attempted to control for various confounding factors, the possibility of omitted variable bias cannot be entirely ruled out. Future research could address these limitations by employing longer-term analysis and exploring additional identification strategies.

References

Abuka, Charles, Ronnie K. Alinda, Camelia Minoiu, José Luis Peydró, and Andrea F. Presbitero, "Monetary policy and bank lending in developing countries: Loan applications, rates, and real effects," *Journal of Development Economics*, 2019, *139*.

Agarwal, Sumit, John Grigsby, Ali Hortaçsu, Gregor Matvos, Amit Seru, and Vincent Yao, "Searching for Approval," *Econometrica*, 2024, *92* (4), 1195–1231.

Amberg, Niklas, Thomas Jansson, Mathias Klein, and Anna Rogantini Picco, "Five Facts about the Distributional Income Effects of Monetary Policy Shocks," *American Economic Review: Insights*, 2022, *4* (3).

Atkinson, Anthony B. and Andrea Brandolini, "On the Identification of the Middle Class," in "Income Inequality" 2019.

Bernanke, Ben S and Mark Gertler, "Inside the Black Box: The Credit Channel of Monetary Policy Transmission," *Journal of Economic Perspectives*, 1995, *9* (4).

BIS, "The distributional footprint of monetary policy," *BIS Annual Economic Report 2021*, 2021, *June*.

Cloyne, James, Clodomiro Ferreira, and Paolo Surico, "Monetary policy when households have debt: New evidence on the transmission mechanism," *Review of Economic Studies*, 2020, *87* (1).

Coibion, Olivier, Yuriy Gorodnichenko, Lorenz Kueng, and John Silvia, "Innocent Bystanders? Monetary policy and inequality," *Journal of Monetary Economics*, 2017, *88*.

Di, Zhu Xiao, Eric Belsky, and Xiaodong Liu, "Do homeowners achieve more household wealth in the long run?," *Journal of Housing Economics*, 2007, *16* (3-4).

Easterly, William, "The middle class consensus and economic development," *Journal of Economic Growth*, 2001, *6* (4).

Hortaçsu, Ali and Chad Syverson, "Product differentiation, search costs, and competition in the mutual fund industry: A case study of S&P 500 index funds," *Quarterly Journal of Economics*, 2004, *119* (2).

Jasova, Martina, Caterina Mendicino, Ettore Panetti, Jose-Luis Peydro, and Dominik Supera, “Monetary Policy, Labor Income Redistribution and the Credit Channel: Evidence from Matched Employer-Employee and Credit Registers,” *SSRN Electronic Journal*, 2021.

Jiménez, Gabriel, Steven Ongena, José-Luis Peydró, and Jesús Saurina, “Credit Supply and Monetary Policy: Identifying the Bank Balance-Sheet Channel with Loan Applications,” *American Economic Review*, 8 2012, *102* (5), 2301–2326.

_ , _ , _ , and _ , “Hazardous Times for Monetary Policy: What Do Twenty-Three Million Bank Loans Say About the Effects of Monetary Policy on Credit Risk-Taking?,” *Econometrica*, 2014, *82* (2), 463–505.

Krueger, Alan, “The Rise and Consequences of Inequality in the United States,” *The Center for American Progress*, 2012.

Kuttner, Kenneth N., “Monetary policy surprises and interest rates: Evidence from the Fed funds futures market,” *Journal of Monetary Economics*, 2001, *47* (3).

Leahy, John V. and Aditi Thapar, “Age Structure and the Impact of Monetary Policy,” *American Economic Journal: Macroeconomics*, 2022, *14* (4).

Ligonniere, Samuel and Salima Ouerk, “ The unequal distribution of credit: Is there any role for monetary policy? ,” 2024.

Miranda-Agrippino, Silvia and Giovanni Ricco, “The Transmission of Monetary Policy Shocks,” *American Economic Journal: Macroeconomics*, 2021, *13* (3).

Ringo, Daniel, “Monetary Policy and Home Buying Inequality,” *Finance and Economics Discussion Series*, 1 2023, (2023-006), 1–48.

Wainer, Allison and Jeffrey Zabel, “Homeownership and wealth accumulation for low-income households,” *Journal of Housing Economics*, 2020, *47*.

Appendices

A Supporting Tables

Table A1: Thresholds of monthly (net) household income across years in Malaysian Ringgit

Year	Bottom 20	20 - 40	40 - 60	60 - 80	Top 20
2016	<2917	2917 - 4360	4360 - 6223	6223 - 9620	>9620
2019	<3090	3090 - 4748	4748 - 6970	6970 - 10670	>10670
2022	<3359	3359 - 5150	5150 - 7544	7544 - 11539	>11539
Growth	15%	15% - 18%	18% - 21%	21% - 20%	>20%

Source: Department of Statistics, Malaysia, Authors' calculations

Table A2: Loan Value Applied

Dependent Variable	Log (Real value of loan applied)		
	(1)	(2)	(3)
Monetary Policy Surprise X Post	0.0310	0.0350	0.0186
	(0.120)	(0.0965)	(0.0869)
10-20 percentile	-0.0167	-0.0024	-0.006
	(0.0478)	(0.0446)	(0.0418)
20-30 percentile	0.199***	0.193***	0.169***
	(0.0626)	(0.0591)	(0.0577)
30-40 percentile	0.310***	0.295***	0.264***
	(0.0658)	(0.0622)	(0.0614)
40-50 percentile	0.422***	0.405***	0.377***
	(0.0676)	(0.0650)	(0.0641)
50-60 percentile	0.535***	0.504***	0.470***
	(0.0725)	(0.0696)	(0.0692)
60-70 percentile	0.661***	0.616***	0.570***
	(0.0755)	(0.0720)	(0.0715)
70-80 percentile	0.735***	0.693***	0.652***
	(0.0744)	(0.0719)	(0.0714)
80-90 percentile	0.862***	0.810***	0.761***
	(0.0773)	(0.0746)	(0.0741)
90-100 percentile	1.118***	1.057***	0.996***
	(0.0804)	(0.0774)	(0.0768)
Monetary Policy Surprise X Post X 10-20 pct	0.0988	0.0692	0.0556
	(0.118)	(0.108)	(0.100)
Monetary Policy Surprise X Post X 20-30 pct	0.0823	0.0493	0.0320
	(0.117)	(0.0954)	(0.0887)
Monetary Policy Surprise X Post X 30-40 pct	0.0382	0.0432	0.0674
	(0.122)	(0.103)	(0.0912)
Monetary Policy Surprise X Post X 40-50 pct	-0.0179	-0.0194	-0.0103
	(0.128)	(0.104)	(0.0951)
Monetary Policy Surprise X Post X 50-60 pct	0.0566	0.0179	0.0004
	(0.131)	(0.103)	(0.0954)
Monetary Policy Surprise X Post X 60-70 pct	-0.125	-0.0991	-0.0627
	(0.131)	(0.105)	(0.0920)
Monetary Policy Surprise X Post X 70-80 pct	-0.112	-0.0968	-0.0670
	(0.123)	(0.0982)	(0.0884)
Monetary Policy Surprise X Post X 80-90 pct	-0.146	-0.132	-0.0995
	(0.128)	(0.103)	(0.0924)
Monetary Policy Surprise X Post X 90-100 pct	-0.171	-0.153	-0.108
	(0.130)	(0.105)	(0.0943)
Time Fixed Effects (FE)	Yes	No	No
Bank-Time FE	No	Yes	Yes
State-Time FE	No	No	Yes
Observations	1448493	1448448	1448448
R-squared	0.281	0.319	0.353

These regressions include controls such as age, gender, employment sector, civil servant status, first loan status and first housing loan status.
Note: Standard errors are clustered at the bank level in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table A3: Probability of Approval

Dependent Variable	Probability of approval		
	(1)	(2)	(3)
Monetary Policy Surprise X Post	0.0578	0.0115	0.0159
	(0.0525)	(0.0465)	(0.0477)
10-20 percentile	0.0055	0.0092	0.0095
	(0.0144)	(0.0082)	(0.0080)
20-30 percentile	0.0512**	0.0478***	0.0473***
	(0.0210)	(0.0115)	(0.0111)
30-40 percentile	0.0593**	0.0534***	0.0527***
	(0.0247)	(0.0162)	(0.0154)
40-50 percentile	0.0574*	0.0616***	0.0607***
	(0.0288)	(0.0196)	(0.0193)
50-60 percentile	0.0622**	0.0682***	0.0668***
	(0.0293)	(0.0173)	(0.0171)
60-70 percentile	0.0589*	0.0537***	0.0525***
	(0.0312)	(0.0165)	(0.0159)
70-80 percentile	0.0759**	0.0827***	0.0812***
	(0.0340)	(0.0205)	(0.0201)
80-90 percentile	0.0707**	0.0740***	0.0725***
	(0.0344)	(0.0196)	(0.0190)
90-100 percentile	0.0659*	0.0744***	0.0720***
	(0.0351)	(0.0198)	(0.0189)
Monetary Policy Surprise X Post X 10-20 pct	0.0152	0.0264	0.0277
	(0.0387)	(0.0332)	(0.0342)
Monetary Policy Surprise X Post X 20-30 pct	-0.0801*	-0.0550	-0.0566
	(0.0428)	(0.0421)	(0.0431)
Monetary Policy Surprise X Post X 30-40 pct	0.0536	0.00775	-0.00328
	(0.0504)	(0.0396)	(0.0405)
Monetary Policy Surprise X Post X 40-50 pct	-0.0971*	-0.0656	-0.0692
	(0.0535)	(0.0477)	(0.0482)
Monetary Policy Surprise X Post X 50-60 pct	-0.140**	-0.115**	-0.120**
	(0.0523)	(0.0483)	(0.0493)
Monetary Policy Surprise X Post X 60-70 pct	-0.0758	-0.0169	-0.0228
	(0.0593)	(0.0426)	(0.0424)
Monetary Policy Surprise X Post X 70-80 pct	-0.0736	-0.0489	-0.0557
	(0.0531)	(0.0434)	(0.0440)
Monetary Policy Surprise X Post X 80-90 pct	-0.117**	-0.0680	-0.0751
	(0.0551)	(0.0483)	(0.0494)
Monetary Policy Surprise X Post X 90-100 pct	-0.0767	-0.0219	-0.0289
	(0.0601)	(0.0488)	(0.0501)
Time Fixed Effects (FE)	Yes	No	No
Bank-Time FE	No	Yes	Yes
State-Time FE	No	No	Yes
Observations	1,409,549	1,409,506	1,409,506
R-squared	0.016	0.111	0.113

These regressions include controls such as age, gender, employment sector, civil servant status, first loan status and first housing loan status.
Note: Standard errors are clustered at the bank level in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table A4: Log (Real value of new loan)

Dependent Variable	Log (Real value of new loan)		
	(1)	(2)	(3)
Monetary Policy Surprise X Post	-0.0126	0.00240	-0.0227
	(0.0724)	(0.0637)	(0.0587)
10-20 percentile	-0.0459	-0.0302	-0.0335
	(0.0471)	(0.0436)	(0.0403)
20-30 percentile	0.149**	0.146***	0.127**
	(0.0580)	(0.0526)	(0.0518)
30-40 percentile	0.268***	0.256***	0.233***
	(0.0618)	(0.0559)	(0.0567)
40-50 percentile	0.381***	0.369***	0.345***
	(0.0646)	(0.0590)	(0.0591)
50-60 percentile	0.495***	0.472***	0.443***
	(0.0699)	(0.0627)	(0.0632)
60-70 percentile	0.619***	0.582***	0.545***
	(0.0717)	(0.0638)	(0.0642)
70-80 percentile	0.715***	0.680***	0.645***
	(0.0720)	(0.0648)	(0.0649)
80-90 percentile	0.841***	0.796***	0.755***
	(0.0768)	(0.0694)	(0.0689)
90-100 percentile	1.074***	1.025***	0.971***
	(0.0792)	(0.0709)	(0.0704)
Monetary Policy Surprise X Post X 10-20 pct	-0.00470	-0.0284	-0.0168
	(0.0866)	(0.0839)	(0.0746)
Monetary Policy Surprise X Post X 20-30 pct	0.0515	0.0139	0.0261
	(0.0858)	(0.0809)	(0.0768)
Monetary Policy Surprise X Post X 30-40 pct	-0.0300	-0.0288	0.0108
	(0.0706)	(0.0731)	(0.0679)
Monetary Policy Surprise X Post X 40-50 pct	-0.0301	-0.0591	-0.0292
	(0.0778)	(0.0715)	(0.0694)
Monetary Policy Surprise X Post X 50-60 pct	0.0615	0.0146	0.0294
	(0.0912)	(0.0752)	(0.0720)
Monetary Policy Surprise X Post X 60-70 pct	-0.146**	-0.118*	-0.0740
	(0.0698)	(0.0655)	(0.0604)
Monetary Policy Surprise X Post X 70-80 pct	-0.168*	-0.191**	-0.143*
	(0.0864)	(0.0776)	(0.0725)
Monetary Policy Surprise X Post X 80-90 pct	-0.185*	-0.203**	-0.150*
	(0.0945)	(0.0818)	(0.0760)
Monetary Policy Surprise X Post X 90-100 pct	-0.188*	-0.234***	-0.177**
	(0.0990)	(0.0728)	(0.0676)
Time Fixed Effects (FE)	Yes	No	No
Bank-Time FE	No	Yes	Yes
State-Time FE	No	No	Yes
Observations	582,174	582,125	582,119
R-squared	0.195	0.258	0.282

These regressions include controls such as age, gender, employment sector, civil servant status, first loan status and first housing loan status.
Note: Standard errors are clustered at the bank level in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table A5: Log (Loan tenure)

Dependent Variable	Log (Loan tenure)		
	(1)	(2)	(3)
Monetary Policy Surprise X Post	0.202	0.944	0.989
	(0.746)	(0.763)	(0.743)
10-20 percentile	0.728***	0.652***	0.641***
	(0.188)	(0.141)	(0.135)
20-30 percentile	0.976***	0.901***	0.880***
	(0.195)	(0.163)	(0.157)
30-40 percentile	1.216***	1.016***	0.994***
	(0.189)	(0.167)	(0.162)
40-50 percentile	1.164***	1.109***	1.084***
	(0.227)	(0.176)	(0.172)
50-60 percentile	1.191***	1.117***	1.082***
	(0.242)	(0.191)	(0.191)
60-70 percentile	1.299***	1.106***	1.060***
	(0.249)	(0.206)	(0.207)
70-80 percentile	1.390***	1.339***	1.291***
	(0.259)	(0.190)	(0.191)
80-90 percentile	1.227***	1.098***	1.045***
	(0.279)	(0.220)	(0.222)
90-100 percentile	0.288	0.193	0.150
	(0.258)	(0.199)	(0.207)
Monetary Policy Surprise X Post X 10-20 pct	-0.980	-1.116	-1.090
	(0.883)	(0.986)	(0.978)
Monetary Policy Surprise X Post X 20-30 pct	-0.796	-1.251	-1.321
	(0.853)	(1.035)	(1.017)
Monetary Policy Surprise X Post X 30-40 pct	-1.160	-1.341	-1.383
	(0.980)	(0.997)	(0.978)
Monetary Policy Surprise X Post X 40-50 pct	-0.362	-1.162	-1.158
	(0.816)	(0.939)	(0.915)
Monetary Policy Surprise X Post X 50-60 pct	-0.364	-1.220	-1.300
	(0.863)	(0.989)	(0.979)
Monetary Policy Surprise X Post X 60-70 pct	-0.503	-0.806	-0.812
	(1.044)	(1.005)	(0.971)
Monetary Policy Surprise X Post X 70-80 pct	-0.579	-1.506	-1.517
	(0.993)	(1.070)	(1.020)
Monetary Policy Surprise X Post X 80-90 pct	-0.290	-0.905	-0.896
	(1.003)	(0.969)	(0.918)
Monetary Policy Surprise X Post X 90-100 pct	-0.231	-0.938	-1.034
	(0.957)	(0.935)	(0.907)
Time Fixed Effects (FE)	Yes	No	No
Bank-Time FE	No	Yes	Yes
State-Time FE	No	No	Yes
Observations	580,302	580,253	580,247
R-squared	0.325	0.374	0.378

These regressions include controls such as age, gender, employment sector, civil servant status, first loan status and first housing loan status.
Note: Standard errors are clustered at the bank level in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table A6: Probability of Applying to More Than One Bank

Dependent Variable	Probability of applying to more than one bank	
	(1)	(2)
Monetary Policy Surprise X Post	-0.0099	-0.0111
	(0.0172)	(0.0185)
10-20 percentile	0.0229***	0.0215***
	(0.0046)	(0.0045)
20-30 percentile	0.0518***	0.0449***
	(0.0043)	(0.0039)
30-40 percentile	0.0632***	0.0556***
	(0.0057)	(0.0051)
40-50 percentile	0.0653***	0.0591***
	(0.0066)	(0.0060)
50-60 percentile	0.0806***	0.0737***
	(0.0074)	(0.0069)
60-70 percentile	0.115***	0.103***
	(0.0076)	(0.0073)
70-80 percentile	0.100***	0.0921***
	(0.0098)	(0.0092)
80-90 percentile	0.124***	0.113***
	(0.0097)	(0.0093)
90-100 percentile	0.131***	0.117***
	(0.0097)	(0.0093)
Monetary Policy Surprise X Post X 10-20 pct	0.0356***	0.0288**
	(0.0124)	(0.0140)
Monetary Policy Surprise X Post X 20-30 pct	0.0868***	0.0690***
	(0.0147)	(0.0166)
Monetary Policy Surprise X Post X 30-40 pct	0.0274*	0.0292
	(0.0152)	(0.0173)
Monetary Policy Surprise X Post X 40-50 pct	0.0364**	0.0346**
	(0.0165)	(0.0167)
Monetary Policy Surprise X Post X 50-60 pct	0.141***	0.131***
	(0.0211)	(0.0235)
Monetary Policy Surprise X Post X 60-70 pct	0.0178	0.0303
	(0.0151)	(0.0181)
Monetary Policy Surprise X Post X 70-80 pct	0.0504**	0.0649**
	(0.0246)	(0.0265)
Monetary Policy Surprise X Post X 80-90 pct	0.0554**	0.0659**
	(0.0224)	(0.0258)
Monetary Policy Surprise X Post X 90-100 pct	0.0475**	0.0611**
	(0.0233)	(0.0259)
Time FE	Yes	No
State-Time FE	No	Yes
Observations	1,160,089	1,160,089
R-squared	0.017	0.029

These regressions include controls such as age, gender, employment sector, civil servant status, first loan status and first housing loan status.
Note: Standard errors are clustered at the bank level in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

B Alternative Size of Event Windows (+/- 21 days)

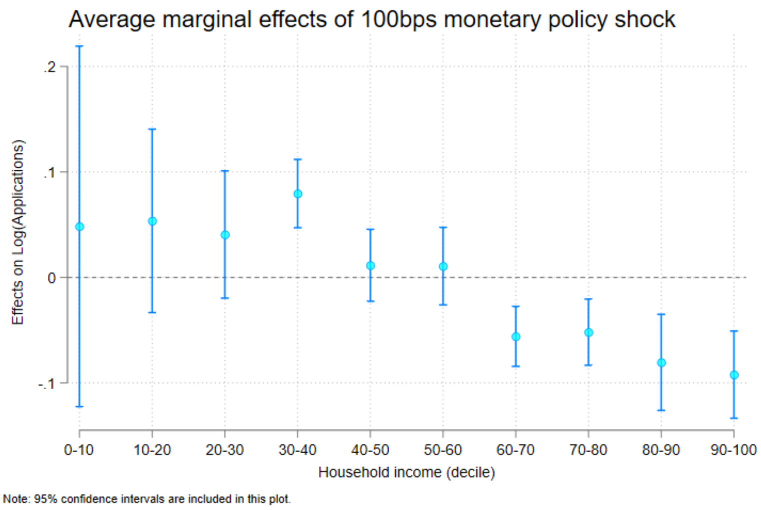


Figure A1: Values of Applications for New Mortgages

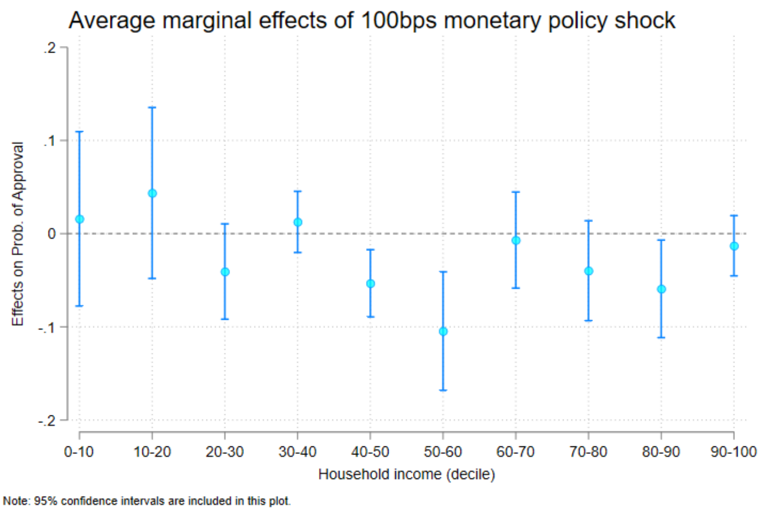


Figure A2: Probability of loan approvals

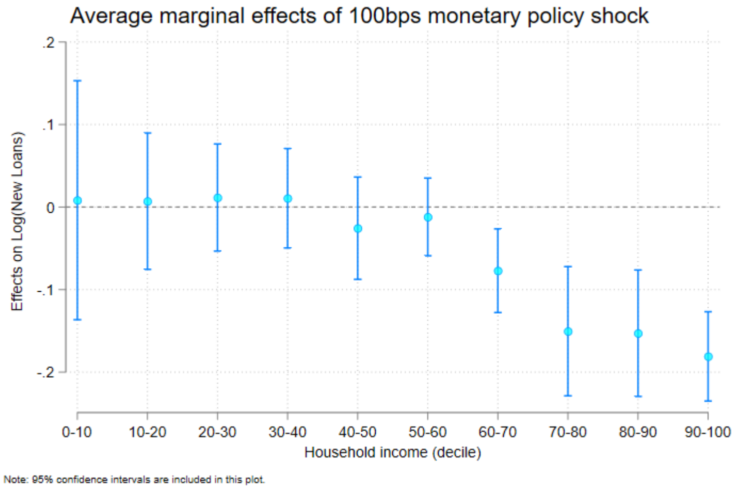


Figure A3: New mortgage loan

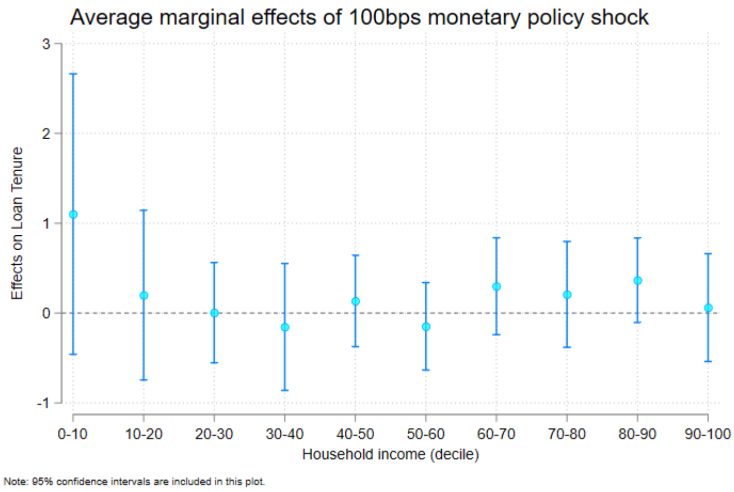


Figure A4: Loan tenure

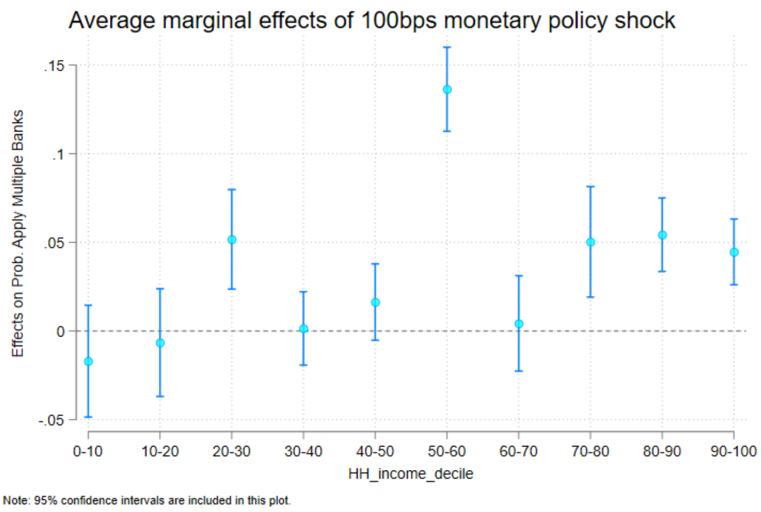


Figure A5: Probability of applying to more than one bank

C Alternative Measures of Household Income and Income Cutoffs

C.1 Alternative 1: William Easterly's definition

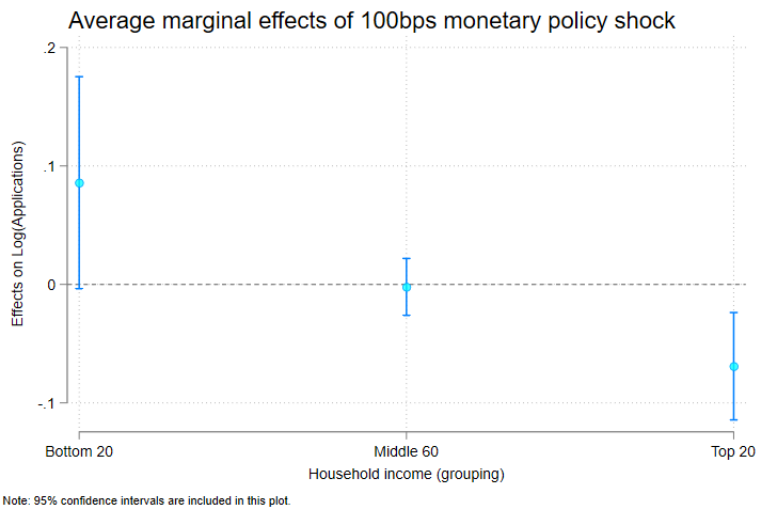


Figure A6: Values of Applications for New Mortgages

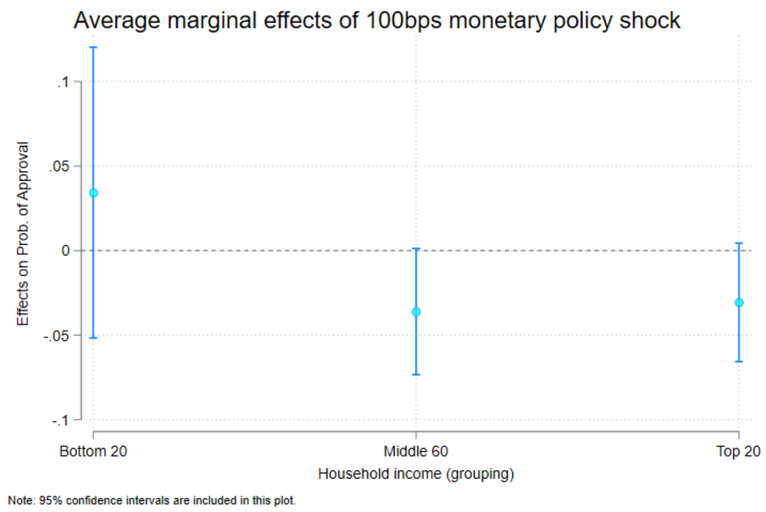


Figure A7: Probability of loan approvals

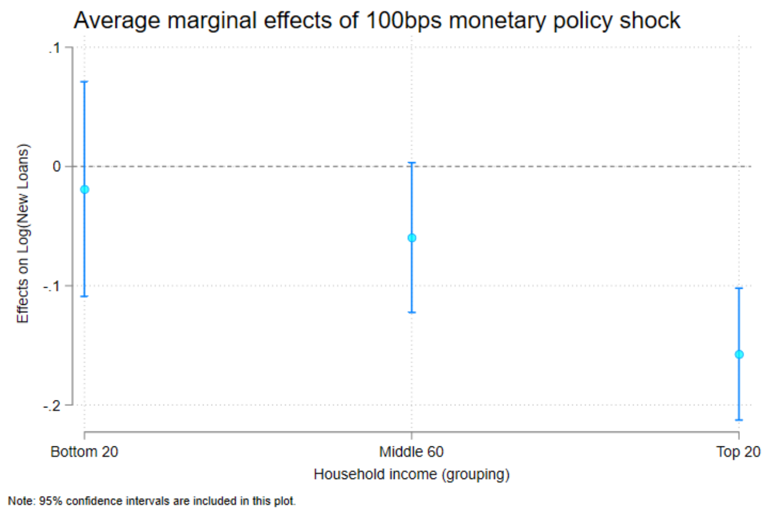


Figure A8: New mortgage loan

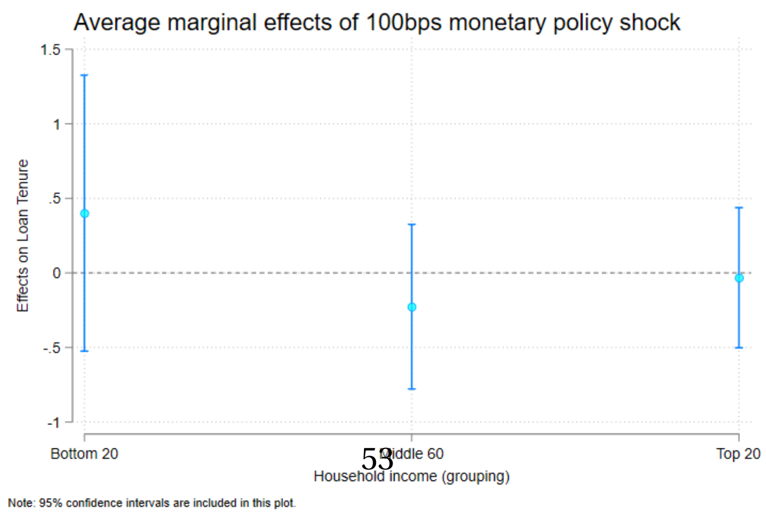


Figure A9: Loan tenure

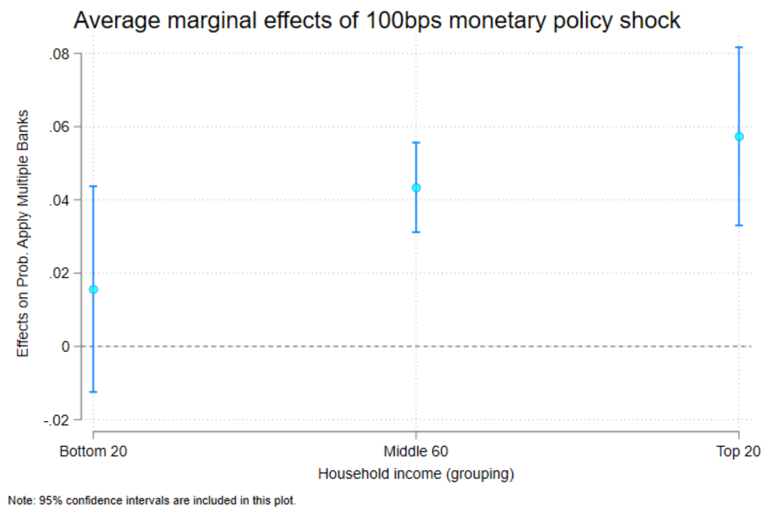


Figure A10: Probability of applying to more than one bank

C.2 Alternative 2: Alan Krueger's definition

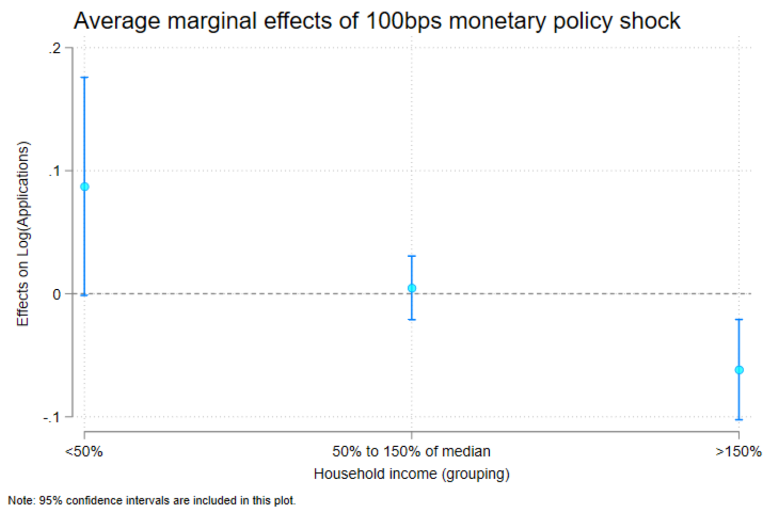


Figure A11: Values of Applications for New Mortgages

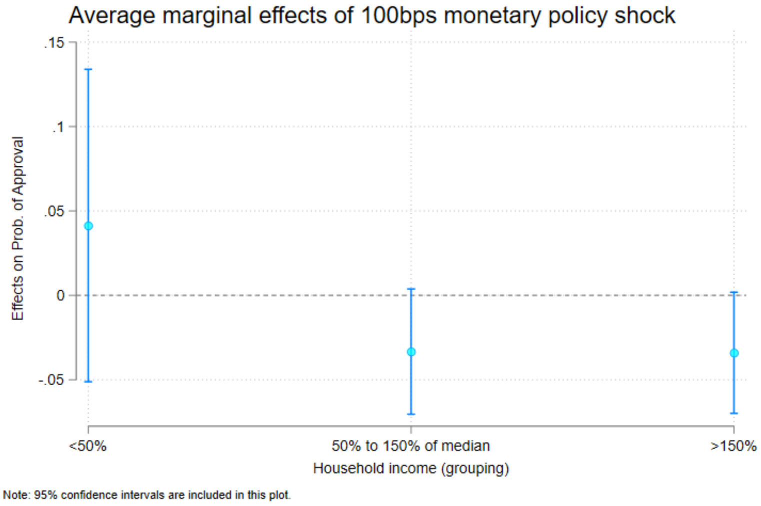


Figure A12: Probability of loan approvals

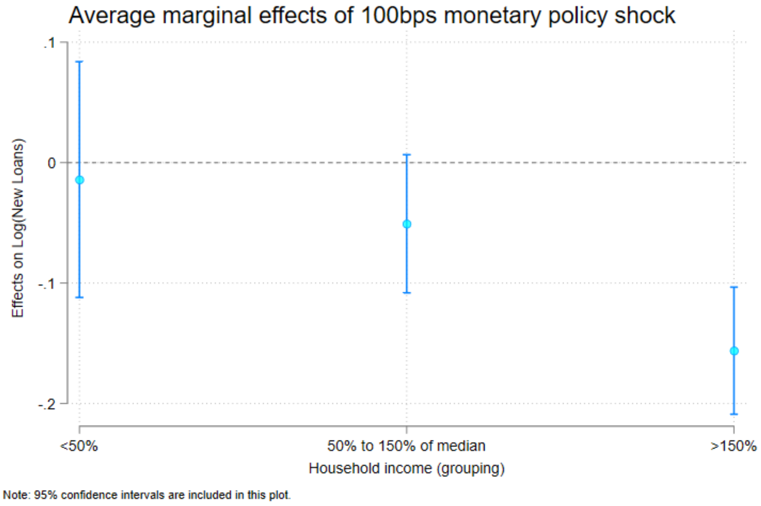


Figure A13: New mortgage loan

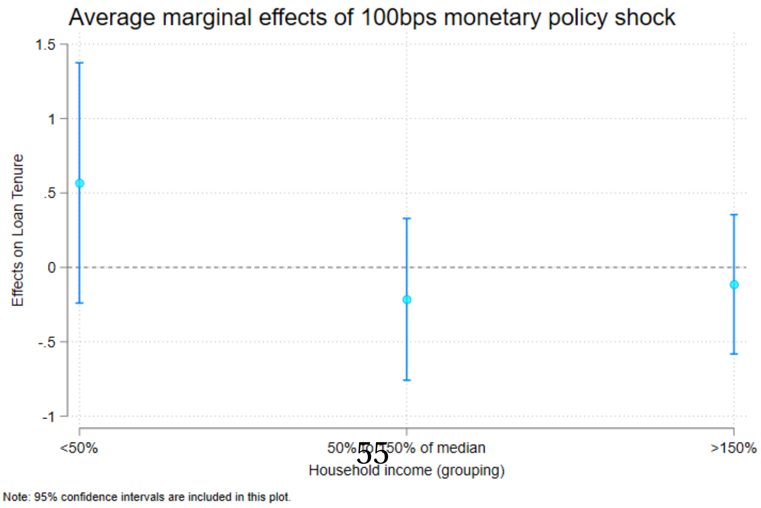


Figure A14: Loan tenure

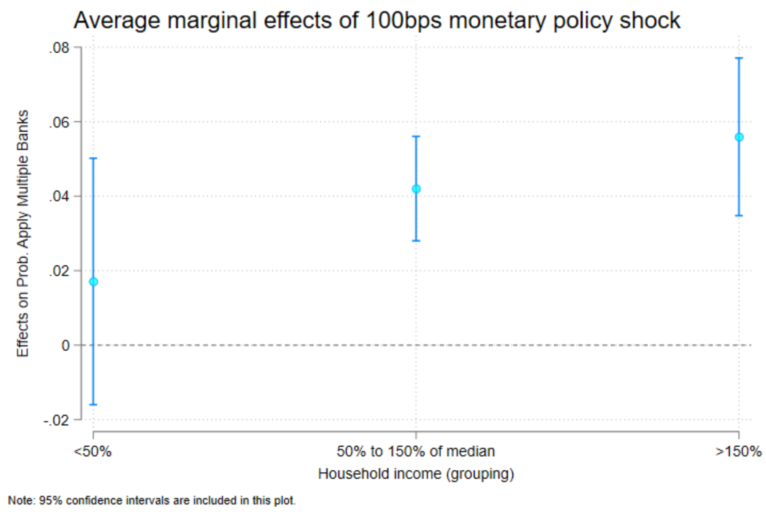


Figure A15: Probability of applying to more than one bank

C.3 Alternative 3: Common domestic (Malaysian) definition

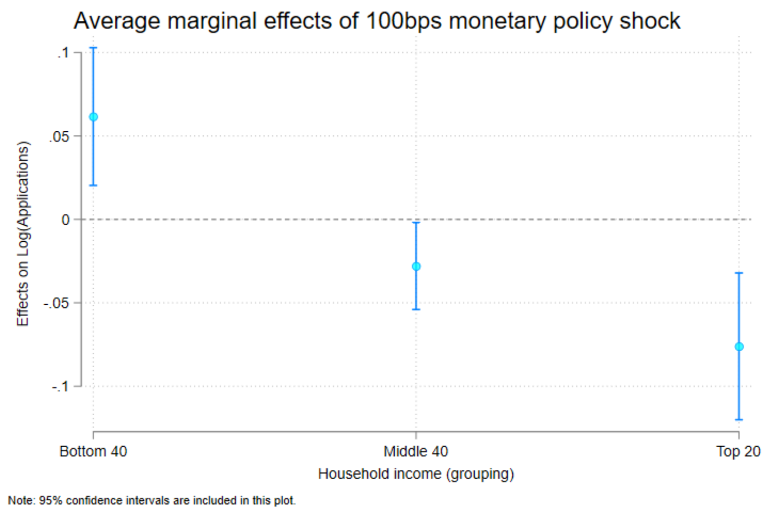


Figure A16: Values of Applications for New Mortgages

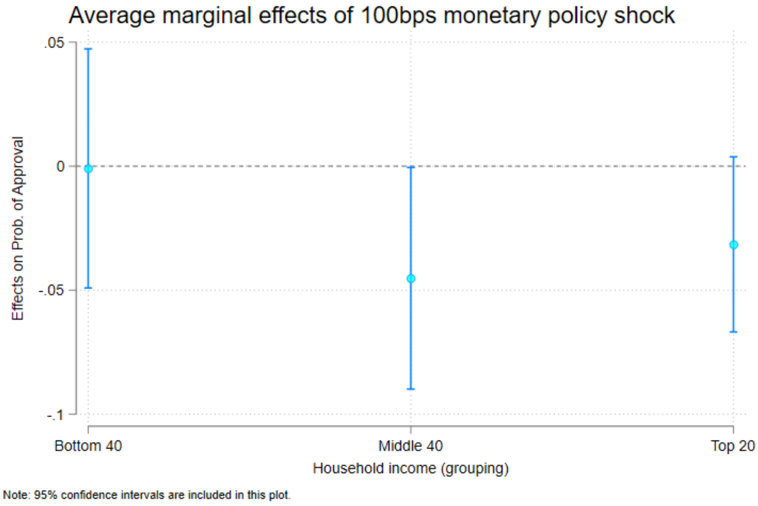


Figure A17: Probability of loan approvals

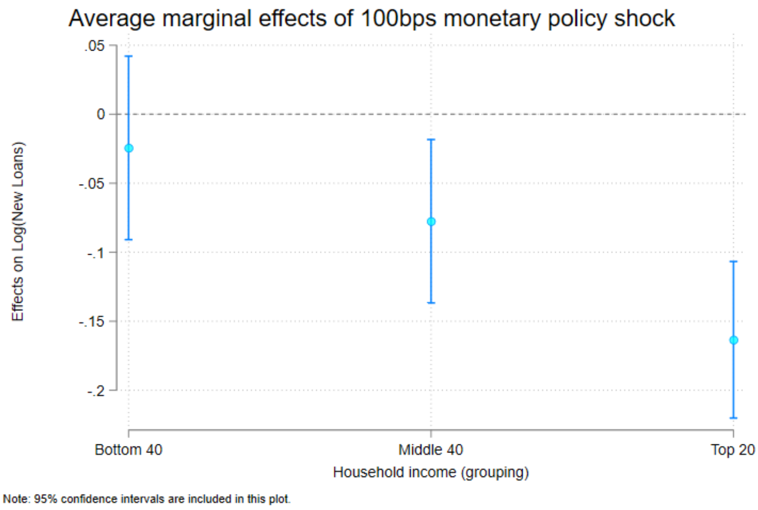


Figure A18: New mortgage loan

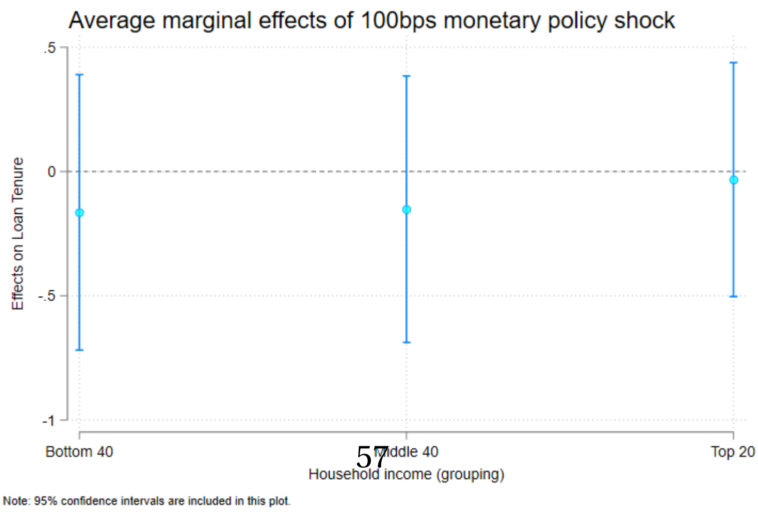


Figure A19: Loan tenure

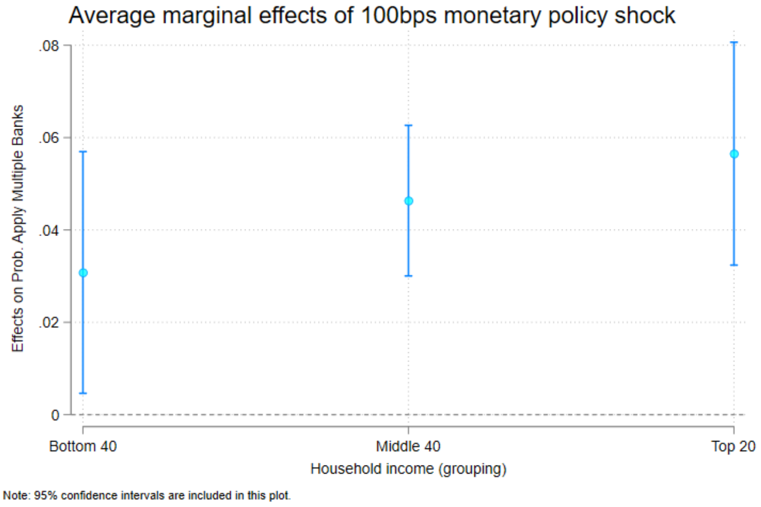


Figure A20: Probability of applying to more than one bank

D Alternative Measure of Monetary Policy

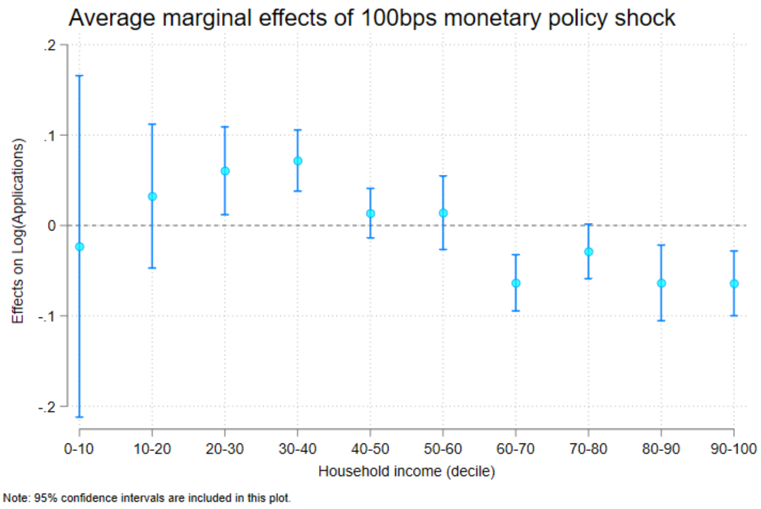


Figure A21: Values of Applications for New Mortgages

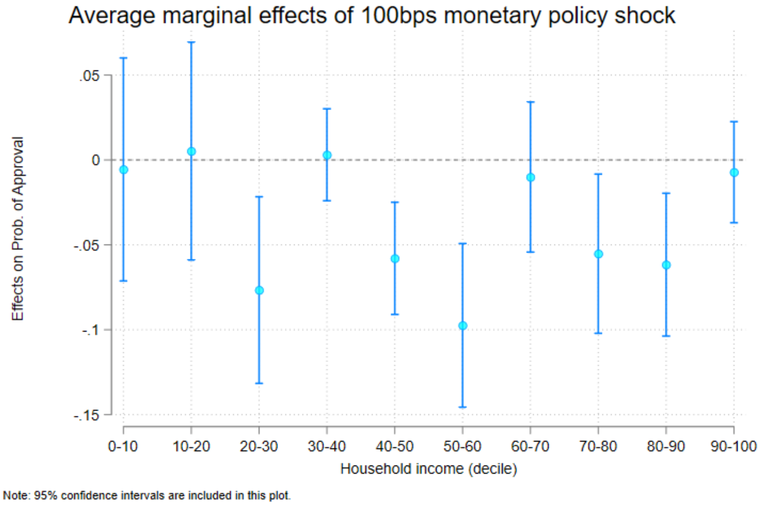


Figure A22: Probability of loan approvals

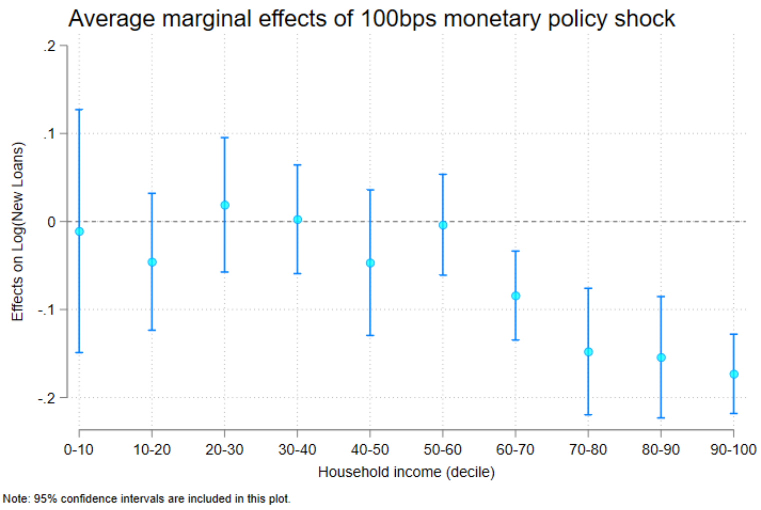


Figure A23: New mortgage loan

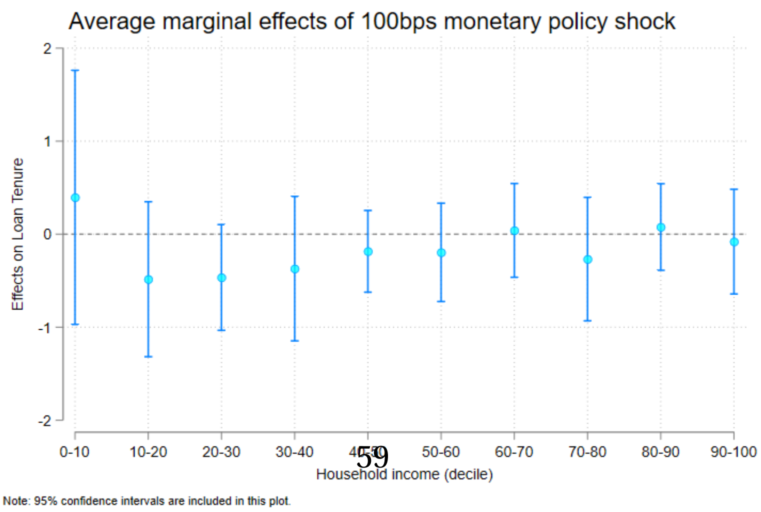


Figure A24: Loan tenure

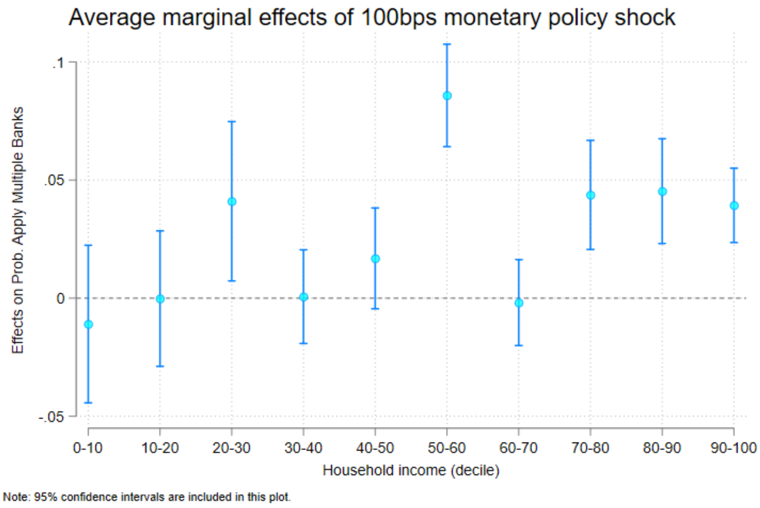


Figure A25: Probability of applying to more than one bank