The Effect of Interest Rates on the Demand for Mortgage Credit in South Africa

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Abstract

This paper uses novel and detailed mortgage origination data to estimate the interest rate elasticity of mortgage demand along the intensive margin in South Africa. I find that homebuyers increase the size of the mortgage they take out by 2.8 percent in response to a 1 percentage point decrease in the prime interest rate. Additionally, I explore the effect on housing demand since homebuyers may adjust their housing preferences when interest rates change. I find that homebuyers purchase 2.3 percent more expensive properties. The resultant impact on the degree of mortgage leverage is economically small. These findings have implications for monetary policy transmission in the housing market and financial stability more generally.

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Contents

Introduction

Buying a house is a sizeable financial commitment that generally requires a loan. This is true in both developed countries – in the U.S., Goldsmith-Pinkham and Shue (2023) show that roughly 70 percent of homebuyers finance their homes with mortgages – and in developing countries – Davids (2020) finds that 60 percent of South African homebuyers in Cape Town take out mortgages to finance their homes. Furthermore, housing also generally represents the largest asset households typically ever own.[1] Therefore, implicit in the decision of how much to spend on a home, is the choice of how much debt to incur. Yet, there is little research on the responsiveness of mortgage demand to changes in the price of debt, despite the significance of this financial undertaking.[2] In this thesis, I investigate the sensitivity of demand for mortgage credit to changes in the interest rate, providing the first estimates of the interest rate elasticity of mortgage demand for South Africa.

The size of the elasticity has important implications at both the micro and macro levels. At the micro level, the choice of debt plays a crucial role in determining the intertemporal allocation of consumer resources, which on aggregate, affects borrowing behavior and consumer spending. Consequently, the elasticity plays a significant role in the transmission of monetary policy.[3] Given that housing constitutes the largest share of the Consumer Price Index (CPI) basket, changes in the interest rate will affect inflation levels if housing demand is highly responsive to interest rate fluctuations. Measuring the elasticity is thus important for understanding the extent to which monetary policy can control inflation and ensure financial stability.[4]

Although the size of a mortgage is directly determined by the purchase price of the property, there are several other financing options that consumers consider when buying a home, for example, the term of the loan, the size of the deposit and the choice between a flexible or fixed rate. The predominant type of mortgage in South Africa is a flexible rate mortgage, where the

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[1]For example, Badarinza et al. (2019) show that in developed and emerging markets, housing constitutes the largest share of household assets, and in emerging markets, more people have real estate assets than any other financial assets. Goldsmith-Pinkham and Shue (2023) also provide evidence that housing accounts for the majority of household wealth for most American households.

[2] Badarinza et al. (2019) also show that in many cases, mortgage debt constitutes the largest share of household liabilities.

[3] See for example, Jordà et al. (2015), who show that loose monetary policy facilitates booms in mortgage lending and house price bubbles, and thus contributes to a heightened risk of financial crises.

[4] The South African Reserve Bank (SARB) follows an inflation targeting framework, using short-term interest rates as a monetary policy tool to maintain CPI at a target level of 3-6 percent.

interest on a home loan varies as a function of the prime interest rate – the national lending rate set by the central bank. Arguably, the most important factor in determining how much borrowers will have to repay over and above the principal loan amount is the mortgage interest rate, though consumers typically have less control over this element of the problem. The actual mortgage interest rate is determined by a discount rate, which refers to the borrower's concession above or below prime. While borrowers are aware of the level of prime, they are not aware of their concession at the time of the loan application, given this is only made available once the application is reviewed (since it depends on the perceived level of risk to the bank which is largely impacted by the down payment size and the borrower's credit record). As such, housing investment decisions are generally made conditional on the contemporaneous level of the prime interest rate. Of salient interest, therefore, is how sensitive consumers' demand for mortgage credit is to changes in the prime interest rate.

Interest rates play an integral role in determining house prices and demand for mortgages. A rapid surge in house prices – caused by low interest rates which drive up housing demand – can create housing bubbles which are important drivers of economic cycles.[5] In fact, Leamer (2007) goes as far as to say that housing *is* the business cycle, due to its prominent role in driving economic recessions. Mian et al. (2017) study the relationship between household debt and business cycles and find that a rise in the household debt to GDP ratio predicts a decline in economic growth and higher unemployment for 30 mostly advanced economies between 1960 and 2012.[6] Put differently, every economic recession of the last 40 years has been preceded by higher lending, specifically to the household sector. As a matter of fact, Reinhart and Rogoff (2009) claim this to be true for the last eight centuries, emphasizing the dangers of excessive debt accumulation in facilitating financial crises.

The boom in household debt can be best explained by a positive shock to the credit supply channel which is associated with low interest rate environments and riskier lending practices (Mian et al., 2017).[7] The shock is characterised by an increased willingness of lenders to

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[5] For example, Mian et al. (2017) find that a rise in household debt (stemming from low mortgage spreads) leads to a large and immediate increase in house prices.

[6] Firm debt growth is found to have a lesser impact on output. One explanation for this is that house prices are highly sensitive to household debt. The expansion of mortgage credit has a significant effect on house prices, leaving households with mortgage debt susceptible to large swings in their net worth.

[7] In their follow up paper, the same authors, Mian et al. (2020), identify that the primary mechanism through which a credit supply expansion affects GDP growth is the credit driven household demand channel. The expansion is associated with an increase in the ratios of non-tradeable to tradeable employment and output, and a relative rise in the price of non-tradeable goods, with the resultant effect of a rise in household debt to income (driven by more consumer loans and mortgage applications). During the expansion phase of the credit cycle, they find that loans to households (including mortgages) grew by 63 percent, and consumer loans by 70 percent, resulting in an average increase in the debt-to-income ratio of 0.21.

provide credit despite the borrower's financial position (Mian & Sufi, 2018). Following the initial credit expansion, their results indicate a predictable decline in household debt and a significant drop in aggregate demand and consumption. The bust phase of the cycle is also associated with forced asset sales, a rise in housing foreclosures and downward pressure on house prices which further depresses economic activity (Mian & Sufi, 2018). Therefore, the interest rate elasticity of mortgage demand is an important policy-relevant parameter, given the role that household debt plays in determining (and amplifying) economic fluctuations, and the role of credit expansion (low interest rates) in driving up household debt to income.

It is also necessary to understand how interest rates affect the degree of leverage taken out on home loans. There is evidence that low interest rates may encourage banks to give out more leverage and take on more risk (Dell'Ariccia et al., 2014). Some authors even attribute the initial housing boom in the U.S. to low down payment requirements and high mortgage approval rates (Khandani et al., 2013). Further, studies have found the severity of economic recessions to be worse in areas of higher household leverage (for example, Mian & Sufi, 2010). Due to the nature of this relationship, the International Monetary Fund (IMF) recognizes loan-to-value (LTV) restrictions as an effective macroprudential tool to mitigate the intensity of housing cycles and lessen their economic impact (Terrier et al., 2011). Because banks in South Africa offer 100 percent home loans, which leaves the credit market particularly susceptible to financial stability risks induced by leverage cycles, determining the impact of interest rates on loan leverage is especially pertinent in the local context.[8]

Despite the importance of mortgage financing conditions, estimates of the interest rate elasticity of mortgage demand are scarce.[9] This is largely due to a lack of exogenous variation in interest rates and considerable data requirements. Isolating the impact of interest rates on mortgage demand empirically, is further complicated by the issue of reverse causality, as well as confounding macroeconomic conditions that affect house prices, mortgage demand and interest rates concurrently. Only a handful of studies have managed to exploit experimental and quasi-experimental variation in interest rates to produce causal estimates of the interest rate elasticity (for example, Fuster & Zafar, 2021; DeFusco & Paciorek, 2017; Best et al., 2020). To the best of my knowledge, no relevant regulations exist for South Africa that would allow for causal work in this area.

[8] In the data I employ in this thesis, I observe the modal mortgage choice among approved mortgage applications is a 100 percent LTV.

[9] Landmark studies by DeFusco and Paciorek (2017) and Fuster and Zafar (2021) focus on the responsiveness of the mortgage size to interest rates and produce small intensive margin semi-elasticities. To the best of my knowledge, there are no existing estimates of this kind for South Africa.

In this paper, I provide the first estimates of the sensitivity of mortgage demand to interest rates for South Africa. Demand is at the intensive margin given that I observe individuals who are active participants in the property market (those with an existing mortgage), rather than prospective homebuyers. I use detailed administrative data from 2014 to 2023 covering over 140,000 approved mortgages from a large mortgage originator in South Africa. For each transaction, I observe basic loan-level information, including the loan amount, loan reason, property value, LTV ratio and interest rate quoted on the loan, as well as important borrower socioeconomic characteristics such as gender, age, income and credit score. Using this data, I estimate the extent to which individual loan size, property purchase price and the LTV ratio respond to interest rates.

I first consider the loan amount requested and the approved loan amount to present conditional correlations of the mortgage demand (semi)-elasticity which is of primary interest. My preferred specification, which includes a bank fixed effect and a province-by-year fixed effect, indicates that the average loan size increases by approximately 2.8 percent for a 1 percentage point reduction in the prime interest rate, holding constant all covariates specified in the model. I then consider changes in housing demand because the change in financing conditions may induce homebuyers to alter the size or quality of the home they are purchasing (Fuster & Zafar, 2021). I find that people spend roughly 2.3 percent more on their homes, though I cannot say whether this response is driven by a change in the quantity or quality of housing. Finally, I estimate the effect of interest rates on the LTV ratio to assess how relative changes in the loan amount and purchase price impact the degree of leverage taken on home loans, and I find that people increase their mortgage LTV by about half a percentage point.

The rich data allows for an extensive list of borrower-related controls, which not only helps isolate the effect of the interest rate, but also offers additional insights on the relative importance of borrower characteristics for mortgage outcomes. These supplementary findings indicate that women homebuyers are associated with larger mortgages, more expensive properties and lower leveraged home loans. Further, first-time homebuyers are associated with larger and higher-leveraged mortgages relative to repeat homebuyers. Additionally, I find other supporting evidence that mortgage and housing choice is correlated with the life cycle phase, highlighting the novelty of using detailed individual-level loan data.[10]

[10] I find that age, income, credit score, marital status and the number of dependents all demonstrate statistically significant relationships to the outcomes of interest that are in line with expectations.

My results contribute to and are in line with similar findings of a modest intensive margin response of mortgage borrowing and housing demand to interest rates, highlighting the important feedback channel from interest rates to house prices and household debt. These findings are insightful for macroeconomists studying the impact of credit in facilitating business cycles, and the role of monetary policy in managing these.

The rest of this paper is organized as follows. Below I review the related literature. I then describe the data and summary statistics. Thereafter, I explain the empirical methodology and discuss possible threats to identification. Lastly, I present the main results before concluding.

Literature Review

A large literature exists that examines the effect of financing conditions on credit demand. Regarding interest rates, much of the focus has been on estimating the elasticity of demand for smaller credit products like credit cards, auto loans and microfinance. This is largely due to the availability of rich microdata and variation in interest rates resulting from direct-randomisation or quasi-experimentation (for example, Gross & Souleles, 2002; Attanasio et al., 2008; Karlan & Zinman, 2008; Dehejia et al., 2012; Karlan & Zinman, 2019). However, research on the responsiveness mortgage credit demand to interest rate changes – the primary focus of this paper – is less abundant, because it requires access to detailed data on mortgage applications and interest rates, which is often difficult to obtain.

As a common alternative, others have approached this topic from a macro-level time series perspective which usually relies on vector autoregressive (VAR) and panel techniques. Kuttner (2014) evaluates several recent time series studies on the effect of interest rates on house prices, and establishes that estimates of the implied semi-elasticity range between 3 and 9. Subsequent studies have, however, pointed out that gradual time series movements in interest rates are likely confounded by other factors affecting demand, and that this method generally yields a wide range of estimates which are sensitive to the choice of analysis sample and empirical specification (Best et al., 2020). Further, VAR and panel techniques typically require stringent identification assumptions that are hard to verify (Fuster & Zafar, 2021).

Only a handful of studies examine the intensive margin of *mortgage demand* (the loan size conditional on obtaining a mortgage) to interest rates using microdata, largely because interest rate fluctuations lack exogenous variation in the cross-section.[11] The literature primarily leverages exogenous variation arising from regulations, taxes and subsidies to obtain causal estimates, though these studies are limited given that this necessitates a natural experiment framework. DeFusco and Paciorek (2017) study bunching responses to a discontinuity in interest rates created by the conforming loan limit (CLL) in the U.S., to provide novel estimates

[11] Interest rates can also affect the choice of whether or not to purchase a home, though evidence on the extensive margin of housing demand is more mixed. For example, Bhutta and Ringo (2021) find that an interest rate reduction significantly increased home buying in the U.S., estimating an extensive-margin semi-elasticity of around 20. Martins and Villanueva (2006) find similar evidence studying a change to the mortgage interest rate subsidy in Portugal. However, by contrast, Gruber et al. (2021) and Jappelli and Pistaferri (2007) both find no extensive margin demand response of home buying to interest rates in Denmark and Italy respectively. The focus of this thesis is on the intensive margin response because estimating the extensive margin elasticity requires observation of the counterfactual scenario in which housing investment does *not* occur, yet data naturally only exists for investments which *do* occur. I leave the extensive margin analysis to future research.

of the interest rate elasticity of mortgage demand.[12] They find that loan size decreases by between 1.5 to 2 percent in response to a 1 percentage point increase in the mortgage interest rate, representing a semi-elasticity of between 1.5 and 2.[13] Fuster and Zafar (2021), on the other hand, use a strategic survey to elicit respondents' willingness to pay for a home under hypothetical interest rate changes. They find a small intensive margin response of *housing demand* (the effect of interest rates on house prices) corresponding to an implied semi-elasticity of around 2.5.

Two recent papers consider the impact of an unexpected 50 basis point reduction in the effective interest rate on loans insured by the Federal Housing Finance Agency (FHA), on mortgage and housing demand. Davis et al. (2020) find that the rate cut increases the value of homes purchased by the equivalent of 3.4 percent for a 1 percentage point reduction in the interest rate, and obtain the same result when considering the mortgage size in place of the property price.[14] Bhutta and Ringo (2021) find a smaller effect of the rate cut on the intensive margins of buying and borrowing, estimating an implied semi-elasticity of around 2 for loan size and property purchase price.

By contrast, Gruber et al. (2021) find a sizeable effect – roughly a 20 percent increase – along the intensive margin of housing demand and mortgage borrowing, studying a tax reform policy in Denmark, while Jappelli and Pistaferri (2007) find no intensive margin effect on mortgage demand from a tax reform on interest rates in Italy. Barring these exceptions, the elasticities obtained in this paper fall largely within the range of estimates in the literature.

This thesis also contribute more generally to the literature on how socioeconomic borrower characteristics affect mortgage outcomes. For example, I observe meaningful differences in outcomes by gender and first-time homebuyer status. Goldsmith-Pinkham and Shue (2023) explore the gender gap in housing returns and find that women spend relatively more on the same property than men, and also sell for less. Additionally, Fang and Munneke (2020) find that women pay significantly higher mortgage rates after controlling for default risk and prepayment probabilities. To the best of my knowledge, there are no existing comparative studies relating to first-time homebuyer status.[15]

[12] Closely related, is the work of Best et al. (2020), who rely on bunching responses to interest rate discontinuities at critical thresholds of the LTV in the U.K. mortgage market, to produce estimates of the intertemporal elasticity of substitution.

[13] The authors do not consider the impact on housing demand, as I do here.

[14] They estimate a semi-elasticity of 2.5 in response to a 73-basis point reduction in interest rates, corresponding to 3.4 for a 1 percentage (100-basis) point change.

[15] Probably the most closely related work on first-time homebuyers is that of Duca et al. (2011), who find that a 1 percentage point higher LTV ratio for first-time homebuyers is associated with a proportionate increase in house

Others have looked more closely at the role of wealth and racial differences in mortgage outcomes. Bhutta et al. (2020) find evidence that borrowers associated with lower income, wealth and credit scores pay above-median rates on their home loans, while Bhutta et al. (2022) find that Black and Hispanic applicants are associated with significantly lower credit scores and higher leverage and are less likely to be pre-approved on their home loans. Moreover, Bhutta and Hizmo (2021) find that Black and Hispanic borrowers pay slightly higher interest rates and opt for lower up-front costs on their mortgages relative to White and non-Hispanic borrowers. Although I do not observe race, these findings are important to note in the South African context, characterized by highly racialized income inequality. Further exploration of how borrower characteristics (such as race, gender, and buyer status) affect mortgage outcomes would be an important avenue for future research.

price growth. They conclude that including the average LTV ratio of first-time homebuyers in models estimating U.S. house price growth yields more sensible and precisely estimated coefficients and improves model fit.

Data and Summary Statistics

A. Data description

In this paper, I use a novel dataset containing information on all approved and accepted mortgage applications obtained from a large mortgage originator in South Africa. Mortgage originators act as intermediaries between home loan applicants and banks, helping homebuyers secure competitive rates on their loans by submitting applications to multiple banks on their behalf. This service enables homebuyers to easily compare a wide range of loan options without having to physically apply for them at separate banking institutions, at no additional cost.[16]

I focus on a subset of mortgages associated with the purchase of existing homes between 2014 and 2023, thereby excluding refinanced mortgages and mortgages to finance the construction of new homes. The dataset includes extensive information on important applicant socioeconomic characteristics such as age, gender, income, credit score, education level, occupation status, buyer status and marital status, as well as all relevant loan-level information including the loan reason (i.e., existing home purchase, refinance, new construction, or renovations), loan amount, property purchase price, contemporaneous prime rate, concession rate, down payment size and the mortgage LTV). It also contains information on the bank which accepted the mortgage, as well as the date and location of the mortgage transaction.

This represents a database of just over 140,000 mortgage applications. When compared against the total number of mortgages granted in South Africa during the same period, as reported by the National Credit Regulator (NCR, 2023), this represents 9 percent of the national total. This number is however understated, given that the national count also includes mortgage refinancing and mortgages for the construction of new homes. As a result, the sample in this paper is likely closer to a 10-25 percent sample of all mortgages for the purchase of existing homes nationally. Importantly, this represents loan applications made through a mortgage originator rather than directly through a bank. However, under the reasonable assumption that consumers who use mortgage originators are similar to those who do not use them, the results can be generalized to the mortgage market as a whole.

Figure 1 displays the time-series evolution of mortgage demand and the prime interest rate over the frame of observation. Across all panels, increases in the number of mortgages, the

[16] Mortgage originators earn commission from the bank at which a home loan is secured, making it an entirely free service to the homebuyer. In South Africa, the commission is a standardized flat rate across all banks, helping to maintain the integrity of the mortgage originator as an independent agent. In other mortgage markets, the commission earned by mortgage originators can vary across banks.

average Rand value of mortgages and property prices, as well as the degree of leverage all coincide with a steep decline in interest rates, most notably observed between 2019 and 2021 in panel (d). Conversely, the sharp incline in interest rates between 2021 and 2023, is consistent with a reduction in panels (a) to (c) during the same window. The figure provides preliminary evidence of an inverse relationship between mortgage credit demand and interest rates.

A closer look at panel (a) shows that the annual number of mortgages is largely increasing from 2014 up until 2021. However, the rate of uptake seems to slow down considerably in 2020, which is consistent with dampened activity in the residential property market due to initial Covid-19 restrictions that regulated the closure of the Deed's Office and real estate agencies. At its highest point in 2021 (when prime is also at its lowest), the annual number of mortgages granted is just short of 25,000. This represents a time when borrowing would have been generally more accessible, due to historically low interest rate levels. Panel (d) shows that the prime interest rate dropped by 300 basis points on average between 2019 and 2021. Thereafter, the annual count of mortgages declines significantly, which coincides with a period of steadily rising interest rates.[17]

A similar trend is observed in panel (b), which graphs the average annual Rand value of mortgages and properties purchased over the period. Similarly, loan sizes and property prices also exhibit a steady increasing pattern up until 2021, before declining sharply thereafter. Moreover, the average mortgage LTV, which is shown in panel (c), resembles a corresponding trend, although it seems to be comparably less sensitive to interest rates changes. Between 2019 and 2023, the overall change in the LTV is a maximum of 1.5 percentage points. At its highest point in 2020, the average LTV in South Africa is approximately 93 percent.

B. Summary statistics

Table 1 provides descriptive statistics for the 142,000 approved mortgage applications originated between 2014 and 2023. Amounts are in real terms, adjusted to 2023 values, using the CPI. There is substantial heterogeneity in the mortgage size and property purchase price, which average around R1.3 million and R1.5 million respectively. These variables are characteristic of a log-normal distribution. As shown in Figure 2, the log-transformed property prices and loan sizes are approximately normally distributed, centred around 14. When exponentiated, this corresponds to roughly R1.2 million, which is close to their means. The

[17] The prime interest rate hit a record low of 7 percent in July 2020, which was maintained until November 2021. Since then, the interest rate has increased steadily by over 400-basis points between 2021 and 2023.

approximate normality in these outcome variables is important for the reliability of the OLS estimates.

In line with typical down payment requirements, the average deposit is roughly just over 10 percent of the property value, which corresponds to an average LTV ratio of about 0.9.[18] Additionally, both the concession rate and the prime interest rate vary significantly over the period, with a standard deviation of approximately 90- and 160-basis points respectively.

Regarding borrower characteristics, the average homebuyer is a male in their late thirties with a gross monthly income of R73,000. There is, however, considerable disparity in earnings, seen by the large standard deviations for gross and net income. The mean credit score is 670, and roughly two-thirds of all borrowers' credit scores fall in the range of 617 to 723. As shown in Table 2, this corresponds with a "fair" to "good" credit rating according to the origination company's credit scoring model.[19]

Moreover, there are virtually the same proportion of married buyers and joint loan applications (which makes sense given that the model type of co-mortgage is joint with a spouse) and almost 38 percent of homebuyers have at least one dependent. Further, more than half of all mortgages are issued to first-time homebuyers and nearly two-thirds of all mortgages are for properties in the Western Cape or Gauteng.

C. Difference in means

The following tables and figures take a closer look at differences in outcomes between key borrower characteristics, namely, gender and first-time homebuyer status. These are important distinctions in the context of understanding how life cycle bias influences housing investment decisions. The results are in line with expectations and show that differences are more pronounced with respect to homebuyer status than for gender.

As shown in Figure 4(a), a higher proportion of men – roughly between 55 and 60 percent – purchase homes in all years of the observation period. However, there is an incremental increase in the share of women buyers since 2014, leading to a notable convergence in

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[18] This is higher than in other contexts. For example, in the U.S., the modal degree of mortgage leverage is 80 percent (Goldsmith-Pinkham & Shue, 2023).

[19] Figure 3 depicts the share of buyers in each credit score band in each year of observation. Across the period, a very small share of homebuyers has a poor credit score rating. The modal credit rating is "good", though a larger share of mortgages were issued to fair-rated homebuyers between 2017 and 2021. Additionally, from 2019 to 2021, the lowest share of buyers with an excellent credit score is observed, which further points to the increased accessibility of mortgage borrowing during this time of low interest rates. Moreover, as the interest rate has risen steadily since 2021, so too has the share of good- and excellent-rated buyers.

homebuying between genders. Table 3 reports the differences in means between male and female homebuyers. All differences (with the exception of the deposit size) are statistically significant. Men request and are approved for bigger home loans than women and buy more expensive properties on average, although, both genders make similar down payments and take out roughly the same amount of leverage. There is also no difference in the average age of male and female homebuyers, though there is evidence of a large gender wage gap. On average, men earn a R17,000 higher gross monthly income than women, and also have considerably higher net incomes. The difference in credit scores, however, is small. Additionally, a larger share of first-time homebuyers are women compared to men (implying a larger share of male repeat homebuyers). Further, on average, a smaller percentage of women homebuyers are married and take out joint mortgages in comparison to men.

Turning now to homebuyer status, Figure 4(b) shows that first-time homebuyers consistently account for just over half of all homes purchased in each year of the observation period. Additionally, Table 4 presents the differences in means between first-time and non-first-time homebuyers. The differences are all are statistically significant and are much larger with respect to homebuyer status than they are for gender.

As expected, the average loan size of a first-time homebuyer is substantially smaller than that of a repeat homebuyer, and the disparity in the average property price is even more pronounced – the average price of a home purchased by a repeat homebuyer is approximately R640,000 more. In addition, their average down payment size is nearly three times larger, and consequently, first-time homebuyers have, on average, much higher LTV ratios and less favorable concession rates.

The average first-time homebuyer is much younger and has significantly lower average earnings (naturally, because they are in earlier career stages). They also have lower average credit scores by 23 points, placing first-time homebuyers a full credit rating below repeat homebuyers on average. This is likely owing to their lower mean earrings, generally higher debt-to-income ratios, and typically shorter credit histories. Additionally, a larger share of repeat homebuyers take out joint mortgages, are married, and have dependents compared to first-time homebuyers, which further points to the well-documented relationship between home ownership and life cycle phase, and highlights the importance of controlling for life-cycle related factors.

Methodology

This section describes the regression methodology and discusses possible threats to identification. I obtain my empirical results from four sets of analyses, where I use a simple linear regression model but focus on different outcome measures.

A. Regression methodology

I first look at how the mortgage size responds to changes in the interest rate to estimate the interest rate elasticity of mortgage demand, which is of innate interest (I also consider the approved loan amount in addition to the amount requested, to understand how the results differ for realised demand). I then focus on the property purchase price to estimate the elasticity of housing demand, since homebuyers may adjust their housing preferences when interest rates change. Finally, I consider the resultant effect on mortgage leverage.

I estimate the effect of interest rates on mortgage and housing demand with the following regression:

$$\log \mathrm{Y}_{i,t} = \beta_0 + \beta_1 prime_t + \beta_2 X_i + \beta_3 Z_t + \gamma_i + \rho_t + e_{i,t} \ldots (1)$$

I estimate Eq. (1) as an ordinary least squares (OLS) regression and include fixed effects (FE) in various specifications outlined below. Standard errors are clustered at the province level to account for within-province outcomes which are likely to be correlated. Demand is at the intensive margin since I observe individuals who are active participants in the property market.[20]

I consider three versions of Eq. (1), where $\mathrm{Y}_{i,t}$ represents inflation-adjusted values of (i) the loan amount requested, (ii) the approved loan amount, and (iii) the property purchase price on mortgage i at time t. I take logarithms of $\mathrm{Y}_{i,t}$ to observe the percentage change in outcomes. $Prime_t$ represents the prime interest rate at the time of the mortgage origination, and in all cases, β_1 is the coefficient of primary interest, which captures the effect of a level change in the interest rate (representing the semi-elasticity) conditional on the controls I employ.

X_i is a vector of time-invariant mortgage and borrower characteristics on mortgage i, that includes the gender, age, homebuyer status, marital status, and number of dependents of the

[20] In other words, I observe how much more or less mortgage credit borrowers demand (i.e., the loan amount) as a result of the interest rate change, and not a change in the number of mortgages issued (which is the extensive margin).

borrower, as well as their real gross monthly income and credit score rating.[21] Age and gross income are split into quintiles to capture non-linearities in their association with the outcomes, where for both variables, the base group is the lowest quintile. The credit rating is defined according to the origination company's scoring model (outlined in Table 2), where the reference category is "poor".[22] Additionally, X_i includes a dummy variable indicating whether a co-applicant is on the mortgage, and a bank fixed effect to capture time-invariant heterogeneity in mortgage approval decisions (for example, accounting for varying risk appetites in bank lending practices).

Z_t is a vector of quarterly-measured macroeconomic control variables at time t (which I obtain from the SARB online statistical query). This includes the residential property price index (RPPI), the real effective exchange rate (REER), the CPI, the log of GDP and the unemployment rate.[23] I also include a Covid dummy to account for the initial hard lockdown period in South Africa, during which home-buying-related activities were halted. This variable takes a 1 if the transaction occurred within a 6-month period starting 1 April 2020 and 0 otherwise.

γ_i is a province fixed effect, which controls for the province in which mortgage i is originated. ρ_t is a year fixed effect, controlling for the year in which the mortgage is originated. Together, these fixed effects control for unobserved location-specific and time-varying heterogeneity.

In addition, I consider the impact of an interest rate change on the mortgage LTV, which measures the ratio of the mortgage amount to the property value (the purchase price). The LTV represents the degree of leverage (i.e., how much of the property is financed with credit) and therefore indicates the level of risk of the loan.

I estimate the effect of interest rates on loan leverage with the following regression:

$$\mathrm{LTV}_{i,t} = \beta_0 + \beta_1 prime_t + \beta_2 X_i + \beta_3 Z_t + \gamma_i + \rho_t + e_{i,t} \dots (2)$$

[21] I chose these variables in line with other studies. For instance, Fuster and Zafar (2021) condition on borrower age, gender, marital status, income and credit score (though they only observe bracket responses for the latter two, not point estimates). Best et al. (2020) observe age, income and first-time homebuyer status (but focus on a sample of refinancers). Davis et al. (2020) condition on credit score, income, race and gender. Moreover, Tan (2012), controls for marital status and the presence of children, noting the relationship between lifecycle phase and homeownership preferences.

[22] Very few observations had a "very poor" rating (a credit score below 500) and were therefore omitted.

[23] These are important variables used in the literature examining the link between credit, house prices, and the macroeconomy (see for example, Goodhart and Hofmann (2008)).

Eq. (2) is identical to Eq. (1), except that the dependent variable is the LTV ratio, measured as the percentage point change in the LTV. A positive β_1 coefficient can be driven either by a larger increase in the loan amount relative to the property value, or a decrease in the property value relative to the loan amount. A proportional change in the mortgage amount and property value would leave the LTV ratio unchanged.

I estimate several variants of the above equations which are presented in Tables 5 to 8. Table 5 contains the results of estimating Eq. (1) with the loan amount requested as the outcome variable, Table 6 with the approved loan amount and Table 7 with the property purchase price. Finally, Table 8 contains the results of Eq. (2) with the LTV as the outcome variable. All tables follow the same construction, where each column shows different sets of controls.

Column (1) presents the simple OLS model without any fixed effects or macroeconomic controls. Column (2) includes the bank fixed effect. I add a province fixed effect in column (3), to control for unobservable province-level characteristics that are constant over time. The macroeconomic controls are only introduced from column (4) onwards. The objective of the quarterly fixed effect in column (5) is to control for unobservable characteristics that are the same for all individuals within a given quarter. In column (6) I replace this with a year fixed effect, which serves a similar purpose, conditioning on year. Finally, in column (7), I interact the province and year fixed effects to control for unobserved time trends within a province. In this instance, β_1 measures the interest rate effect among housing transactions originating in the same bank, in the same province and year.

B. Threats to identification

As established, obtaining causal estimates for the interest rate demand elasticity requires exogenous variation in interest rates, making it otherwise impossible to isolate the direction of causality between interest rates, house prices and mortgage demand. In South Africa, the central bank deliberately adjusts the repo rate (which directly impacts the level of the prime interest rate) to control inflation and maintain price stability, making any variation in the prime interest rate, by definition, endogenous.

In other contexts, some papers have managed to exploit specific regulatory features that introduce a source of exogenous variation in interest rates. For example, the CLL in the U.S. (DeFusco & Paciorek, 2017)[24], or the notched interest rate schedule in the U.K. (Best et al.,

[24] Loans exceeding the CLL – which is set by the FHA – are charged comparably higher interest rates than loans below the limit. DeFusco and Paciorek (2017) observe a bunching of borrowers around the CLL, creating a nonlinearity in loan sizes which they use to back out causal estimates of the mortgage demand elasticity. Their

2020)[25]. Unfortunately, South Africa lacks any kind of regulatory features which might allow for a quasi-experimental framework. However, although the estimates in this paper have no causal interpretation, the vast number of controls makes for highly robust conditional correlations.

Nevertheless, there are obvious concerns with this approach, despite measures to tighten the *ceteris paribus* conditions. The fundamental issue in obtaining precise estimates of the interest-rate elasticity, is managing the degree of bias introduced by confounding omitted variables. My results speak to the expectation of mortgage and housing demand conditional on *observed* variation in the interest rate and the employed controls. However, since I am unable to resolve *all* counterfactuals arising from omitted or endogenously determined variables, this warrants a discussion of some limitations, which are organized as three main threats to identification.

i. Cross-sectional threats

Cross-sectional threats include any source of unexplained variation in the cross-section that may confound the relationship between mortgage demand, housing demand and interest rates. One example at the individual level, is borrower characteristics, which are known to influence the types of homes people buy and the amount of mortgage credit they require. The fact that I control for an array of socioeconomic borrower characteristics reduces the risk of this element as a source of bias. However, I am unable to control for unobserved property quality which can introduce bias if homebuyers adjust the quality of their homes when interest rates change.

Another potential concern arises from the strong correlation between property values and their geographic location. Although the province fixed effect eliminates correlated omitted variables that are constant within each province, any variation at the sub-province level – which may be driven by disparities at the municipal-, city- or suburb-level[26] – remains a potential source of unexplained, within-province heterogeneity.

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identification relies on the fact that the jump in interest rates induces borrowers who would otherwise take out jumbo loans (above the CLL) to instead bunch right at the limit.

[25] U.K. banks offer notched mortgage interest rate schedules which increase as a stepwise function of the degree of leverage on the home loan at the time of origination. Best et al. (2020) find evidence that borrowers reduce their leverage to a level below the notch to avoid higher interest rates, creating bunching below critical LTV thresholds. In a similar vein to DeFusco and Paciorek (2017), they use this bunching response to obtain causal estimates of the intertemporal elasticity of substitution.

[26] For example, average property prices in Cape Town are significantly higher relative to the Western Cape. In 2023, the main contributor to the national RPPI rate was the Western Cape, with the highest year-on-year increase in the provincial level RPPI (5.5 percent), driven primarily by the City of Cape Town having the highest metropolitan level inflation (Statistics South Africa, 2024).

ii. Time-series threats

Time-series variables that are correlated with both the interest rate and mortgage or housing demand will produce biased estimates of the interest rate elasticity if unexplained. Of primary concern, are macroeconomic variables that cause a spurious correlation between interest rates, house prices, and ultimately the demand for housing, since housing-investment decisions are strongly determined by economic activity. However, the fact that I include macroeconomic controls alleviates the concern of endogeneity arising from omitted variables. Further, I also account for trending patterns in these variables with time fixed effects.

The quarterly fixed effect accounts for seasonal fluctuations over and above what might be captured by the macro-economic controls, while the year fixed effect accounts for more aggregate variation in economic activity. It is therefore unlikely that my estimates are influenced by omitted time-series factors, although, I am unable to rule out that simultaneity bias induced by the bidirectional flow of causality from house prices to interest rates does not compromise my overall findings.

iii. Panel threats

Housing demand may be influenced not only by time-invariant differences across provinces, but also by time-varying differences (i.e., local time trends in property prices).[27] This can be thought of as panel issue, since property demand varies disproportionately across provinces over time as a result. I take care of this concern with the interaction between the province and year fixed effects, which acts as an additional robustness to account for time trending differences in property demand across the country.

[27] See Figure 5, in which I graph the annual average RPPI in each province of South Africa. It is evident that the Western Cape and Northern Cape display higher than average property price growth across the period.

Results

In this section, I begin by describing the results of estimating Eq. (1) with the loan amount *requested* as the dependent variable. The regression results are presented in Table 5. Table 6 contains the parallel estimates from using the *approved* loan amount as the outcome of Eq. (1). I then examine the effect of interest rates on housing demand in Table 7, i.e. Eq. (1) with the property value as the outcome variable. For clarity, I discuss these tables jointly since the estimated coefficients on prime (the interest rate semi-elasticities) are immediately comparable. They represent the percentage change in the size of the mortgage and the property value, respectively, in response to a 1 percentage point – 100-basis point – decrease in the interest rate. The tables follow the same construction with columns (1) to (7) showcasing different sets of controls. Across all tables, all specifications illustrate a robust negative relationship to interest rates at the 0.01 level.

A. Interest rates

In column (1) of Table 5, without any fixed effects, I find that a 1 percentage point reduction in the interest rate is associated with an 8 percent increase in the size of the mortgage requested, holding all covariates specified in the model constant. This corresponds to an interest rate semi-elasticity of mortgage demand of 8, though I explore how much of this effect can be attributed to other factors, by introducing more detailed controls.

In column (2) I include a bank fixed effect and find little impact on the magnitude of the semi-elasticity. This is true also with respect to the province fixed effect in column (3), which indicates that unobserved between-bank and between-province variation does not explain the relationship between interest rates and the amount of mortgage credit that borrowers request.

On the other hand, the inclusion of macro-level control variables in column (4) reduces the semi-elasticity by 18 percent and improves the model fit. This provides evidence that macroeconomic conditions influence housing investment decisions through their correlation with the interest rate and credit demand.[28] There is, however, minimal change when accounting for quarterly-level differences in column (5), which suggests that the relationship between

[28] Similarly large changes in the coefficients on gender, first-time homebuyer status, marital status, age and the Covid dummy are also observed in column (4). Most notably, the covid lockdown variable flips from -0.025 to 0.093 and is highly significant (before adding the year fixed effect in column (6), which suggests that the lockdown variable has no additional explanatory power over and above the variation accounted for by including of a year fixed effect, which already internalises annual, unobserved heterogeneity.

interest rates and mortgage demand is not strongly correlated with unobserved seasonal variation, over and above controlling for macroeconomic conditions.

By contrast, the inclusion of a year fixed effect in column (6) substantially reduces the interest rate semi-elasticity of mortgage demand to 2.8. That is, allowing for annual temporal changes, a 1 percentage point decrease in the prime interest rate is associated with an increase in mortgage credit demand of 2.8 percent, holding all specified covariates constant. This effect is 58 percent smaller than in an identical specification without a year fixed effect, implying that the relationship is more sensitive to aggregate (yearly) temporal changes than short-term (quarterly) fluctuations.[29] Encouragingly, the estimate is practically the same in column (7), my preferred specification, where I interact the province and year fixed effects to concurrently control for unobserved location-specific and time-specific heterogeneity.

The same appears to be true with respect to realized mortgage demand (the approved mortgage amount), with practically identical coefficients on the prime interest rate in Table 6, which follow the same trajectory across columns as in the previous table. The preferred specifications in Tables 5 and 6 both explain approximately 55 percent of the variation in mortgage size and produce estimates of the interest rate semi-elasticity which are broadly in line with those obtained in recent literature. These findings imply that, in addition to borrowers requesting larger home loans when interest rates decrease, banks are also willing to lend more.

These estimates are economically quite small. During the observation period, the average prime interest rate is approximately 9 percent. As such, a one percentage point decrease from that mean (an 11 percent decrease) implies a 2.8 percent increase in the average size of a mortgage. One possible explanation for this modest behavioural response could be other binding financial constraints such as down payment requirements.[30] If homebuyers are liquidity constrained, lower interest rates may not be sufficient motivation to take out larger mortgages. On the other hand, even if homebuyers could afford more expensive houses and larger mortgages for the same monthly repayment (as a result of the lower interest rate), debt-averse individuals may instead prefer to opt for a lower monthly mortgage payment. Another reason

[29] Some of the macro variables have small but significant effects on loan size (and the property price) in column (4). The magnitude of the coefficients hardly change with the quarterly fixed effect (implying that the macroeconomic controls already explain unobserved quarterly variation). However, many of these controls become insignificant with the year fixed effect (except the residential property price index and the log of GDP which have small effects). This provides further evidence that the yearly fixed effect accounts for most of the unobserved temporal variation in loan applications and property prices initially explained by the macroeconomic variables.

[30] Fuster and Zafar (2021) show that households are much more sensitive to a change in the required down payment size than they are to interest rate changes.

why homebuyers may be less inclined to adjust their mortgage size than otherwise expected, is the long-term nature of mortgage debt. The predominant type of mortgage in South Africa is a flexible rate mortgage, usually taken over 20 or 30 years. As such, the decision of how much mortgage debt to incur may be less influenced by short-term fluctuations in interest rates, implying a potentially larger long-run behavioural response.[31]

Turning to Table 7, property values also exhibit a consistent negative relationship to interest rates that is highly significant, and there is a similar pattern of decreasing coefficient effects across specifications. In the baseline case without any fixed effects, the associated increase in property spend, for a 1 percentage point decrease in the interest rate, is approximately 7.5 percent, holding all specified controls constant. Conditional on mortgage applications being approved by the same bank, the coefficient on prime in column (2) is again similar, as it is in column (3), accounting for level differences in property prices across provinces. Moreover, controlling for macroeconomic conditions and quarterly-level time variation in columns (4) and (5) respectively, moderately reduces the interest rate effect.

As before, the most notable difference is observed in column (6) with the inclusion of a year fixed effect. Among housing transactions occurring within the same year, I find that a 1 percentage point decrease in the prime interest rate is associated with a 2.3 percent increase in the value of homes purchased, holding all specified covariates constant. No change is observed when accounting for trending differences within a province in column (7). Despite the lack of plausibly exogenous variation in the interest rate variable, it is reassuring that the nature and strength of these relationships remains consistent with tighter *ceteris paribus* restrictions.

The result implies a semi-elasticity of housing demand along the intensive margin to interest rates of roughly 2.3, which is smaller than the estimate for mortgage demand by half a percentage point. Although these estimates are within the range of those in the literature, others find the same interest rate elasticities for mortgage and housing demand (such as, Davis et al., 2020; Bhutta & Ringo, 2021).[32] The difference in findings may be explained by the fact that in South Africa, because there are no restrictions on the mortgage LTV, borrowers are free to increase their mortgage credit more, relative to the property value (which would result in higher leverage); whereas in the U.S. for example, most homebuyers choose to maintain an LTV of

[31] For instance, Karlan and Zinman (2019) measure much more elastic demand responses to interest rate changes over longer horizons.
[32] Table 9 compares estimates of the mortgage demand and housing demand semi-elasticities obtained in this paper to those in other papers.

exactly 80 percent, because exceeding this degree of leverage typically requires the purchase of private mortgage insurance (DeFusco & Paciorek, 2017).

Indeed, Table 8 provides supporting evidence that borrowers do take out higher leveraged home loans in response to an interest rate reduction. The results are obtained from estimating Eq. (2), which measures the percentage point change in the mortgage LTV. Across all columns (with the exceptions of columns (4) and (5)), I observe half a percentage point increase in the LTV ratio for a 1 percentage point decrease in the interest rate, holding constant all specified controls. Although the coefficients are statistically different from zero at the 0.01 level, the effect is economically small. This result can be explained by the fact that the LTV is not affected by interest rates directly, but through the resultant impact on mortgage and housing demand.

B. Borrower characteristics

Since all of the specifications include detailed controls for socioeconomic characteristics of the borrower, my results also speak to the correlation between borrower characteristics and mortgage outcomes. For simplicity, I discuss the tables jointly, referring specifically to column (7), the preferred specification.

Considering the effect of gender, women are associated with larger home loans relative to men, and also purchase more expensive properties, all else equal. This outcome is in line with that of Goldsmith-Pinkham and Shue (2023), who find that women in the U.S. spend approximately 2 percent more on the same property than men do, after controlling for market timing.[33] I find the conditional correlation on gender to be about 2.5 times bigger with respect to property prices than it is with respect to the loan amount. That women spend more on properties relative to the loan amount they receive, explains why women are associated with 1 percentage point lower LTV ratios compared to men, all else equal. The statistically different LTVs between men and women is an important finding in the context of gendered differences in housing outcomes, which Goldsmith-Pinkham and Shue (2023) provide evidence of assuming a *uniform* LTV of 80 percent for men and women. Accounting for gendered differences in leverage could potentially alter these findings.

As far as the effect of age, only applicants in the oldest quintile demonstrate a significant negative relationship to the loan size. However, this result doesn't appear to be driven by the nature of the properties they purchase, since there is no significant relationship between age

[33] The disparity is attributable to the finding that women tend to negotiate smaller discounts relative to the list price and experience more negative negotiation-related outcomes (Goldsmith-Pinkham & Shue, 2023).

and the price of the home after controlling for other borrower characteristics. Rather, one possible explanation is that older people tend to have higher levels of savings and are generally more risk averse.[34] The finding that older people do not purchase homes of a significantly different value, but are associated with having smaller loans, could imply that older buyers make larger down payments on their homes. This intuition is further substantiated by the negative relationship observed between age and the LTV, which is statistically significant across all quintiles and strengthens as a function of age.

I also find that the mortgage amount, the value of the home and the degree of mortgage leverage, are all increasing functions of earnings, all other things being equal. This is evidenced by the increasing magnitude of the coefficients across gross income quintiles, which are statistically significant at the 0.01 level. Most notably, homebuyers in the top income bracket, are associated with home loans (and properties) worth more than double that of homebuyers in the lowest income bracket. The result is as expected, given that gross income is a direct input in determining home loan affordability, and more generally, because wealthier individuals can afford higher monthly repayments and tend to be less risk averse.[35]

The relationship of mortgage size to credit score also displays a positive association that is largely significant. This is true more so in respect of the approved amount – which has larger coefficients that are more significant – than the amount requested, suggesting that credit scores are potentially more important for banks determining the approval of a mortgage, than for the applicants requesting them. Additionally, credit score status is also positively related to the property value but is largely insignificant for the degree of leverage on the home loan.

In a similar vein, first-time homebuyers are associated with 3 percent larger mortgages relative to repeat homebuyers, at the 0.05 level. They also tend to buy less expensive properties, although this difference is not statistically significant when controlling for lifecycle-related factors, like age, income, credit score, et cetera. As would be expected, first-time homebuyers are also associated with having considerably higher leveraged loans by comparison – I find that they have 4.5 percentage point higher LTV ratios than repeat homebuyers, holding all covariates constant. If this result is not driven by the purchase of statistically lower-value homes, it could suggest that first-time homebuyers make smaller down payments, consistent with the notion that they have lower levels of savings.

[34] For example, Barsky et al. (1997) find that the elderly hold a greater proportion of their total assets in the form of savings (as opposed to stocks and bonds), due to exhibiting greater levels of risk aversion. Further, Riley and Chow (1992), also find that risk aversion increases with age for people over 65.

[35] For example, Riley and Chow (1992) show that risk aversion decreases as a function of income, and most significantly for the very wealthy.

The lack of statistical significance on the co-applicant variable, after considering other socioeconomic characteristics, could be explained by its high correlation with marital status.[36] Indeed, I find that marital status is significantly and positively associated with both the size of the mortgage and the purchase price of the property, holding all else constant. I also find a negative correlation with the size of the LTV, implying that married and divorced homebuyers are associated with lower leveraged loans than single homebuyers. The result appears to be driven by higher property values relative to the loan amount.

Contrary to expectations that housing consumption increases with household size (Tan, 2012), I find that homebuyers with 2 or more dependents (a measure of family size) are associated with the purchase of less expensive properties. However, they are also associated with smaller, but higher leveraged home loans, which may be attributed to tighter budget constraints due to the increased financial responsibility of having more dependents. The result appears to be true only for larger families, since the effect is not significant for applicants with only 1 dependent across all outcomes. By and large, these findings show that housing investment decisions and mortgage outcomes are strongly influenced by life-cycle related factors.

[36] In the dataset, the majority of co-mortgages are of the type “joint with a spouse”.

Conclusion

In this paper, I use detailed administrative, loan-level data in order to estimate the interest rate semi-elasticity of mortgage demand along the intensive margin in South Africa. My estimates imply that borrowers increase the size of their mortgage by about 2.8 percent, in response to a 1 percentage point decrease in the prime interest rate. Moreover, I also investigate the effect of interest rates on housing demand, by looking at the effect of an interest rate reduction on the value of homes purchased, and I find that borrowers spend approximately 2.3 percent more on their homes. The resultant effect on the degree of mortgage leverage is positive, but economically small.

My results, though not causal, are within the range of recent estimates in the literature. Overall, these findings contribute to the consensus that the intensive margin responsiveness of mortgage borrowing and housing demand to interest rates is modest (especially in comparison to estimates of the extensive-margin response). This modest response to interest rate changes may be explained by other binding financial constraints, the long-term nature of mortgage debt or behavioural biases such as debt aversion. The findings are important for policymakers and macroeconomists studying the role of monetary policy in facilitating housing market dynamics, and financial stability more generally. For instance, loose monetary policy may not be as effective in stimulating mortgage borrowing and housing demand than in other contexts, since these are not highly responsive to interest rate changes (at least not along the intensive margin). Given that housing carries the largest weight in the CPI basket, this raises questions about the effectiveness of monetary policy on inflation stabilization.

This points to some important avenues for further research. Firstly, my results do not speak to the possible effect of interest rates on the extensive-margin decision of whether or not to buy a home, which is important for understanding the full effect of interest rates on mortgage and housing demand, and naturally also for monetary policy transmission. Secondly, while my supplementary findings shed some light on the relative importance of borrower characteristics for mortgage outcomes, these results are only preliminary, and more work can be done to fully investigate sources of heterogeneity in elasticities among different borrowers.

References

Attanasio, O. P., Koujianou Goldberg, P., & Kyriazidou, E. (2008). Credit constraints in the market for consumer durables: Evidence from micro data on car loans. *International Economic Review, 49*(2), 401–436. https://doi.org/10.1111/j.1468-2354.2008.00485.x

Badarinza, C., Balasubramaniam, V., & Ramadorai, T. (2019). The household finance landscape in emerging economies. *Annual Review of Financial Economics, 11*(1), 109–129. https://doi.org/10.1146/annurev-financial-110118-123106

Barsky, R. B., Juster, F. T., Kimball, M. S., & Shapiro, M. D. (1997). Preference parameters and behavioral heterogeneity: An experimental approach in the health and retirement study. *The Quarterly Journal of Economics, 112*(2), 537–579. https://doi.org/10.1162/003355397555280

Best, M. C., Cloyne, J. S., Ilzetzki, E., & Kleven, H. J. (2020). Estimating the elasticity of intertemporal substitution using mortgage notches. *The Review of Economic Studies, 87*(2), 656–690. https://doi.org/10.1093/restud/rdz025

Bhutta, N., Fuster, A., & Hizmo, A. (2020). *Paying too much? Price dispersion in the US mortgage market* (Working Paper No. 2020-062). Federal Reserve Board. https://doi.org/10.17016/FEDS.2020.062

Bhutta, N., & Hizmo, A. (2021). Do minorities pay more for mortgages? *The Review of Financial Studies, 34*(2), 763–789. https://doi.org/10.1093/rfs/hhaa047

Bhutta, N., Hizmo, A., & Ringo, D. (2022). *How much does racial bias affect mortgage lending? Evidence from human and algorithmic credit decisions* (Working Paper No. 2020-067). Federal Reserve Board. https://doi.org/10.17016/FEDS.2022.067

Bhutta, N., & Ringo, D. (2021). The effect of interest rates on home buying: Evidence from a shock to mortgage insurance premiums. *Journal of Monetary Economics, 118*, 195–211. https://doi.org/10.1016/j.jmoneco.2020.10.001

Davids, A. (2020). *The cape of good homes: exchange rate depreciations, foreign demand and house prices.* https://dx.doi.org/10.2139/ssrn.3349815

Davis, M. A., Oliner, S. D., Peter, T. J., & Pinto, E. J. (2020). The impact of federal housing policy on housing demand and homeownership: Evidence from a quasi-experiment. *Journal of Housing Economics, 48*, 101670. https://doi.org/10.1016/j.jhe.2020.101670

DeFusco, A. A., & Paciorek, A. (2017). The interest rate elasticity of mortgage demand: Evidence from bunching at the conforming loan limit. *American Economic Journal: Economic Policy, 9*(1), 210–240. https://doi.org/10.1257/pol.20140108

Dehejia, R., Montgomery, H., & Morduch, J. (2012). Do interest rates matter? Credit demand in the Dhaka slums. *Journal of Development Economics, 97*(2), 437–449. https://doi.org/10.1016/j.jdeveco.2011.06.001

Dell'Ariccia, G., Laeven, L., & Marquez, R. (2014). Real interest rates, leverage, and bank risk-taking. *Journal of Economic Theory, 149*, 65–99. https://doi.org/10.1016/j.jet.2013.06.002

Duca, J. V., Muellbauer, J., & Murphy, A. (2011). House prices and credit constraints: Making sense of the US experience. *The Economic Journal, 121*(552), 533–551. https://doi.org/10.1111/j.1468-0297.2011.02424.x

Fang, L., & Munneke, H. J. (2020). Gender equality in mortgage lending. *Real Estate Economics, 48*(4), 957–1003. https://doi.org/10.1111/1540-6229.12198

Fuster, A., & Zafar, B. (2021). The sensitivity of housing demand to financing conditions: Evidence from a survey. *American Economic Journal: Economic Policy, 13*(1), 231–265. https://doi.org/10.1257/pol.20150337

Goldsmith-Pinkham, P., & Shue, K. (2023). The gender gap in housing returns. *The Journal of Finance, 78*(2), 1097–1145. https://doi.org/10.1111/jofi.13212

Goodhart, C., & Hofmann, B. (2008). House prices, money, credit, and the macroeconomy. *Oxford Review of Economic Policy, 24*(1), 180–205. https://doi.org/10.1093/oxrep/grn009

Gross, D. B., & Souleles, N. S. (2002). Do liquidity constraints and interest rates matter for consumer behavior? Evidence from credit card data. *The Quarterly Journal of Economics, 117*(1), 149–185. https://doi.org/10.1162/003355302753399472

Gruber, J., Jensen, A., & Kleven, H. (2021). Do people respond to the mortgage interest deduction? Quasi-experimental evidence from Denmark. *American Economic Journal: Economic Policy, 13*(2), 273–303. https://doi.org/10.1257/pol.20170366

Jappelli, T., & Pistaferri, L. (2007). Do people respond to tax incentives? An analysis of the Italian reform of the deductibility of home mortgage interests. *European Economic Review, 51*(2), 247–271. https://doi.org/10.1016/j.euroecorev.2006.04.003

Jordà, Ò, Schularick, M., & Taylor, A. M. (2015). Betting the house. *Journal of International Economics, 96*(Suppl. 1), S2–S18. https://doi.org/10.1016/j.jinteco.2014.12.011

Karlan, D. S., & Zinman, J. (2008). Credit elasticities in less-developed economies: Implications for microfinance. *American Economic Review, 98*(3), 1040–1068. https://doi.org/10.1257/aer.98.3.1040

Karlan, D. S., & Zinman, J. (2019). Long-run price elasticities of demand for credit: Evidence from a countrywide field experiment in Mexico. *The Review of Economic Studies, 86*(4), 1704–1746. https://doi.org/10.1093/restud/rdy046

Khandani, A. E., Lo, A. W., & Merton, R. C. (2013). Systemic risk and the refinancing ratchet effect. *Journal of Financial Economics, 108*(1), 29–45. https://doi.org/10.1016/j.jfineco.2012.10.007

Kuttner, K. N. (2014). Low interest rates and housing bubbles: Still no smoking gun. In D. D. Evanoff, C. Holthausen, G. G. Kaufman & M. Kremer (Eds.), *The role of central banks in financial stability: How has it changed?* (Vol. 30., pp. 159–185). World Scientific Publishing Co. Pte. Ltd. https://doi.org/10.1142/8720

Leamer, E. E. (2007). *Housing is the Business Cycle* (Working Paper No. 13428). National Bureau of Economic Research. https://doi.org/10.3386/w13428

Martins, N. C., & Villanueva, E. (2006). The impact of mortgage interest-rate subsidies on household borrowing. *Journal of Public Economics, 90*(8-9), 1601–1623. https://doi.org/10.1016/j.jpubeco.2005.09.007

Mian, A., & Sufi, A. (2010). *Household Leverage and the Recession of 2007 to 2009* (Working Paper No. 15896). National Bureau of Economic Research. https://doi.org/10.3386/w15896

Mian, A., & Sufi, A. (2018). Finance and business cycles: The credit-driven household demand channel. *Journal of Economic Perspectives, 32*(3), 31–58. https://doi.org/10.1257/jep.32.3.31

Mian, A., Sufi, A., & Verner, E. (2017). Household debt and business cycles worldwide. *The Quarterly Journal of Economics, 132*(4), 1755–1817. https://doi.org/10.1093/qje/qjx017

Mian, A., Sufi, A., & Verner, E. (2020). How does credit supply expansion affect the real economy? The productive capacity and household demand channels. *The Journal of Finance, 75*(2), 949–994. https://doi.org/10.1111/jofi.12869

National Credit Regulator. (2023). *Consumer credit market report: Fourth quarter, December 2023.* https://www.ncr.org.za/documents/CCMR/CCMR%202023Q4.pdf

Reinhart, C. M., & Rogoff, K. S. (2009). *This time is different: Eight centuries of financial folly*. Princeton University Press. https://doi.org/10.2307/j.ctvcm4gqx

Riley, W. B., & Chow, K. V. (1992). Asset allocation and individual risk aversion. *Financial Analysts Journal, 48*(6), 32–37. https://doi.org/10.2469/faj.v48.n6.32

Statistics South Africa. CPI_COICOP_5 [Data set]. Version 1.2.0. Pretoria: Statistics South Africa [producer], Unreleased. Johannesburg: EconData [distributor], 2024.

Statistics South Africa. (2024). *Statistical release. Residential property price index: January 2024.* https://www.statssa.gov.za/publications/P0160/P0160January2024.pdf

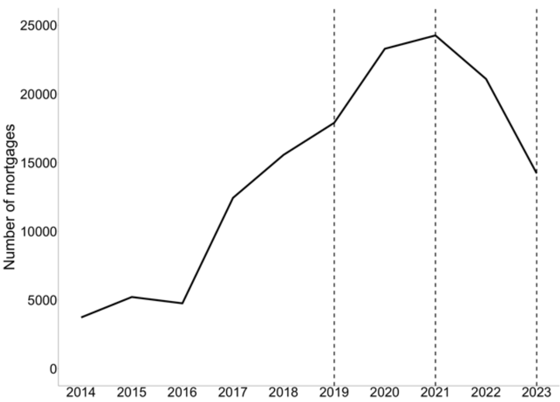
Tan, T. (2012). Meeting first-time buyers' housing needs and preferences in greater Kuala Lumpur. *Cities, 29*(6), 389–396. https://doi.org/10.1016/j.cities.2011.11.016

Terrier, M. G., Valdes, M. R., Mora, M. C., Chan-Lau, M. J., Valdovinos, C. F., Garcia-Escribano, M. M., Medeiros, M. C., Tang, M., Martin, M. V., & Walker, W. C. (2011). *Policy instruments to lean against the wind in Latin America* (Working Paper No. 2011-159). International Monetary Fund. https://www.imf.org/external/pubs/ft/wp/2011/wp11159.pd

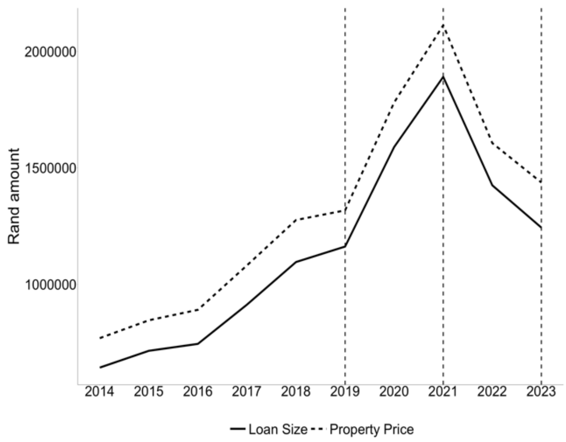
Figures

Figure 1: Time-series evolution of mortgages and the prime interest rate

This figure illustrates the time-series evolution of (a) the number of mortgages, (b) the average Rand value of mortgages and property prices, (c) the average mortgage LTV ratio and (d) the prime interest rate between 2014 and 2023. There are 3 dashed vertical lines, representing periods of a sharp decline and incline in the interest rate between 2019 and 2021, and 2021 and 2023, respectively.

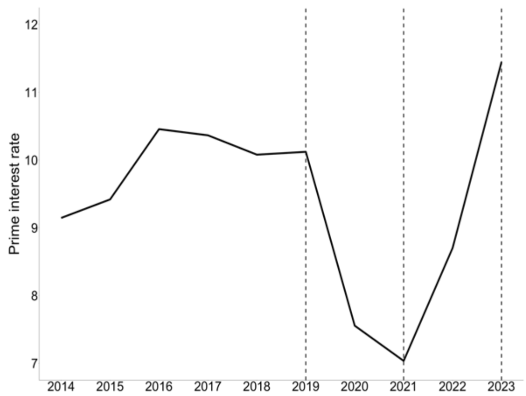


(a) Number of mortgages



(b) Rand value of mortgages and properties

(c) Mortgage LTV ratio



(d) Prime interest rate

Figure 2: Density plot of main outcome variables

This figure illustrates the density plot of the log-transformed values of loan size and property purchase price.

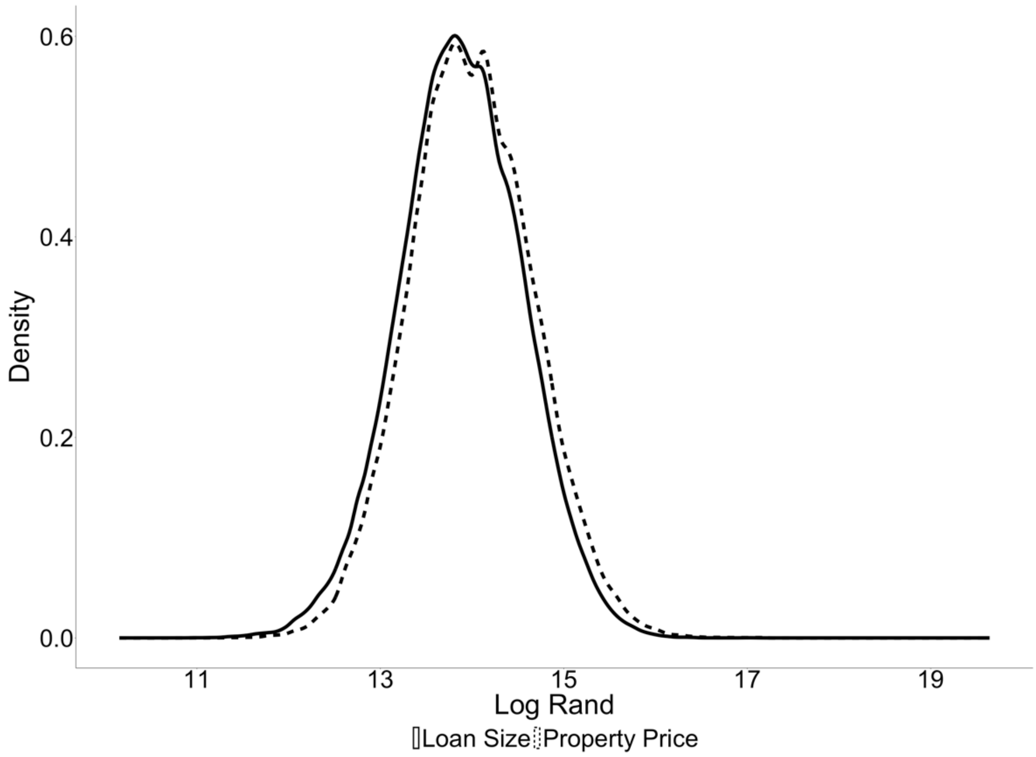


Figure 3: Share of homebuyers by credit score rating

This figure illustrates the share of homebuyers in each year of the observation period grouped by credit score rating: excellent, fair, good and poor. Please refer to Table 2 for a detailed explanation of these categories.

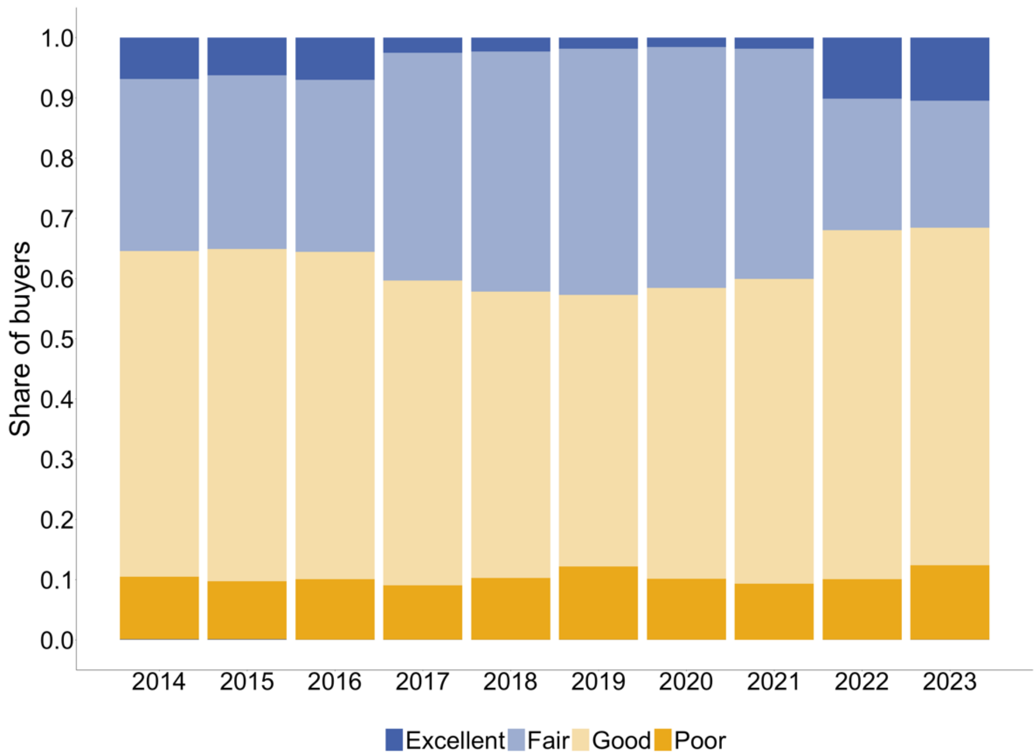
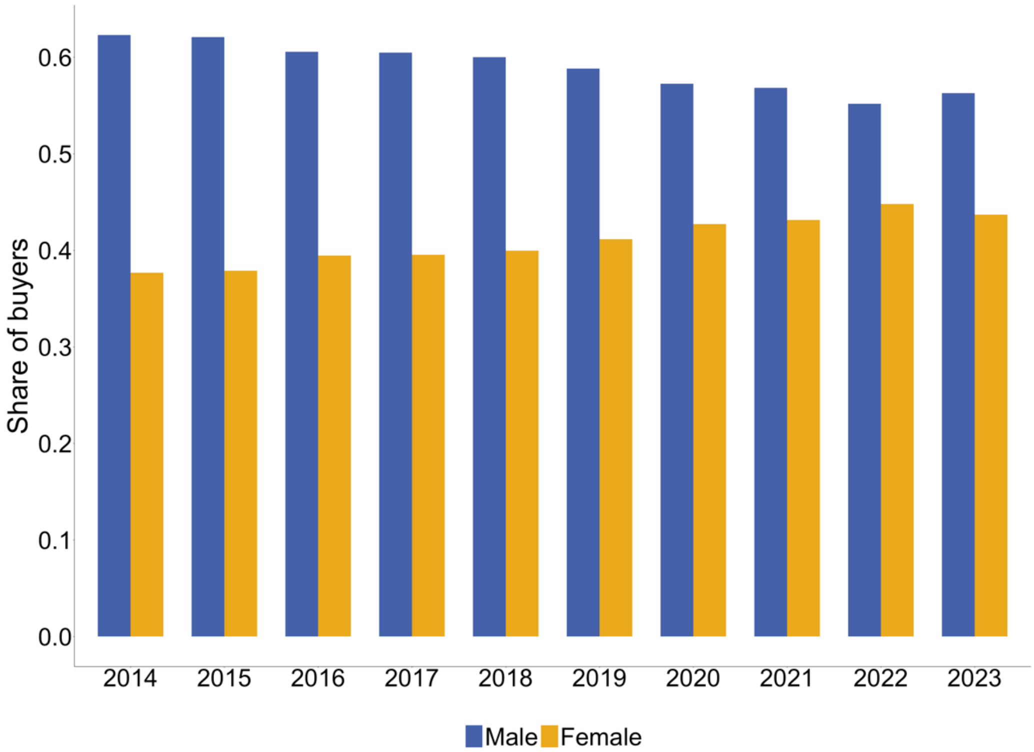
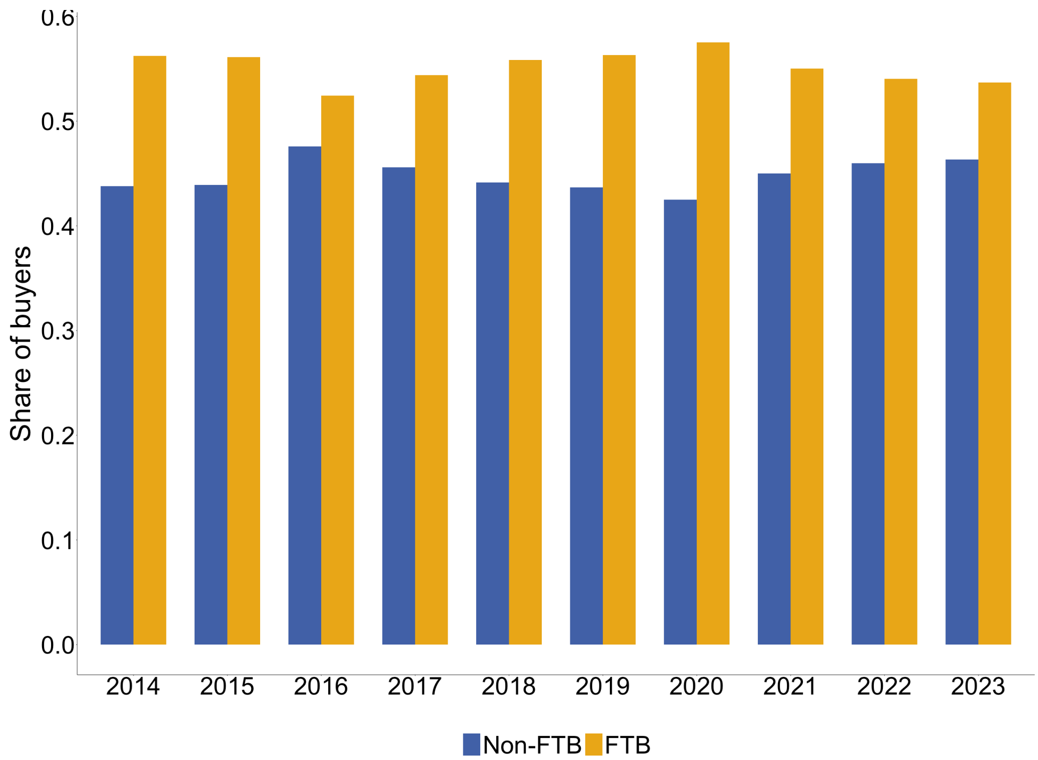


Figure 4: Share of homebuyers by gender and homebuyer status

This figure illustrates the share of homebuyers in each year of the observation period grouped by (a) gender and (b) first-time homebuyer status.



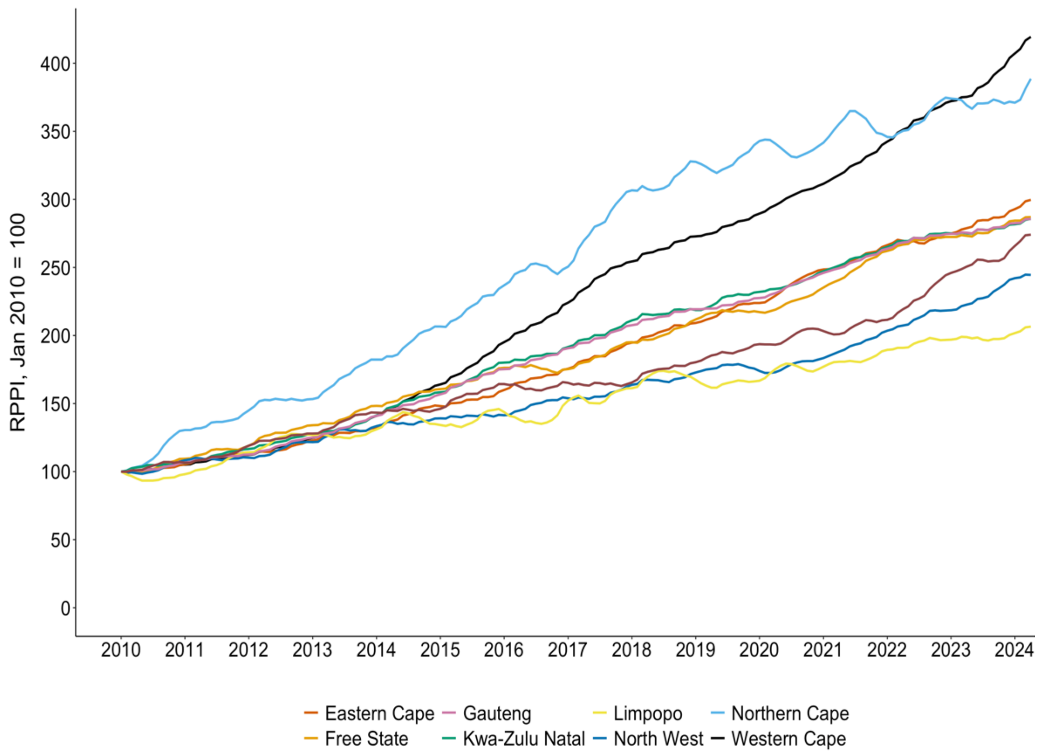
(a) Share of homebuyers by gender



(a) Share of homebuyers by buyer status

Figure 5: RPPI across different provinces in South Africa

This figure illustrates the annual average residential property price index, based to January 2010, for South Africa's nine provinces. Indices are deflated using Housing, Owner's Equivalent Rent.



Tables

Table 1: Summary statistics

This table reports summary statistics for the 142,000 approved mortgage applications originated between 2014 and 2023. I focus on a subset of mortgages associated with the purchase of existing homes. All monetary amounts are in real terms.

Variable	Mean	Standard deviation
Requested amount	R1,341,781	(R998,620)
Accepted amount	R1,330,162	(R988,457)
Property purchase price	R1,512,232	(R1,678,409)
Deposit	R171,596	(R1,271,995)
LTV ratio	0.91	(0.59)
Concession	0.24	(0.91)
Prime interest rate	9.07	(1.57)
Applicant age	37	(9)
Application real gross income	R73,237	(R70,420)
Application real net income	R34,197	(R49,140)
Applicant credit score	670	(53)
Female buyer	42.01%	
First-time homebuyer	55.33%	
Co-application	42.65%	
Married	42.66%	
Has dependents	37.81%	
Western Cape or Gauteng	64.80%	
N	142,448	

Table 2: Credit scoring model

This table displays the associated credit score range for each credit rating: excellent, fair, good and poor. The credit ratings are based on the mortgage origination company's credit scoring model.

Credit score	Credit rating
500 – 610	Poor
611 – 660	Fair
661 – 780	Good
781 – 850	Excellent

Table 3: Differences in means by gender

This table reports differences in means between male and female homebuyers. I also report P-values.

Variable	Male	Female	Difference in means	P-value
Requested amount	R1,413,686	R1,242,536	R171,150	0.000
Accepted amount	R1,400,434	R1,233,170	R167,264	0.000
Property purchase price	R1,585,246	R1,411,454	R173,793	0.000
Deposit	R172,743	R170,012	R2,731	0.701
LTV ratio	0.92	0.91	0.01	0.000
Concession	0.22	0.26	-0.04	0.000
Prime interest rate	9.09	9.05	0.04	0.000
Applicant age	37	37	0	0.000
Application real gross income	R80,249	R63,559	R16,690	0.000
Application real net income	R37,400	R29,776	R7,624	0.000
Applicant credit score	671	668	3	0.000
First-time homebuyer	52.68%	58.98%	-0.063	0.000
Co-application	52.07%	29.63%	0.224	0.000
Married	52.28%	29.37%	0.229	0.000
Has dependents	39.9%	34.92%	0.050	0.000
Western Cape or Gauteng	64.22%	65.61%	-0.014	0.000
N	82,602	59,846		

Table 4: Differences in means by homebuyer status

This table reports differences in means between first-time and non-first-time homebuyers. I also report P-values.

Variable	Repeat homebuyer	First-time homebuyer	Difference in means	P-value
Requested amount	R1,595,917	R1,136,582	R459,334	0.000
Accepted amount	R1,581,445	R1,127,266	R454,179	0.000
Property purchase price	R1,866,050	R1,226,544	R639,506	0.000
Deposit	R270,467	R91,763	R178,704	0.000
LTV ratio	0.88	0.94	-0.06	0.000
Concession	-0.01	0.44	-0.45	0.000
Prime interest rate	9.09	9.06	0.03	0.000
Applicant age	41	34	7	0.000
Application real gross income	R97,170	R53,912	R43,258	0.000
Application real net income	R43,211	R26,919	R16,292	0.000
Applicant credit score	683	660	23	0.000
Female	38.57%	44.79%	-0.062	0.000
Co-application	48.88%	37.61%	0.113	0.000
Married	55.25%	32.48%	0.228	0.000
Has dependents	44.21%	32.64%	0.116	0.000
Western Cape or Gauteng	68.3%	61.98%	0.063	0.000
N	63,636	78,812		

Table 5: Log (mortgage amount requested)

This table reports coefficient results from estimating Eq. (1) with the log of the requested mortgage amount as the outcome variable. Columns showcase different sets of controls. Omitted categories: age quintile 1; gross income quintile 1; poor credit score. Standard errors (in parentheses) are clustered by province. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Prime	-0.080***	-0.081***	-0.081***	-0.066***	-0.064***	-0.028***	-0.028***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.006)	(0.006)
Female	0.025***	0.024***	0.021***	0.012***	0.012***	0.010**	0.011**
	(0.005)	(0.005)	(0.004)	(0.003)	(0.003)	(0.003)	(0.003)
First-time homebuyer	0.052**	0.050**	0.062***	0.040***	0.040***	0.033**	0.033**
	(0.018)	(0.018)	(0.012)	(0.012)	(0.012)	(0.011)	(0.012)
Co-applicant	0.014	0.017	-0.000	0.012	0.012	0.015	0.015
	(0.019)	(0.019)	(0.009)	(0.009)	(0.009)	(0.008)	(0.008)
Married	0.072***	0.070***	0.062***	0.071***	0.072***	0.073***	0.074***
	(0.005)	(0.005)	(0.009)	(0.010)	(0.010)	(0.010)	(0.010)
Divorced	0.055***	0.053***	0.061***	0.071***	0.071***	0.072***	0.072***
	(0.009)	(0.009)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
1 dependant	-0.041**	-0.041**	-0.044**	-0.038	-0.038	-0.039	-0.039
	(0.015)	(0.015)	(0.019)	(0.023)	(0.023)	(0.023)	(0.024)
2+ dependents	-0.035**	-0.036**	-0.030***	-0.025**	-0.026**	-0.025**	-0.025**
	(0.011)	(0.011)	(0.008)	(0.011)	(0.010)	(0.011)	(0.011)
Age quintile 2	0.011*	0.014**	0.017**	0.004	0.004	0.003	0.002
	(0.006)	(0.006)	(0.007)	(0.007)	(0.007)	(0.008)	(0.007)
Age quintile 3	0.011	0.015*	0.022*	0.005	0.005	0.002	0.002
	(0.007)	(0.007)	(0.010)	(0.012)	(0.012)	(0.012)	(0.012)
Age quintile 4	0.012	0.016	0.026**	-0.001	-0.001	-0.004	-0.004
	(0.010)	(0.011)	(0.008)	(0.009)	(0.009)	(0.009)	(0.009)
Age quintile 5	-0.069***	-0.063***	-0.053***	-0.079***	-0.079***	-0.083***	-0.083***
	(0.013)	(0.014)	(0.008)	(0.007)	(0.007)	(0.007)	(0.007)
Gross income quintile 2	0.445***	0.443***	0.445***	0.418***	0.417***	0.404***	0.404***
	(0.035)	(0.035)	(0.039)	(0.038)	(0.038)	(0.039)	(0.039)
Gross income quintile 3	0.703***	0.699***	0.700***	0.657***	0.656***	0.637***	0.637***
	(0.044)	(0.044)	(0.048)	(0.047)	(0.048)	(0.049)	(0.049)
Gross income quintile 4	0.938***	0.929***	0.930***	0.873***	0.872***	0.848***	0.848***
	(0.054)	(0.053)	(0.058)	(0.056)	(0.057)	(0.059)	(0.059)
Gross income quintile 5	1.276***	1.250***	1.245***	1.175***	1.173***	1.144***	1.144***
	(0.059)	(0.058)	(0.062)	(0.059)	(0.060)	(0.063)	(0.063)
Fair credit score	0.015	0.016	0.012	0.025**	0.025**	0.021**	0.021**
	(0.011)	(0.011)	(0.008)	(0.009)	(0.009)	(0.009)	(0.009)
Good credit score	0.057*	0.057*	0.043**	0.049**	0.050**	0.055**	0.055**
	(0.025)	(0.025)	(0.014)	(0.017)	(0.017)	(0.017)	(0.016)
Excellent credit score	0.066*	0.062	0.039*	0.026	0.029	0.054**	0.055**
	(0.033)	(0.033)	(0.018)	(0.020)	(0.019)	(0.017)	(0.017)
Covid lockdown	-0.021***	-0.024***	-0.025***	0.093***	0.092***	0.006	0.006
	(0.005)	(0.005)	(0.005)	(0.013)	(0.011)	(0.008)	(0.008)
RPPI				0.007***	0.006***	0.003***	0.003**
				(0.001)	(0.001)	(0.001)	(0.001)
REER				-0.003***	-0.003***	0.000	0.000
				(0.000)	(0.000)	(0.000)	(0.000)
CPI				-0.021***	-0.027***	0.001	0.001
				(0.002)	(0.003)	(0.002)	(0.002)
Log (GDP)				0.930***	0.955***	-0.307**	-0.304**
				(0.177)	(0.171)	(0.093)	(0.112)
Unemployment rate				0.006**	0.006**	0.006**	0.006*
				(0.002)	(0.002)	(0.002)	(0.003)
Constant	13.855***	13.869***	13.870***	-1.195	-1.553	17.666***	17.608***
	(0.022)	(0.020)	(0.044)	(2.716)	(2.628)	(1.348)	(1.681)
Observations	142,335	142,335	142,335	142,335	142,335	142,335	142,335
R-squared	0.505	0.510	0.529	0.546	0.546	0.551	0.551
Bank fixed effect	×	✓	✓	✓	✓	✓	✓
Province fixed effect	×	×	✓	✓	✓	✓	×
Quarter fixed effect	×	×	×	×	✓	×	×
Year fixed effect	×	×	×	×	×	✓	×
Province*Year fixed effect	×	×	×	×	×	×	✓

Table 6: Log (mortgage amount approved)

This table reports coefficients results from estimating Eq. (1) with the log of the approved mortgage amount as the outcome variable. Columns showcase different sets of controls. Omitted categories: age quintile 1; gross income quintile 1; poor credit score. Standard errors (in parentheses) are clustered by province. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Prime	-0.080***	-0.081***	-0.081***	-0.065***	-0.064***	-0.029***	-0.029***
	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)	(0.006)	(0.006)
Female	0.027***	0.026***	0.023***	0.013***	0.013***	0.011**	0.011**
	(0.006)	(0.006)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
First-time homebuyer	0.052**	0.050**	0.062***	0.039***	0.039**	0.033**	0.032**
	(0.019)	(0.018)	(0.012)	(0.012)	(0.012)	(0.011)	(0.012)
Co-applicant	0.017	0.019	0.002	0.014	0.014	0.017*	0.018*
	(0.020)	(0.020)	(0.009)	(0.009)	(0.009)	(0.008)	(0.008)
Married	0.073***	0.071***	0.063***	0.073***	0.073***	0.075***	0.075***
	(0.006)	(0.006)	(0.011)	(0.011)	(0.011)	(0.012)	(0.012)
Divorced	0.054***	0.053***	0.060***	0.071***	0.071***	0.072***	0.072***
	(0.010)	(0.010)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
1 dependant	-0.041**	-0.041**	-0.044**	-0.037	-0.038	-0.039	-0.038
	(0.014)	(0.015)	(0.018)	(0.023)	(0.023)	(0.023)	(0.023)
2+ dependents	-0.036**	-0.038***	-0.032***	-0.027**	-0.027**	-0.027**	-0.026**
	(0.011)	(0.011)	(0.008)	(0.010)	(0.010)	(0.010)	(0.011)
Age quintile 2	0.006	0.010	0.013	-0.001	-0.001	-0.002	-0.003
	(0.006)	(0.006)	(0.007)	(0.007)	(0.007)	(0.008)	(0.008)
Age quintile 3	0.005	0.010	0.017	-0.000	-0.000	-0.003	-0.004
	(0.007)	(0.007)	(0.011)	(0.012)	(0.012)	(0.013)	(0.013)
Age quintile 4	0.006	0.011	0.021**	-0.007	-0.007	-0.010	-0.011
	(0.010)	(0.011)	(0.008)	(0.009)	(0.009)	(0.010)	(0.010)
Age quintile 5	-0.077***	-0.070***	-0.060***	-0.087***	-0.087***	-0.091***	-0.092***
	(0.013)	(0.013)	(0.008)	(0.007)	(0.007)	(0.007)	(0.007)
Gross income quintile 2	0.444***	0.442***	0.444***	0.416***	0.415***	0.401***	0.401***
	(0.035)	(0.035)	(0.039)	(0.038)	(0.038)	(0.040)	(0.040)
Gross income quintile 3	0.701***	0.697***	0.698***	0.653***	0.652***	0.632***	0.632***
	(0.044)	(0.044)	(0.049)	(0.048)	(0.048)	(0.050)	(0.050)
Gross income quintile 4	0.936***	0.927***	0.928***	0.869***	0.868***	0.843***	0.842***
	(0.054)	(0.054)	(0.059)	(0.057)	(0.057)	(0.060)	(0.060)
Gross income quintile 5	1.273***	1.246***	1.241***	1.168***	1.167***	1.136***	1.136***
	(0.060)	(0.058)	(0.062)	(0.060)	(0.061)	(0.064)	(0.064)
Fair credit score	0.026**	0.027**	0.023**	0.037***	0.036***	0.033***	0.033***
	(0.010)	(0.011)	(0.008)	(0.008)	(0.008)	(0.009)	(0.009)
Good credit score	0.074**	0.075**	0.060***	0.067***	0.068***	0.073***	0.073***
	(0.024)	(0.025)	(0.014)	(0.017)	(0.017)	(0.016)	(0.016)
Excellent credit score	0.084**	0.080**	0.058**	0.044*	0.048**	0.074***	0.074***
	(0.034)	(0.034)	(0.018)	(0.020)	(0.020)	(0.018)	(0.018)
Covid lockdown	-0.019***	-0.022***	-0.022***	0.104***	0.104***	0.005	0.006
	(0.005)	(0.005)	(0.005)	(0.014)	(0.013)	(0.008)	(0.008)
RPPI				0.007***	0.006***	0.003***	0.004**
				(0.001)	(0.001)	(0.001)	(0.001)
REER				-0.003***	-0.003***	0.000	0.000
				(0.000)	(0.000)	(0.000)	(0.000)
CPI				-0.023***	-0.029***	0.002	0.002
				(0.002)	(0.003)	(0.002)	(0.002)
Log (GDP)				1.003***	1.032***	-0.299**	-0.277*
				(0.191)	(0.187)	(0.112)	(0.127)
Unemployment rate				0.006**	0.007**	0.006*	0.006*
				(0.003)	(0.003)	(0.003)	(0.003)
Constant	13.840***	13.856***	13.856***	-2.345	-2.772	17.571***	17.193***
	(0.024)	(0.022)	(0.046)	(2.930)	(2.874)	(1.638)	(1.894)
Observations	142,335	142,335	142,335	142,335	142,335	142,335	142,335
R-squared	0.501	0.507	0.526	0.544	0.544	0.550	0.550
Bank fixed effect	×	✓	✓	✓	✓	✓	✓
Province fixed effect	×	×	✓	✓	✓	✓	×
Quarter fixed effect	×	×	×	×	✓	×	×
Year fixed effect	×	×	×	×	×	✓	×
Province*Year fixed effect	×	×	×	×	×	×	✓

Table 7: Log (property purchase price)

This table reports coefficients results from estimating Eq. (1) with the log of the property purchase price as the outcome variable. Columns showcase different sets of controls. Omitted categories: age quintile 1; gross income quintile 1; poor credit score. Standard errors (in parentheses) are clustered by province. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Prime	-0.075***	-0.076***	-0.075***	-0.063***	-0.061***	-0.023***	-0.023***
	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)	(0.006)	(0.006)
Female	0.039***	0.038***	0.035***	0.026***	0.026***	0.024***	0.025***
	(0.006)	(0.006)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
First-time homebuyer	-0.019	-0.020	-0.007	-0.027	-0.027	-0.034	-0.034
	(0.026)	(0.026)	(0.020)	(0.019)	(0.019)	(0.019)	(0.019)
Co-applicant	0.004	0.007	-0.015	-0.004	-0.004	-0.001	-0.000
	(0.022)	(0.022)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
Married	0.100***	0.098***	0.087***	0.096***	0.096***	0.097***	0.098***
	(0.006)	(0.006)	(0.010)	(0.010)	(0.010)	(0.011)	(0.011)
Divorced	0.085***	0.083***	0.091***	0.100***	0.100***	0.101***	0.101***
	(0.012)	(0.012)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
1 dependant	-0.045***	-0.045***	-0.049**	-0.043*	-0.043*	-0.045*	-0.044*
	(0.011)	(0.012)	(0.016)	(0.020)	(0.020)	(0.021)	(0.021)
2+ dependents	-0.048***	-0.049***	-0.042***	-0.038***	-0.038***	-0.038***	-0.037***
	(0.012)	(0.012)	(0.009)	(0.011)	(0.011)	(0.011)	(0.011)
Age quintile 2	0.013*	0.016**	0.019**	0.007	0.007	0.006	0.006
	(0.006)	(0.006)	(0.007)	(0.007)	(0.007)	(0.008)	(0.008)
Age quintile 3	0.018*	0.023**	0.032**	0.016	0.016	0.013	0.013
	(0.008)	(0.008)	(0.013)	(0.014)	(0.014)	(0.014)	(0.014)
Age quintile 4	0.039***	0.044***	0.056***	0.031**	0.031**	0.028*	0.028*
	(0.008)	(0.009)	(0.011)	(0.012)	(0.012)	(0.013)	(0.013)
Age quintile 5	0.024*	0.030**	0.043***	0.019	0.018	0.015	0.014
	(0.012)	(0.012)	(0.011)	(0.011)	(0.012)	(0.012)	(0.012)
Gross income quintile 2	0.400***	0.398***	0.402***	0.376***	0.375***	0.361***	0.361***
	(0.026)	(0.025)	(0.030)	(0.029)	(0.029)	(0.030)	(0.031)
Gross income quintile 3	0.639***	0.635***	0.638***	0.597***	0.596***	0.576***	0.576***
	(0.033)	(0.033)	(0.039)	(0.038)	(0.038)	(0.039)	(0.039)
Gross income quintile 4	0.859***	0.850***	0.853***	0.800***	0.798***	0.773***	0.772***
	(0.041)	(0.040)	(0.046)	(0.044)	(0.044)	(0.046)	(0.046)
Gross income quintile 5	1.184***	1.159***	1.154***	1.089***	1.088***	1.056***	1.055***
	(0.044)	(0.042)	(0.047)	(0.045)	(0.045)	(0.048)	(0.048)
Fair credit score	0.012	0.012	0.006	0.018*	0.018*	0.014	0.013
	(0.013)	(0.013)	(0.009)	(0.009)	(0.009)	(0.010)	(0.010)
Good credit score	0.080**	0.080**	0.061***	0.067**	0.067**	0.073***	0.073***
	(0.032)	(0.032)	(0.018)	(0.020)	(0.020)	(0.020)	(0.020)
Excellent credit score	0.102**	0.096**	0.066**	0.056**	0.058**	0.087***	0.087***
	(0.041)	(0.041)	(0.020)	(0.022)	(0.022)	(0.020)	(0.020)
Covid lockdown	-0.027***	-0.029***	-0.029***	0.087***	0.088***	0.002	0.002
	(0.005)	(0.004)	(0.005)	(0.011)	(0.011)	(0.009)	(0.008)
RPPI				0.006***	0.006***	0.003***	0.003**
				(0.001)	(0.001)	(0.001)	(0.001)
REER				-0.003***	-0.003***	0.001**	0.001**
				(0.000)	(0.000)	(0.000)	(0.000)
CPI				-0.022***	-0.027***	0.002	0.003
				(0.002)	(0.003)	(0.003)	(0.003)
Log (GDP)				0.989***	1.027***	-0.302**	-0.303**
				(0.136)	(0.137)	(0.096)	(0.113)
Unemployment rate				0.004	0.005	0.005*	0.005
				(0.003)	(0.003)	(0.003)	(0.003)
Constant	13.963***	13.978***	13.979***	-1.872	-2.446	17.716***	17.761***
	(0.025)	(0.024)	(0.044)	(2.085)	(2.090)	(1.358)	(1.663)
Observations	142,335	142,335	142,335	142,335	142,335	142,335	142,335
R-squared	0.483	0.488	0.519	0.533	0.533	0.539	0.539
Bank fixed effect	×	✓	✓	✓	✓	✓	✓
Province fixed effect	×	×	✓	✓	✓	✓	×
Quarter fixed effect	×	×	×	×	✓	×	×
Year fixed effect	×	×	×	×	×	✓	×
Province*Year fixed effect	×	×	×	×	×	×	✓

Table 8: LTV ratio

This table reports coefficients results from estimating Eq. (2) with the mortgage LTV as the outcome variable. Columns showcase different sets of controls. Omitted categories: age quintile 1; gross income quintile 1; poor credit score. Standard errors (in parentheses) are clustered by province. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Prime	-0.004***	-0.005***	-0.005***	-0.002***	-0.002***	-0.005***	-0.005***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)
Female	-0.007***	-0.007***	-0.007***	-0.008***	-0.008***	-0.008***	-0.008***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
First-time homebuyer	0.050***	0.049***	0.048***	0.046***	0.046***	0.046***	0.046***
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Co-applicant	0.010***	0.009***	0.013***	0.014***	0.014***	0.014***	0.014***
	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Married	-0.018***	-0.017***	-0.015***	-0.014***	-0.014***	-0.014***	-0.014***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Divorced	-0.021***	-0.021***	-0.021***	-0.020***	-0.020***	-0.020***	-0.020***
	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)
1 dependant	0.001	0.001	0.002	0.003	0.003	0.003	0.003
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
2+ dependents	0.006**	0.006**	0.005***	0.006***	0.006***	0.006***	0.006***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Age quintile 2	-0.005***	-0.004***	-0.005***	-0.006***	-0.006***	-0.006***	-0.006***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Age quintile 3	-0.010***	-0.010***	-0.011***	-0.013***	-0.013***	-0.014***	-0.014***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Age quintile 4	-0.023***	-0.023***	-0.025***	-0.028***	-0.028***	-0.028***	-0.028***
	(0.003)	(0.003)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Age quintile 5	-0.067***	-0.066***	-0.067***	-0.070***	-0.070***	-0.070***	-0.071***
	(0.006)	(0.006)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
Gross income quintile 2	0.029***	0.029***	0.028***	0.025***	0.025***	0.025***	0.025***
	(0.008)	(0.008)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
Gross income quintile 3	0.040***	0.040***	0.038***	0.034***	0.034***	0.034***	0.034***
	(0.008)	(0.008)	(0.007)	(0.008)	(0.008)	(0.008)	(0.008)
Gross income quintile 4	0.048***	0.048***	0.047***	0.041***	0.041***	0.041***	0.041***
	(0.009)	(0.009)	(0.008)	(0.009)	(0.009)	(0.009)	(0.009)
Gross income quintile 5	0.053***	0.053***	0.052***	0.045***	0.044***	0.045***	0.045***
	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.012)	(0.012)
Fair credit score	0.014***	0.014***	0.015***	0.017***	0.017***	0.017***	0.017***
	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Good credit score	0.001	0.002	0.005	0.005*	0.006*	0.006*	0.006*
	(0.005)	(0.005)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Excellent credit score	-0.006	-0.006	-0.000	-0.002	-0.002	-0.003	-0.003
	(0.006)	(0.006)	(0.003)	(0.002)	(0.003)	(0.003)	(0.003)
Covid lockdown	0.007***	0.006***	0.006***	0.018***	0.017***	0.003*	0.004**
	(0.001)	(0.001)	(0.001)	(0.003)	(0.003)	(0.001)	(0.002)
RPPI				0.001	0.001	-0.000	0.000
				(0.000)	(0.000)	(0.000)	(0.000)
REER				-0.001***	-0.001***	-0.001***	-0.001***
				(0.000)	(0.000)	(0.000)	(0.000)
CPI				-0.001**	-0.002**	0.000	-0.001
				(0.000)	(0.001)	(0.000)	(0.000)
Log (GDP)				0.044	0.038	0.016	0.040
				(0.063)	(0.063)	(0.045)	(0.046)
Unemployment rate				0.002**	0.002**	0.001	0.000
				(0.001)	(0.001)	(0.000)	(0.000)
Constant	0.911***	0.912***	0.911***	0.126	0.210	0.686	0.254
	(0.011)	(0.012)	(0.004)	(0.970)	(0.956)	(0.694)	(0.712)
Observations	142,335	142,335	142,335	142,335	142,335	142,335	142,335
R-squared	0.075	0.077	0.091	0.095	0.095	0.096	0.097
Bank fixed effect	×	✓	✓	✓	✓	✓	✓
Province fixed effect	×	×	✓	✓	✓	✓	×
Quarter fixed effect	×	×	×	×	✓	×	×
Year fixed effect	×	×	×	×	×	✓	×
Province*Year fixed effect	×	×	×	×	×	×	✓

Table 9: Comparison of elasticity estimates

This table displays a comparison of estimates of the interest rate semi-elasticities of mortgage demand and housing demand obtained in the literature.

Paper	Mortgage demand semi-elasticity	Housing demand semi-elasticity
DeFusco and Paciorek (2017)	1.5 – 2	-
Fuster and Zafar (2021)	-	2.5
Davis et al. (2019)	3.4	3.4
Bhutta and Ringo (2021)	2	2
This paper	2.8	2.3