Policy-Driven Boom and Bust in the Housing Market: Evidence from Mongolia

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This paper examines the effects of a mortgage interest rate subsidy on booms and busts in the housing market by analyzing the Housing Mortgage program in Mongolia. We find that the most recent housing boom in Mongolia occurred from the second quarter (Q2) of 2012 to first quarter (Q1) of 2014, and that the subsequent housing bust lasted 4 years. Both house-specific factors and macroeconomic variables had a significant influence on housing price dynamics. Mortgage interest rate semielasticity and real household income elasticity were estimated as −3 and 1.4, respectively. Dynamic analysis of the estimated vector error correction models suggests that the country's policy intervention in the mortgage market—introducing an interest rate subsidy on mortgage loans for residential properties of up to 80 square meters—drove the recent housing boom in Mongolia.

Keywords: booms and busts, house prices, Mongolia, mortgage interest rate subsidy

JEL codes: C53, D14, E32, E51, G21

I. Introduction

The global financial crisis (GFC) has revived interest in what determines housing price dynamics and how macroeconomic policies should respond to booms and busts

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in housing prices. Housing is a fundamental part of households' total wealth, and households devote a large part of lifetime incomes to acquiring it. Hence, the housing sector and its financing have been at the heart of public policy, and fluctuations in housing prices have received a great deal of attention from policy makers and homeowners. Several papers (McQuinn and O'Reilly 2008; Agnello and Schuknecht 2011; Lambertini, Mendicino, and Punzi 2013; Tu, de Haan, and Boelhouwer 2018; Zhang and Yi 2018) find that global, macroeconomic, financial market, demographic, house-specific factors, changes in expectations, and deregulation of the housing market are critical determinants of housing prices. As housing sector development requires adequate financing, governments have implemented programs to subsidize interest rates on mortgages. Recent studies that rely on the credit view (Favara and Imbs 2015; Di Maggio and Kermani 2017; Mian, Sufi, and Verner 2017a; Justiniano, Primiceri, and Tambalotti 2019) show that booms and busts in housing markets are due to changes in credit supply, driven by loose lending constraints in mortgage markets. In contrast, other papers (Case and Shiller 2003; Lambertini, Mendicino, and Punzi 2013; Kanik and Xiao 2014; Ferrero 2015; Ascari, Pecora, and Spelta 2018) argue that house-price expectation and exogenous preference shocks drive housing boom–bust cycles. The papers also emphasize that other competing hypotheses, such as a prolonged period of low interest rates and the liberalization of credit standards, have only minor effects on housing price dynamics. Very few papers (Martins and Villanueva 2006; Hofstetter, Tovar, and Urrutia 2011; Zhao 2019) explicitly assess the effects of mortgage interest rate subsidies, especially on household borrowing, housing finance, and mortgage default probabilities of mortgage loans.

In this context, this paper empirically examines the effects of a mortgage interest rate subsidy on booms and busts in the housing market by analyzing a massive mortgage program in Mongolia called the Housing Mortgage (HM) program. The HM program was launched in 2013 as a part of the quasi-fiscal operations implemented by the government and the Bank of Mongolia (BOM). The program provides a mortgage interest rate subsidy to individuals who want to purchase an apartment financed by a mortgage loan. The HM program also allows individuals to refinance existing retail mortgage loans with a subsidized 8% interest rate. Under the HM program, the BOM also provides cheap mortgage-targeted financing to banks, leading to rapid mortgage credit growth. As of the end of 2018, subsidized mortgage loans outstanding reached 3.32 trillion togrog (MNT), equivalent to 10.2% of gross domestic product (GDP). Though the HM program initially aimed to reduce Ulaanbaatar's air pollution through the development of the housing sector and support young couples with low incomes, it also led to rapid increases in apartment prices during the period 2013–2014. Evidence and lessons from Mongolia's experience would be highly relevant for developing countries to avoid policy-driven booms and busts in housing markets and to help design good mortgage-financing schemes. Our paper contributes to the existing literature in two ways. First, it provides empirical evidence on the characterization of housing boom–bust phases. The paper also estimates the interest rate elasticity of housing prices using three different datasets, including pooled cross-sectional, panel, and time series data, for a commodity-exporting and developing country. Second, as far as we are aware, it is one of the first attempts to study the role of mortgage interest rate subsidies in booms and busts in housing prices.

Much empirical work has been done to analyze the underlying forces in housing prices. Studies focused on demand-side factors primarily relied on interest rates and the availability of credit. The literature on the user-cost model of housing services (Poterba 1984; Díaz and Luengo-Prado 2008) highlights the relationship between interest rates and house prices. When interest rate increases, according to the research, a housing investor (including owner-occupiers) would prefer to invest in a bank deposit (and earn the interest rate) than purchase a home (and earn the rental yield). A vast literature (Abraham and Hendershott 1992; Goodhart and Hofmann 2008; Iossifov, Cihak, and Shanghavi 2008; Adams and Fuss 2010; Berlemann and Freese 2013; Nneji, Brooks, and Ward 2013; DeFusco and Paciorek 2017) shows that a negative relationship exists between interest rates and house prices, and that low real interest rates have significant effects on housing price dynamics. These studies also find that demand-side factors such as inflation, GDP, fiscal deficit, current account deficit, money supply, credit, nonperforming loans, employment, unemployment, total population, active population, construction costs, industrial production, and housing stock are associated with housing prices. Agnello and Schuknecht (2011) provide empirical evidence for the role of international factors such as global liquidity on probabilities of booms and busts occurring in housing markets. Ferrero (2015) finds that domestic factors such as credit and preference shocks can explain the negative correlation between house prices and current account balance. Supply-side factors can also matter. The Alonso–Muth–Mills (AMM) model established by Alonso (1964), Muth (1969), Mills (1967), and Wheaton (1974) suggests that a range of supply-side factors such as the shortage of appropriately zoned land that increases development costs (the value of land), poor transport infrastructure (cost of transport), and frictions that increase the cost of new housing development affects the cost of new housing and reduces its supply. The higher cost and lower supply of new housing also increase the price of the existing stock of housing. These factors also explain how housing prices are differentiated geographically.

Working with macro variables, several papers (Sutton 2002; Tsatsaronis and Zhu 2004; Iacoviello 2005; Iacoviello and Minetti 2008; Bjørnland and Jacobsen 2010; Kanik and Xiao 2014; Panagiotidis and Printzis 2016; Mian, Sufi, and Verner 2017b; Justiniano, Primiceri, and Tambalotti 2019) also examine the relationship between interest rates, credits, and housing prices using quantitative macroeconomic methods such as vector autoregression (VAR) models, vector error correction models (VECMs), and dynamic stochastic general equilibrium models. The model-based approach focuses on the role of house prices in the monetary policy transmission mechanism, the role of the housing market in macroeconomic fluctuations, and the reaction of house prices to structural shocks (such as monetary policy and technology shocks). Though there are potential feedback effects between the housing market and credit supply expansions, the weight of empirical evidence suggests that housing prices are more likely to be a response to credit supply rather than a cause (Mian, Sufi, and Verner 2017b; Mian and Sufi 2018). Iacoviello (2005) shows that the existence of nominal debt contracts and collateral constraints tied to housing prices amplifies demand shocks but stabilizes supply shocks. Iacoviello and Minetti (2008) provide evidence supporting the existence of a credit channel (especially a bank lending channel) of monetary policy in the housing market. Mian, Sufi, and Verner (2017b) find that a shock to household debt leads to large and immediate increases in house prices, followed by substantial mean reversion 4 years after the initial shock. Justiniano, Primiceri, and Tambalotti (2019) argue that the focus of discussion should shift from borrowing constraints to lending constraints when it comes to understanding the boom phase of the housing price cycle.

The recent micro literature highlighting the importance of house-specific factors focuses on interactions with macroeconomic factors. For example, Galati, Teppa, and Alessie (2011) find that house-specific factors, such as year of construction, presence of a garden, presence of parking, and macro factors including the long-term real interest rate, unemployment rate, and dependency ratio (ratio of population aged 65 and above to population aged 15–64) significantly affect housing price dynamics. Zhang and Yi (2018) show that the location of the house, surrounding environment, and housing characteristics such as the number of bedrooms, the size of the living area, and the number of floors are essential determinants of house prices in Beijing.

The empirical studies on the determinants of housing price dynamics in advanced countries are extensive, but those in developing and emerging markets are relatively scarce. In Mongolia, Doojav (2007) finds that house-specific factors and the surrounding environment play an essential role in determining apartment prices in Ulaanbaatar using hedonic regression analysis. Based on the VECM, Demid (2013) shows that household income, concrete prices, and mortgage loans are vital drivers of apartment prices.

The remainder of this paper is structured as follows. Section II provides an overview of the macroeconomic environment, mortgage market development, and details of the HM program in Mongolia. The section also identifies boom and bust episodes in the housing market. Section III presents the model of housing prices and discusses estimation techniques. Section IV describes the data and reports empirical results, including estimates of income and interest rate elasticities and the contribution of the mortgage interest rate subsidy to the boom and bust in house prices for the period 2013–2014. Finally, Section V concludes the paper with policy implications.

II. Overview of Housing and Mortgage Markets in Mongolia

A. Housing and Mortgage Markets: The Housing Mortgage Program

The Mongolian economy is subject to large supply and demand shocks. On the supply side, Mongolia is a geographically large and landlocked country that experiences harsh winter conditions, all of which point to high transport costs and the potential for supply bottlenecks. On the demand side, mineral exports are a crucial driver of the economy but are volatile due to global commodity demand and price shocks (Barnett, Bersch, and Ojima 2012). In the last decade, the Mongolian economy has experienced boom–bust cycles on several occasions.

In response to adverse external shocks, politically driven expansionary policies were implemented for the period 2012–2016. The central bank's quasi-fiscal operations (policy lending programs) were launched in late 2012 when the political demand for higher spending mounted. As budget revenue growth gradually slowed in the midst of declining foreign direct investment and weakening export revenues, the central bank's power to issue currency was seen as a reliable source of financing that could be tapped to support growing spending demand without revenue constraints. Hence, the government relied on the central bank as an alternative financing source for fiscal operations. The political demand was exceptionally high for a price stabilization program (PSP), including the HM program.[1]

[1]Such quasi-fiscal lending programs implemented by the BOM blurs the boundary between the central bank's balance sheet and the government budget, thereby undermining the role of the central bank as an independent keeper of price stability. The exceptionally large monetary and quasi-fiscal stimulus provided through various programs risks ratcheting up inflation, increasing public debt, adding to balance of payment pressures, and heightening banking sector vulnerabilities. Loose monetary and fiscal policies to buffer the economy from external shocks supported the economic growth for a while, but at the cost of economic vulnerabilities.

Public demand for affordable housing has been growing in Mongolia as household average income is relatively low compared to housing prices. As a result, the government has been intervening in the construction sector for the past 20 years and sees the intervention as a way of supporting economic growth. Government housing policies in Mongolia have been oriented toward both large-scale housing construction programs and subsidized mortgage loan programs. In 2004, the government initiated the 4-year "40,000 apartments program" to promote housing supply and provided financing of MNT32.7 billion (through a government bond of MNT28.3 billion and Asian Development Bank project financing of MNT4.4 billion) to participant banks who, in turn, lent the funds to participating construction companies. In 2009, the new government formed during the June 2008 parliamentary election implemented another initiative called the "4,000 apartments program" to support the construction sector. Under the program, public servants who had worked for the public sector for 3 or more years could take out a mortgage of (up to) MNT40 million at an 8% annual interest rate for up to 20 years. They could use this loan to buy an apartment held by banks as collateral for construction companies' loans. In 2010 and 2012, the government approved two other programs: the "100,000 apartments program" (75,000 apartments in Ulaanbaatar and 25,000 apartments in other provinces) to stimulate housing supply; and the "Regulation on 6% subsidized mortgage loan" to promote housing affordability. The 6% subsidized mortgage loan program was implemented for only 5 months until the June 2012 parliamentary election. During this time, about 1,000 individuals acquired these subsidized loans of up to MNT50 million with up to 20 years to pay to buy apartments that were less than 55 square meters (m^2) and built under the "100,000 apartments program."

Though several government housing programs were implemented before 2013, the results were not enough compared to the existing public demand for affordable housing. Moreover, mortgage market development was weak. For instance, at the end of 2012, the ratio of total mortgage loans to GDP was only 5.1%, which was seven times lower than the ratio in Japan and Hong Kong, China and more than 10 times lower than in advanced economies. About 29,900 borrowers obtained mortgage loans. The share of mortgage loans was 12.1% of total loans outstanding. The average mortgage annual interest rate was 15.3%, too high for an average-income household to buy an apartment using the mortgage loan. Out of 306,800 Ulaanbaatar households, 39% were living in apartments.

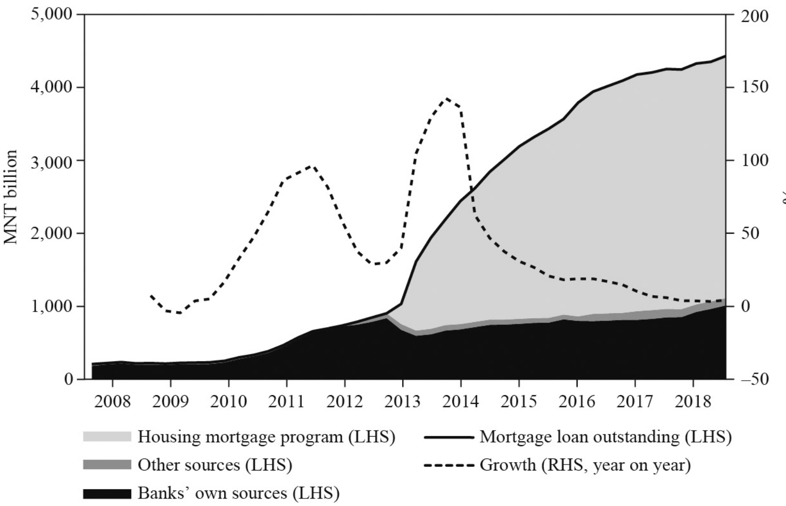
Preoccupation with the presumed adverse effects of high inflation and high public demand for affordable housing led the newly appointed government in 2012 to initiate the PSP. The program aimed to introduce sustainable housing financing schemes and stabilize domestic prices, not only of food and petroleum but also of imported raw materials for construction. The PSP started in October 2012 when the government and the BOM signed a memorandum of understanding on the "Joint implementation of the medium-term program to stabilize prices of key commodities and products." The parliament approved the implementation of the PSP as it was included in the monetary policy guidelines for 2013 and 2014 and the action plan of the government for 2012–2016. The initial aim of the PSP was "to prevent any potential crisis and to stabilize the economy" (BOM 2013). The involvement of the BOM, which has a mandate to ensure price stability, in the quasi-fiscal operations raised a concern about central bank independence.

Along with the supply-side stimulus program, the BOM launched the HM program within the PSP to stimulate housing demand. The program would provide cheap mortgage loans to households at a subsidized interest rate of 8%, which was almost half of the market mortgage lending rates. The objective of the HM program was to establish a sustainable mortgage financing scheme to reconcile housing supply with demand, increase housing affordability, and provide people with a safe and healthy environment to live in. The idea of the mortgage financing scheme was based on the secondary mortgage market. Under the HM program, the BOM provided credit to commercial banks at a 4% interest rate, which banks onlent to households at an 8% interest rate for up to 20 years. Since late 2013, some of the subsidized mortgages have been securitized into residential mortgage-backed securities issued by the Mongolian Ipotek Corporation, which was purchased by the BOM to refinance banks' funding sources for other HM loans. Loan eligibility criteria set a limit on the apartment size that can be purchased with the loan at a maximum of 80 m^2 (the subsidized mortgage loan can only be used for buying apartments) and required that loan applicants' minimum monthly income exceed MNT1 million (derived from a debt-to-income ratio of 45%). The down payment is 30% of the purchased apartment's value. Under the HM program, the existing mortgage loans at the market interest rate were automatically transferred to the subsidized mortgage loans. Existing commercial mortgage borrowers switched to the subsidized loan program, and the subsidized program almost fully absorbed new mortgage loan demand. In March 2016, the BOM made further amendments to the HM program: (i) the mortgage interest rate was lowered from 8% to 5% for houses purchased in specific areas such as new settlement areas and three suburban districts in Ulaanbaatar, ger districts for redevelopment plans, and rural areas in 21 provinces; and (ii) the maturity of the mortgage loan was extended from 20 years to 30 years.

By the end of 2018, the commercial banks had issued mortgage loans worth MNT4.43 trillion (equivalent to 14% of GDP) to 93,865 borrowers. Out of the total mortgage loans outstanding, 75% (MNT3.32 trillion) was financed under the HM program to 69,529 borrowers (Figures 1 and 2). Mortgage loan growth accelerated sharply during 2013–2014 after the HM program was introduced, but then gradually declined. The mortgage interest rate subsidy boosted mortgage loans by about 150% in 2013. Mortgage loan growth has slowed since 2014 as market demand has gradually been fulfilled. After a new government was formed in the June 2016 parliamentary election, the government and the BOM stopped the PSP, except for the HM program. However, the BOM's financing for the HM program loans was significantly reduced.

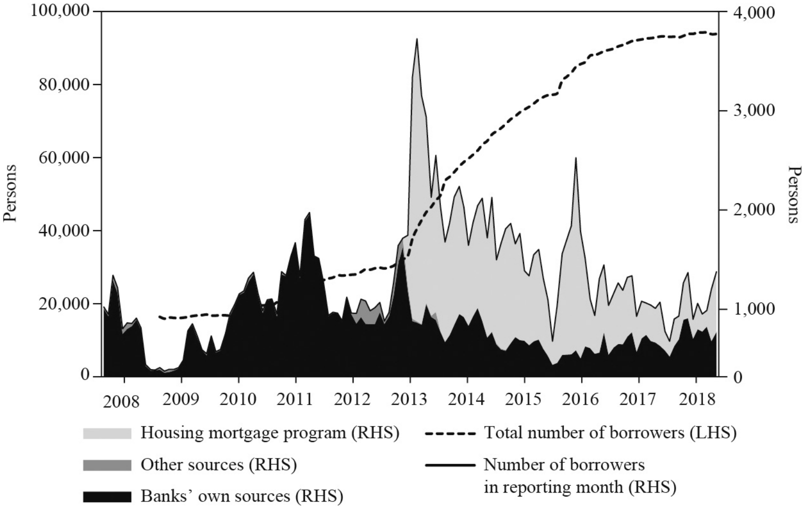
In the first half of 2013, the average mortgage interest rate (weighted average of market and subsidized interest rates) was 16.6%. After introducing the HM program (i.e., the interest rate subsidy on mortgage loans), the average interest rate fell to 9.2%. The initial subsidy shock in the mortgage interest rate was 7.4 percentage points. The mortgage interest rate was 9.9% on average for the period June 2013–March 2016. When the BOM further reduced the mortgage interest rate to 5%, the weighted average mortgage rate decreased to 8.5%. As the supply of HM program loans was slashed, the weighted average mortgage interest rate started to increase during 2017–2018. Starting from Q4 2016, the BOM stopped financing the HM program by expanding its balance

Figure 1. **Mortgage Loans Outstanding**



LHS = left-hand side, RHS = right-hand side.
Source: The Bank of Mongolia.

Figure 2. **Number of Borrowers**



LHS = left-hand side, RHS = right-hand side.
Source: The Bank of Mongolia.

sheet. Instead, the BOM financed the HM program using repayments of existing mortgage loans.

B. Booms and Busts in the Housing Market

This section identifies the booms and busts in Mongolia's housing market. The analysis is based on real housing price quarterly data over the period 2010–2018.[2] Real housing price is measured as the ratio of the nominal housing price index (HPI) to the consumer price index (CPI). The HPI is calculated by Tenkhleg Zuuch LLC, one of the largest real estate data hubs in Mongolia. Following Agnello and Schuknecht (2011), we use a simple statistical approach and define booms and busts in real house prices as significant, persistent deviations from long-term trends. The approach builds on the heterodox methodology that requires detrending the level of the observed variable before employing a turning-point definition of the cycle. First, we identify the housing price cycle by refiltering the housing price series. To measure significant and

[2]Tenkhleg Zuuch real estate agency started calculating monthly housing price index (HPI) based on hedonic regression methods since January 2013. Before that, the National Statistical Office (NSO) of Mongolia was estimating HPI based on district weights and baskets of apartments. In the analysis, we use quarterly HPI calculated by Tenkhleg Zuuch; hence, back-casting of the HPI is based on quarterly growth of the NSO's HPI.

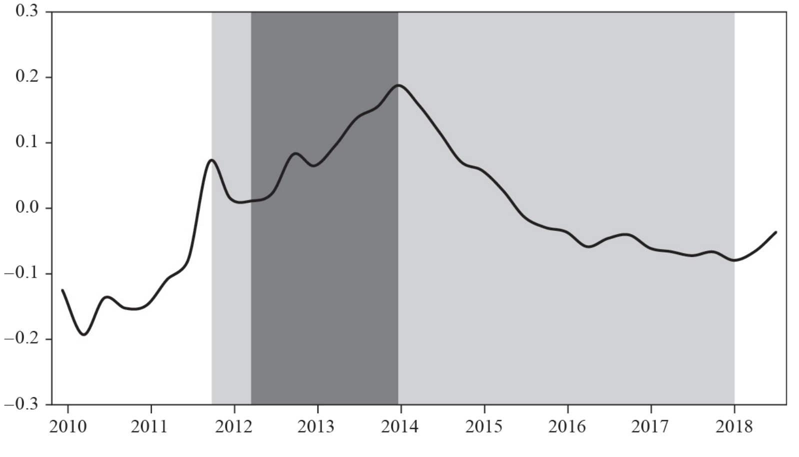
persistent deviations from long-term deviations, we employ a Hodrick–Prescott filter on ex-post data instead of the recursive Hodrick–Prescott filter. We also set a very high smoothing parameter ($\lambda = 10{,}000$) to reflect housing price cycles that are much longer than typical business cycles. Second, we define the characteristics of the cyclical phases of the housing market using EViews's Bry Boschan Quarterly add-in that implements the "triangular methodology" proposed by Harding and Pagan (2002).

The persistence is computed as the temporal distance between turning points in the detrended real housing prices series. The magnitude is measured as the size of the changes in levels of the series from peak to trough and from trough to peak.

Figure 3 shows the boom and bust phases of real housing prices (shaded dark and light, respectively) compared to "normal" periods (nonshaded) over time. The recent boom from Q2 2012 to Q1 2014 lasted almost 2 years and resulted in an above-trend increase in real house prices by 17.7%. The bust from Q1 2014 to Q1 2018 lasted 4 years, and real house prices declined by 33.2% from peak to trough.

The factors contributing to the boom–bust cycles, specifically the role of the mortgage interest rate subsidy implemented under the HM program, are examined in Section V.

Figure 3. **Real Housing Price Gaps and Boom–Bust Phases**



Notes: The series is the cyclical component of the real housing price index, which is persistent deviations from long-term trends. The deviation is measured in absolute values, meaning that 0.1 is equivalent to 10%. The dark shaded area denotes the boom phase, while the light (gray) area indicates the bust phase. Housing price gaps are computed as deviations of real housing prices from trend, obtained using the Hodrick–Prescott filter ($\lambda = 10{,}000$).
Source: Authors' calculations using the real housing price index and EViews's Bry Boschan Quarterly add-in.

III. Determinants of Housing Prices and Estimation Methodology

This section discusses the theoretical foundation of the explanatory factors considered in the empirical analysis and the estimation methodologies used to identify the determinants of housing prices.

A. Factors Driving Housing Prices

Changes in housing prices are the result of many underlying forces, including demand-side (macroeconomic) and supply-side (and house-specific) factors. First, we employ a simple model in identifying key demand-side factors of housing prices. The model considers a representative household that consumes housing and a nonhousing composite good to maximize its utility subject to a budget constraint. The household gains a separable utility through consuming both housing and the composite good, with constant elasticity of substitution of the intertemporal consumption of the two goods. The household also faces a periodic budget constraint, as spending on consumption and repayment on a mortgage loan must be balanced with income. We also assume that (i) the amount of mortgage repayment (both the amortized amount and interest) on housing in each period is a fixed fraction of the total loan and (ii) households face a borrowing constraint, such that the expected value of their collateralizable housing stock at period t must be high enough to guarantee lenders of total loan repayment. The first strong assumption ignores the repayment schemes originated in different types of mortgage contracts. The implication of this simplification is discussed extensively in Tu, de Haan, and Boelhouwer (2018).

In the model, a household tries to arrive at the optimal utility in the form of

$$u(P_t, C_t) = \frac{a_1}{1-m} C_t^{1-m} + \frac{a_2}{1-n} P_{h,t}^{1-n}, \tag{1}$$

where $P_{h,t}$ and C_t are the housing price and real spending on the composite good, respectively; m and n are the elasticities of intertemporal substitution and housing price, respectively; and a_1 and a_2 are preference-related parameters.

The representative household maximizes lifetime utility

$$\sum \beta^t u(P_{h,t}, C_t) \tag{2}$$

subject to

$$C_t + \gamma L_t = Y_t, \tag{3}$$

where β is the discount factor; the mortgage loan L_t is a percentage of the housing price; Y_t represents real income; i_t is the mortgage interest rate; and γ is a constant.

Equation (3) implies that the household's income (Y_t) is spent on a composite good (C_t) and a periodic amount to repay the loan and associated interest (γL_t). Households face a borrowing constraint: the expected value of their collateralizable housing stock at period t must be high enough to guarantee lenders of loan repayment such that $(1+i_t)L_t = \theta P_{h,t}$, where θ captures the loan-to-value ratio and housing stock.

The optimal solution of the household problem yields

$$\frac{u_{p_h}}{u_c} = \frac{1+i_t}{\gamma^{\theta}}. \tag{4}$$

Combining equations (3) and (4) leads to the flexible house–price relationship expressed by the interest rate and expenditure on the composite good:

$$P_{h,t} = c_0 C_t^{\frac{m}{n}} (1+i_t)^{-\frac{1}{n}}, \tag{5}$$

where $c_0 = (\frac{a_2}{a_1}\gamma\theta)^{\frac{1}{n}}$. As higher income stimulates consumer demand, we assume that consumption (spending on the composite good) is determined by household income:

$$C_t = a_0 Y_t^{\mu}, \tag{6}$$

where a_0 and μ are parameters.

Combining equations (5) and (6), we obtain demand-oriented house prices in the flexible form of

$$P_{h,t} = c_0(a_0)^{\frac{m}{n}} Y_t^{\mu\frac{m}{n}} (1+i_t)^{-\frac{1}{n}}. \tag{7}$$

Converting equation (7) into real terms using aggregate price (P_t), we reach the empirical equation of the real housing price

$$\ln P_{h,t}^r = \alpha_0 + \alpha_1 \ln Y_t^r - \alpha_2 i_t + \alpha_3 \ln P_t, \tag{8}$$

where $P_{h,t}^r = \frac{P_{h,t}}{P_t}$ is real housing price; $Y_t^r = \frac{Y_t}{P_t}$ is real income; $\alpha_0 = \ln(c_0(a_0)^{\frac{m}{n}})$; $\alpha_1 = \mu\frac{m}{n}$; $\alpha_2 = \frac{1}{n}$; and $\alpha_3 = \mu\frac{m}{n} - 1$. Equation (8) indicates that real house prices are determined by the real household income level, nominal mortgage interest rate, and CPI. The resulting specification (8) is fully in line with empirical studies (Baffoe-Bonnie 1998 for the United States; Assenmancher-Wesche and Gerlach 2008 for 17 countries; Lee 2009 for Australia; Andrews 2010 for the Organisation for Economic Co-operation and Development (OECD) countries; Panagiotidis and Printzis 2016 for Greece). Intuitions of the determinants are as follows. First, higher household income allows households to take on more debt and spend a larger share of income on housing and related debt service. Hence, a higher income is positively associated with a higher probability of a housing boom (Goodhart and Hofmann 2008). Second, the mortgage interest rate affects household debt financing conditions, that is, a decrease in the cost of borrowing encourages housing demand. Thus, a mortgage interest rate decrease should increase the probability of a boom (Andrews 2010). Third, increases in aggregate price result in lower real user costs, which promote investment in housing. The higher demand for housing may lead to higher housing prices; hence, higher aggregate prices are associated with higher housing prices (Poterba 1984, Panagiotidis and Printzis 2016).

Since we have only annual population and demographic data in Mongolia, these variables are not included in our monthly estimations. Specification (8) describes the Mongolian housing market and the main interest of the paper in the sense that the mortgage interest rate captures the effect of the interest rate subsidy under the HM program, and effects of quantitative measures such as liquidity provided by the BOM are reflected in household income and CPI. Therefore, the specification can help control the simultaneous effects of these quantitative interventions.

In addition to the demand-side (macroeconomic) determinants, some supply-side factors highlighted by the AMM model (Kulish, Richards, and Gillitzer 2012), such as transportation cost and cost of new housing, are considered in the empirical analysis. Because of data limitation, the transportation cost is proxied by the house's location (distance from the city center and a dummy for house district), and a dummy for construction type (building material) is chosen as a proxy for the cost of housing. Building on existing studies (Galati, Teppa, and Alessie 2011; Zhang and Yi 2018), other house-specific factors such as age, size of living space, having a parking, and having a garden are also added in pooled cross-sectional and panel data estimations.

B. Estimation Methodology

To examine the determinants of housing prices in Mongolia, we attempt to use all available information, including pooled cross-sectional, panel, and time series datasets. For instance, pooled cross-sectional data allow us to study the effect of house-specific factors and analyze the effect of the HM program using the difference-in-difference (DiD) method. District-level panel data are used to check the robustness of pooled cross-section results and to assess the effect of air pollution on housing prices as Ulaanbaatar is one of the most heavily polluted capital cities in the world. The time series data help to analyze the macroeconomic determinants of housing prices and to examine the shock decomposition of boom and bust phases in the housing market. As macro variables are also included in the pooled cross-sectional and panel data analyses, their results also provide robustness checks for macroeconomic determinants obtained from the time series analysis. Therefore, these empirical methods (i.e., pooled cross-section, panel, and time series methods) complement one another and help provide a full picture of the determinants of housing prices and the robustness of the interest and income elasticities.

For each dataset, we employ different estimation methods. For instance, the DiD method, pooled ordinary least squares (POLS), and generalized least squares (GLS) are used for pooled cross-sectional data. Static POLS and GLS for district and time fixed effects (FEs) are employed for the panel data. The VECM, which provides a framework for studying long-run economic relations, is used for time series data. The features of the methods are described in the following.

1. Difference-in-Difference

DiD on pooled cross-sectional data is generally used to investigate the impact of policy measures. Hence, we employ the DiD method to evaluate the effect of the HM program on the housing market. For the DiD estimation, the housing price equation is expressed as follows:

$$\ln(P_{it}) = \beta_0 + \beta_1 D_i + \beta_2 \text{Post}_t + \gamma(D_i \times \text{Post}_t) + H_i \beta_{3,X_i} + Z_t \beta_{4,Z_t} + \varepsilon_{it}, \tag{9}$$

where i and t indicate individual houses and time, respectively; P_{it} is the real housing price; D_i is a dummy variable, where $D_i = 1$ if the living space has up to $80\,\text{m}^2$ (under the HM program, the interest rate subsidy only applies for houses of up to $80\,\text{m}^2$) and $D_i = 0$ if the living space is larger than $80\,\text{m}^2$; Post_t is also a binary variable, where $\text{Post}_t = 1$ for the HM program period and $\text{Post}_t = 0$ otherwise; the product $D_i \times \text{Post}_t$ is the dummy variable used for measuring the treatment effect of the HM program; H_i is a set of house-specific variables, such as year of construction, living space, and presence of parking and a garden; and Z_t is a set of macroeconomic variables, including log of real income, nominal mortgage rate, and log of CPI. The coefficients have the following meanings: β_0 is a constant term; β_1 is the treatment group-specific effect; β_2 is a time trend common to control and treatment groups; β_{3,X_i} is the vector of parameters capturing the effects of house-specific variables; β_{4,Z_t} is the vector of parameters capturing the effects of macroeconomic variables; γ captures the effect of the HM program; and ε_{it} is the disturbance term.

2. Pooled Ordinary Least Squares and Generalized Least Squares Estimators

POLS and GLS estimators are used to measure the effect of micro and macro variables on house prices based on panel data. For the estimators, the regression equation is set as follows:

$$\ln(P_{it}) = \mathbf{H}_{it}\beta + u_{it}, \tag{10}$$

where P_{it} is real housing price; $\mathbf{H}_{it}$ includes all determinants including house-specific factors and macroeconomic variables; β is the vector of parameters; and u_{it} is the idiosyncratic error. POLS provides the best linear unbiased estimator and consistent estimator of β under the following assumptions: (i) $E(\mathbf{H}'_{it}u_{it}) = 0$; (ii) rank $E(\sum_{t=1}^{T} \mathbf{H}'_{it}\mathbf{H}_{it}) = K$, $i = 1, 2, \ldots, K$; and (iii) $E(u_{it}^2 \mathbf{H}'_{it}\mathbf{H}_{it}) = \sigma^2 E(\mathbf{H}'_{it}\mathbf{H}_{it})$, $t = 1, 2, \ldots, T$, where $\sigma^2 = E(u_{it}^2)$, and $E(u_{it}u_{is}\mathbf{H}'_{it}\mathbf{H}_{is}) = 0$, $t \neq s$, $t, s = 1, 2, \ldots, T$. The last assumption implies $E(u'_{it}u_{it}) = \sigma^2 I_T$, meaning that the unconditional variances are constant and the unconditional covariances are zero (Wooldridge 2002). POLS is still a consistent estimator if the first two assumptions hold. When $E(u'_{it}u_{it}) = \sigma^2 I_T$ does not hold and the first two assumptions hold, then GLS analysis is as efficient as POLS.

3. Vector Error Correction Model

VECM is employed in estimating the long-run housing price equation for time series data. Let us consider the VAR(p) model:

$$y_t = \sum_{i=1}^{p} \Pi_i y_{t-i} + \varepsilon_t, \tag{11}$$

where y_t is an $n \times 1$ vector composed of $I(0)$ and $I(1)$ variables (i.e., log of real housing price, log of real income, nominal mortgage rate, and log of CPI); n is the number of endogenous variables in the system; p is the number of lags of the endogenous variables; Π_i is the matrix of coefficients; and ε_t is a martingale difference sequence with constant conditional variance Σ_ε (abbreviated mds(Σ_ε)) with finite fourth moments. Since each of the variables in the system is $I(0)$ or $I(1)$, the determinantal polynomial $|\Pi(z)|$ contains at most n unit roots, with $\Pi(z) = I - \sum_{i=1}^{p} \Pi_i z^i$. When there are fewer than n unit roots, then the variables are cointegrated, in the sense that a certain linear combination of the y_t's are $I(0)$.

To derive the VECM, subtract y_{t-1} from both sides of equation (11) and rearrange the equation as

$$\Delta y_t = \Pi y_{t-1} + \sum_{i=1}^{p-1} \Phi_i \Delta y_{t-i} + \varepsilon_t, \tag{12}$$

where $\Pi = -I_n + \sum_{i=1}^{p} \Pi_i$, which has rank $r = \text{rank}(\Pi)$, and $\Phi_i = -\sum_{j=i+1}^{p} \Pi_j$, $i = 1, \ldots, p-1$. Let α denote an $n \times r$ matrix whose columns form a basis for the row space of Π, so that every row of Π can be written as a linear combination of the rows of α'. Thus, we can write $\Pi = \delta\alpha'$, where δ is an $n \times r$ matrix with full column rank.

Equation (12) then becomes

$$\Delta y_t = \delta w_{t-1} + \sum_{i=1}^{p-1} \Phi_i \Delta y_{t-i} + \varepsilon_t, \tag{13}$$

where $w_t = \alpha' y_t$. Solving equation (13) for w_{t-1} shows that $w_{t-1} = (\delta'\delta)^{-1}\delta'$ $[\Delta y_t - \sum_{i=1}^{p-1} \Phi_i \Delta y_{t-i} - \varepsilon_t]$, so that w_t is $I(0)$. Thus, linear combinations of the potentially $I(1)$ elements of y_t formed by the columns of α are $I(0)$, and the columns of α are cointegrating vectors. $w_t = 0$ can be interpreted as the "equilibrium" (long-run relations among variables) of the dynamical system, w_t as the "equilibrium errors," and equation (13) describes the self-correcting mechanism of the system (Watson 1994). In the empirical analysis, maximum eigenvalue and trace tests and variants of likelihood ratio (LR) type tests are employed to determine the cointegrating rank (r). The long-run equation of housing price is used to assess the effect of the mortgage interest rate subsidy implemented under the HM program on housing price dynamics.

IV. Data

In this paper, we employ three types of datasets: pooled cross-sectional, panel, and time series data. Descriptions of the datasets are detailed in the following.

A. Pooled Cross-Sectional Data

We use a raw database of Ulaanbaatar housing price surveys conducted by Tenkhleg Zuuch real estate agency. Tenkhleg Zuuch calculates the HPI using hedonic regressions on the monthly survey data, which only include apartments. The pooled cross-sectional data cover the period January 2013 to September 2018, and the total number of observations is 272,799. House-specific variables in pooled cross-sectional data and their descriptions are shown in Table 1.

Because of data limitation, only house asking prices are available in Mongolia. The statistical characteristics of the variables are shown in Table A.1 of the Appendix. The average age of a house at the time of the survey is 9.6 years, and the average living space of apartments is about 60 m^2. Two-thirds of apartments have parking, about half of them have a garden, and 72% were built using a concrete frame. The average distance of an apartment from the center of the city is 4.6 kilometers.

In addition to the data shown in Table 1, the pooled cross-sectional data estimation also consists of macroeconomic variables (Z_t) such as the mortgage interest

Table 1. **Description of House-Specific Variables**

Variable	Description
Housing prices	House asking prices collected from surveys conducted by Tenkhleg Zuuch
Real housing prices	Housing price is adjusted for the consumer price index
House characteristics	
Age	Years since construction at the time of survey (in years)
Living space	Area of house in square meters
Living space squared	Area of house squared
Parking	Dummy = 1 if the apartment has parking, 0 otherwise
Garden	Dummy = 1 if the apartment has a garden, 0 otherwise
Distance	Distance from the city center in kilometers
Construction type	
Concrete frame	Construction dummy = 1 if construction type is a concrete frame, 0 otherwise
High-density concrete	Construction dummy = 1 if construction type is high-density concrete, 0 otherwise
Iron Caracas	Construction dummy = 1 if construction type is iron Caracas, 0 otherwise
Brick apartment	Construction dummy = 1 if construction type is a brick house, 0 otherwise
Wooden and brick apartment	Construction dummy = 1 if construction type is a wooden and brick house, 0 otherwise
Prefabricated apartment	Construction dummy = 1 if construction type is a prefabricated house, 0 otherwise
Ulaanbaatar districts	
District 1 (Bayangol)	District dummy = 1 if the apartment is in Bayangol district, 0 otherwise
District 2 (Bayanzurkh)	District dummy = 1 if the apartment is in Bayanzurkh district, 0 otherwise
District 3 (Nalaikh)	District dummy = 1 if the apartment is in Nalaikh district, 0 otherwise
District 4 (Songinokhairkhan)	District dummy = 1 if the apartment is in Songinokhairkhan district, 0 otherwise
District 5 (Sukhbaatar)	District dummy = 1 if the apartment is in Sukhbaatar district, 0 otherwise
District 6 (Khan-Uul)	District dummy = 1 if the apartment is in Khan-Uul district, 0 otherwise
District 7 (Chingeltei)	District dummy = 1 if the apartment is in Chingeltei district, 0 otherwise

Source: Housing price surveys conducted by Tenkhleg Zuuch LLC.

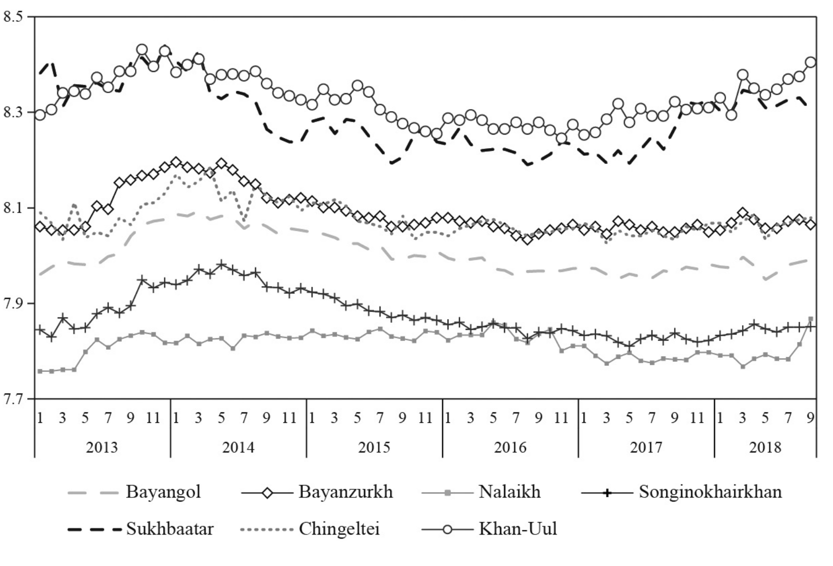
rate, the natural logarithm of real household income, and the natural logarithm of CPI for the period January 2013 to September 2018. Mortgage interest rate is calculated as the weighted average interest rate of mortgage loans (i.e., weighted average of the market and the subsidized interest rates) and the data are collected from the BOM's Statistical Bulletin. Real household income is measured as a ratio of nominal household income to CPI, and monthly nominal household income is calculated using EViews's low- to high-frequency method (linear match last) on the average quarterly household income collected from the Household Socio-Economic Survey conducted by the National Statistical Office (NSO) of Mongolia. CPI is the nationwide CPI and the data are taken from the NSO.

B. Panel Data

Using the raw database of the housing price surveys, we construct a panel data based on district classification. The panel data covering the period January 2013 to September 2018 for Ulaanbaatar districts are used to examine how house-specific factors and macroeconomic variables affect house prices. Average prices of newly constructed residential properties in Ulaanbaatar districts are shown in Figure 4. The districts' average house prices have moved together over time.

House characteristics and macroeconomic variables (mortgage interest rate, real household income, and CPI) are also included in the panel estimation. For the panel data, house characteristics (i.e., living space, age, and distance) are measured as an average for houses within each district at a certain period. As air pollution has been a big issue in Ulaanbaatar and air quality differs among districts, we assume that it is a crucial factor affecting the house buyer's choice. Since each district's time series data of air pollution are reported, we include the variable in the panel estimation. Each district's air pollution, which is measured by nitrogen dioxide, is collected from the database of the Ministry of Environment and Tourism. Macroeconomic variables are the same as in the pooled cross-sectional data.

Figure 4. **Average Prices of Residential Properties in Ulaanbaatar by District**



1 = January, 3 = March, 5 = May, 7 = July, 9 = September, 11 = November.
Note: The *y*-axis represents the natural logarithms of average prices of residential properties.
Source: Authors' calculations based on the raw database of housing price surveys conducted by Tenkhleg Zuuch LLC.

C. Time Series Data

Data used in the VECM estimation include the monthly time series of four variables for the period January 2013 to September 2018. These variables include the natural logarithm of a real housing price index (ln(RHPI)), natural logarithm of real household income (ln(RHI)), natural logarithm of CPI (ln(CPI)), and nominal mortgage interest rate (MIR). The average nominal household income and CPI are retrieved from the NSO of Mongolia. The mortgage interest rate (weighted average rate of mortgage loans issued in the reporting month) and overall HPI calculated by Tenkhleg Zuuch are obtained from the BOM. CPI is used to adjust nominal variables to find real variables. In addition to the overall HPI, we calculate two more HPIs using hedonic modeling and time dummy variable method. The hedonic regression approach conceptually founded by Lancaster (1966) and Rosen (1974) is employed to constrict the HPI for residential properties of up to 80 m^2, which can be bought by a mortgage loan with a subsidized interest rate under the HM program. The time dummy variable method initially developed by Court (1939) is used to build another HPI as an alternative to the overall HPI. In constructing new HPIs, we use the same database from Tenkhleg Zuuch that was used in constructing the overall HPI and follow the procedures described by Eurostat (2013).

The newly constructed HPIs are much smoother than the overall HPI, particularly for the period 2016–2017. Moreover, the HPI for residential properties of up to 80 m^2 grows faster than the other two HPIs during the boom phase (i.e., Q2 2012–Q1 2014 period).

V. Empirical Results

A. Estimation

1. Pooled Cross-Sectional Regression Analysis

DiD, POLS, and GLS methods on the pooled cross-sectional data are used to examine the house-specific and macro determinants of real housing prices, particularly the effects of the HM program on housing prices. The DiD estimation covers the period January 2013 to December 2013, and the first 5 months are classified as the pre-HM program period, while the last 7 months are the HM program period. The estimation results are shown in Table 2.

Most variables in the regressions are statistically significant at the 1% significance level. The signs of the estimated coefficients are in line with their economic meanings. Older houses are less expensive, and the presence of parking and a garden increases real house prices. For each kilometer from the center of the city, real house prices fall by over 2% for GLS and DiD methods. Housing types significantly affect house prices. For housing type (quality), the omitted variable is prefabricated apartments. The estimation shows that houses made from high-density concrete and iron Caracas are more expensive, while concrete frame and brick houses are cheaper

Table 2. **Estimation Results of Pooled Ordinary Least Squares, Generalized Least Squares, and Difference-in-Difference Models**

	Dependent Variable: Log (Real Housing Prices)		
Independent Variables	**POLS**	**GLS**	**DiD**
House characteristics			
Living space	0.023***	0.027***	0.023***
	(0.00)	(0.00)	(0.00)
Living space squared	−0.0001***	−0.0001***	−0.0001***
	(0.00)	(0.00)	(0.00)
Age	−0.004***	−0.005***	−0.002***
	(0.00)	(0.00)	(0.00)
Parking	0.064***	0.055***	0.031***
	(0.00)	(0.00)	(0.00)
Garden	0.008***	0.009***	−0.003
	(0.00)	(0.00)	(0.00)
Distance	−0.009***	−0.028***	−0.024***
	0.023***	(0.00)	(0.00)
Construction type			
Concrete frame	−0.086***	−0.102***	−0.052***
	(0.00)	(0.00)	(0.01)
High-density concrete	0.063***	0.082***	0.197***
	(0.00)	(0.00)	(0.01)
Iron Caracas	0.298***	0.233***	0.259***
	(0.01)	(0.01)	(0.05)
Brick apartment	−0.097***	−0.083***	−0.073***
	(0.00)	(0.00)	(0.01)
Wooden and brick apartment	0.062***	0.076***	−0.061***
	(0.01)	(0.01)	(0.02)
District interaction term			
District 1 # living space	0.003***	0.001***	0.001***
District 2 # living space	0.003***	0.001***	0.001***
District 3 # living space	−0.000	0.008***	0.006***
District 5 # living space	0.004***	0.002***	0.003***
District 6 # living space	0.004***	0.003***	0.002***
District 7 # living space	0.004***	0.002***	0.002***

Continued.

Table 2. *Continued.*

	Dependent Variable: Log (Real Housing Prices)		
Independent Variables	**POLS**	**GLS**	**DiD**
Macroeconomic variables			
Mortgage interest rate (in level)	−0.024***	−0.026***	
	(0.00)	(0.00)	
ln(real income)	1.085***	1.140***	
	(0.01)	(0.01)	
ln(CPI)	−0.970***	−1.013***	
	(0.01)	(0.01)	
Treatment dummy (D_i)			0.078***
Post time dummy (Post_t)			0.037***
Policy effect ($D_i \times \text{Post}_t$)			0.032***
Constant	6.938***	6.431***	17.419***
	(0.13)	(0.11)	(0.02)
Observations	272,799	272,799	20,748
Adjusted R^2	0.876	0.864	0.911
Sample period	Jan 2013–Sep 2018	Jan 2013–Sep 2018	Jan 2013–Dec 2013

DiD = difference-in-difference, GLS = generalized least squares, POLS = pooled ordinary least squares.
Notes: Coefficient estimates are shown with their standard errors in parentheses. *** indicates significance at 1% level.
Source: Authors' calculations.

compared to prefabricated houses. The omitted variable for districts is District 4 (Songinokhairkhan), since housing prices in this district are the lowest.

All macro variables, such as mortgage interest rate, real household income, and CPI, have a significant impact on real house prices. The estimated interest rate elasticity is about 2.5, and elasticities of the real household income and CPI are close to one. The estimated elasticities are in line with the results of studies surveyed by Iossifov, Cihak, and Shanghavi (2008). The DiD regression is estimated only for the period January 2013 to December 2013, reflecting the fact that the HM program started in June 2013 and our sample started in January 2013.[3]

Real housing prices increased by 3.7% on average (β_2) during the first 7 months of the HM program (i.e., between June 2013 and December 2013). Prices for residential properties with a living space of up to 80 m^2 grew by 7.8% on average (β_1) during 2013. The coefficient (γ) on the product ($D_i \times \text{Post}_t$), capturing the effects of

[3]Since maximum pretreatment period is 6 months, posttreatment period is chosen as 6 months in the regression.

the HM program on the housing price, is estimated at 0.032. The estimation implies that the HM program potentially led to a 3.2% increase in real housing prices for the period June 2013 to December 2013.

2. Panel Data Regression Analysis

To examine the effects of house-specific and macroeconomic variables on district housing prices, we conduct panel data analyses using static POLS, only district fixed-effect (FE [district]), and only time fixed-effect (FE [time]) methods. The panel data estimation results are shown in Table 3.

The house-specific factors, except for distance in the FE (district) and FE (time) methods, have statistically significant effects on real housing prices. The results are robust for all estimation methods. The signs of the estimated parameters are the same as discussed in the pooled cross-sectional data analysis. A novel result is that real housing prices tend to be cheaper for houses located in areas with higher air pollution measured by nitrogen dioxide. According to the static POLS estimation, apartments are cheaper if they are farther from the city center.

For static POLS and FE (district) methods, the interest rate elasticity and income elasticity are statistically significant at the 1% level and estimated as 1.6–1.9 and 0.65–0.82, respectively. The FE specification eliminates omitted-variable bias caused by excluding unobserved variables that change over time but are the same across districts in each period. For FE (time) estimation, the elasticities are estimated as statistically insignificant since the method controls macro variables by including dummies for each period. The results may imply that the observed macro variables (CPI, household income, and mortgage interest rate) are endogenous and determined by other variables (i.e., commodity prices, foreign direct investment, cash transfers, etc.) not included in the estimation.

3. Time Series Analysis

As there are no time series data of supply-side factors (and micro-housing attributes), we estimate the VECM for demand-side determinants as specified in equation (8). As the HPI includes only apartments (not single-family homes, semidetached homes, or terraced houses), we assume that apartment prices are determined by the macro variables. Before estimating the model, we conduct univariate unit root tests by applying the Augmented Dickey–Fuller (ADF) test for stationarity of these variables. The ADF test statistics are summarized in Table A.2 of the Appendix.

Table 3. **Estimation Results of Pooled Ordinary Least Squares and Fixed-Effect Estimators**

	Dependent Variable: ln(Real Housing Prices) by Districts		
Independent Variables	**Static POLS**	**FE (District)**	**FE (Time)**
House characteristics			
Living space	0.113***	0.042***	0.032***
	(0.01)	(0.01)	(0.00)
Living space squared	−0.001***	−0.000***	−0.000***
	(0.00)	(0.00)	(0.00)
Age	−0.006***	−0.013***	−0.015***
	(0.00)	(0.00)	(0.00)
Distance	−0.013***	−0.004	−0.001
	(0.00)	(0.00)	(0.004)
Air pollution (measured by NO_2)	−0.006***	−0.003**	−0.003***
	(0.00)	(0.00)	(0.00)
Macroeconomic variables			
Mortgage interest rate	−0.016***	−0.019***	0.026
	(0.00)	(0.00)	(0.07)
ln(CPI)	−0.862***	−0.785***	−0.540
	(0.07)	(0.04)	(0.62)
ln(real income)	0.652***	0.824***	−0.60
	(0.08)	(0.06)	(2.38)
Constant	9.395***	9.296***	27.600
	(1.31)	(0.93)	(30.90)
Observations	483	483	483
Adjusted R^2	0.962	0.875	0.922
Sample period	Jan 2013–Sep 2018	Jan 2013–Sep 2018	Jan 2013–Sep 2018

CPI = consumer price index, FE = fixed effect, NO_2 = nitrogen dioxide, POLS = pooled ordinary least squares.
Notes: Coefficient estimates are shown with their standard errors in parentheses. ** and *** indicate significance at 5% and 1% levels, respectively. Coefficients for time dummies are not shown in the table.
Source: Authors' calculations.

The test results show that all four variables (i.e., log of real house prices, log of CPI, log of real household income, and mortgage interest rate) are $I(1)$. In particular, the null hypothesis that each series in levels has a unit root is not rejected, and the null hypothesis that the first difference of each series has a unit root is rejected at the 1% significance level.

We then determine the appropriate number of lags for the VECM. We estimate three versions of the VECM with different real HPIs: (i) overall HPI calculated by Tenkhleg Zuuch, (ii) HPI for residential properties of up to 80 m^2, and (iii) HPI constructed with a time dummy. Results of the lag selection criteria are shown in Table A.3 of the Appendix. For the VAR with overall HPI, the LR test, final prediction error (FPE), and Akaike information criterion (AIC) suggest five lags, but the Schwarz Bayesian information criterion (SBIC) and Hannan–Quinn information criterion (HQIC) indicate one and two lags, respectively. For the VAR with HPI for properties of up to 80 m^2, the LR test and FPE suggest four lags, while AIC, SBIC, and HQIC indicate five, one, and two lags, respectively. For the VAR with HPI constructed with a time dummy, FPE and HQIC suggest two lags, while the LR test, AIC, and SBIC indicate four, five, and one, respectively. However, for the three versions of VAR, only the VAR(2) model simultaneously satisfies all corresponding diagnostic tests, including joint normality, no serial correlation, and no heteroskedasticity in the residual matrix at the 5% significance level. Thus, the VECM(1) (i.e., error correction form of VAR[2] model) is employed for all estimations. The trace and eigenvalue cointegration tests are conducted to determine the number of cointegrations among the four variables in the model.

For all three versions, the cointegration equation shown in equation (8) with a constant is estimated. The test results are shown in Table A.4 of the Appendix. For all three versions, both trace and eigenvalue tests suggest that one cointegrating rank can exist among these variables at the 5% significance level. Since all variables in the systems are $I(1)$, the cointegrating relationship is not caused by the inclusion of a stationary variable. Since one cointegrating relationship exists between these variables, the specification of VECM must be appropriately developed.

The weak exogeneity test is used to find the proper specification of the VECM (i.e., a system of equations or a single equation). The test results are shown in Table A.5 of the Appendix. For all three versions, the null hypothesis that the variable is weakly exogenous is rejected for HPI and real household income, while the hypothesis is not rejected for CPI and mortgage interest rate at the 5% significance level. The result is in line with the theoretically suggested equation (8), suggesting that real housing prices are determined by macroeconomic variables. As the mortgage interest rate is subsidized under the HM program in Mongolia, it is purely exogenous, and CPI is driven more by the exchange rate, policy rate, and supply factors such as meat and fuel prices in Mongolia.

The weak exogeneity tests also suggest that a system of HPI and real household income equations (where CPI and mortgage interest rate are weakly exogenous) must be employed in estimating a cointegrating vector, α'. To this end, the joint restriction $\delta_{\mathrm{MIR}} = \delta_{\mathrm{CPI}} = 0$ (which is not rejected by the data as the LR test statistic is $\chi^2(2) = 1.41$, the p-value of the LM test is 0.5 for overall HPI, $\chi^2(2) = 1.99$, the p-value of LM test is 0.37 for the HPI for residential properties of up to 80 m^2, $\chi^2(2) = 1.79$, and the p-value of the LM test is 0.41 for HPI constructed with a time

Table 4. **Estimation Results of the Vector Error Correction Model**

	Dependent Variable: Δ ln(real HPI)		
Independent Variables	**Overall HPI**	**HPI for Residential Properties of Up to 80 Square Meters**	**HPI Constructed with a Time Dummy**
Long-run relationship			
ln(CPI (−1))	−0.934***	−1.072***	−1.025***
	(0.119)	(0.102)	(0.115)
ln(real income (−1))	1.454***	1.411***	1.403***
	(0.156)	(0.133)	(0.149)
MIR (−1)	−0.027***	−0.029***	−0.030***
	(0.005)	(0.004)	(0.004)
Constant	−10.908	−9.641	−9.745
Short-run relationship			
Error correction term	−0.126*	−0.134*	−0.132*
	(0.038)	(0.032)	(0.032)
Δ ln(real HPI (−1))	−0.074	−0.057	−0.018
	(0.124)	(0.122)	(0.121)
Δ ln(CPI (−1))	−0.148	−0.025	−0.027
	(0.233)	(0.194)	(0.212)
Δ ln(real income (−1))	−0.001	−0.031	−0.043
	(0.133)	(0.113)	(0.123)
Δ (MIR (−1))	0.002	0.002	0.003
	(0.002)	(0.002)	(0.002)
Constant	−0.004*	−0.005***	−0.004*
	(0.002)	(0.002)	(0.002)
Observations	67	67	67
Adjusted R^2	0.186	0.284	0.255

CPI = consumer price index, HPI = housing price index, MIR = mortgage interest rate.
Notes: Coefficient estimates are shown with their standard errors in parentheses. * and *** indicate significance at 10% and 1% levels, respectively.
Source: Authors' calculations.

dummy) is imposed on the VECMs to obtain efficient estimators for the parameters of the cointegrating vector. For all three versions, the VECM with one lag and the weakly exogenous restriction is estimated, and results of both long-run and short-run relationships of the real housing price equations are shown in Table 4.

For all three versions, the long-run elasticity of each explanatory variable has the theoretically expected sign and is statistically significant at the 1% significance level, suggesting that the real household income, mortgage interest rate, and CPI affect real housing prices. The real income elasticity is estimated as $\alpha_1 = 1.4$, which is in line with existing studies (Hofman 2005 for the Netherlands, Oikarinen 2005 for Finland, Jacobsen and Naug 2005 for Norway). The interest rate semielasticity is estimated at $\alpha_2 = 0.03$, suggesting that a 1 percentage decrease in the average mortgage interest rate leads to a 3% increase in the real housing price. The estimated value of the semielasticity is modest and closer to the results obtained in existing studies (Meen 2002 for United Kingdom, Jacobsen and Naug 2005 for Norway). Comparing with other countries, magnitudes of the estimated elasticities are closer to those found in Jacobsen and Naug (2005) for Norway, which is also a resource-rich and small open economy. The estimated elasticities of the VECM are also closer to the estimated values using the pooled cross-sectional data. All findings imply that the mortgage interest rate subsidy and macroeconomic policies significantly affect real housing price.

Another interesting result is that VECM feedback takes place through real housing prices and real household income adjustments. The error correction coefficients of the real housing price equation ($\delta_{\mathrm{HPI}} = -0.13$) have the expected sign. The result suggests that any deviation from the long-run equilibrium is corrected at the rate of 13% each month, and it takes about 8 months to return to the long-run equilibrium. In the short run, the macroeconomic determinants have an insignificant effect on real housing price.

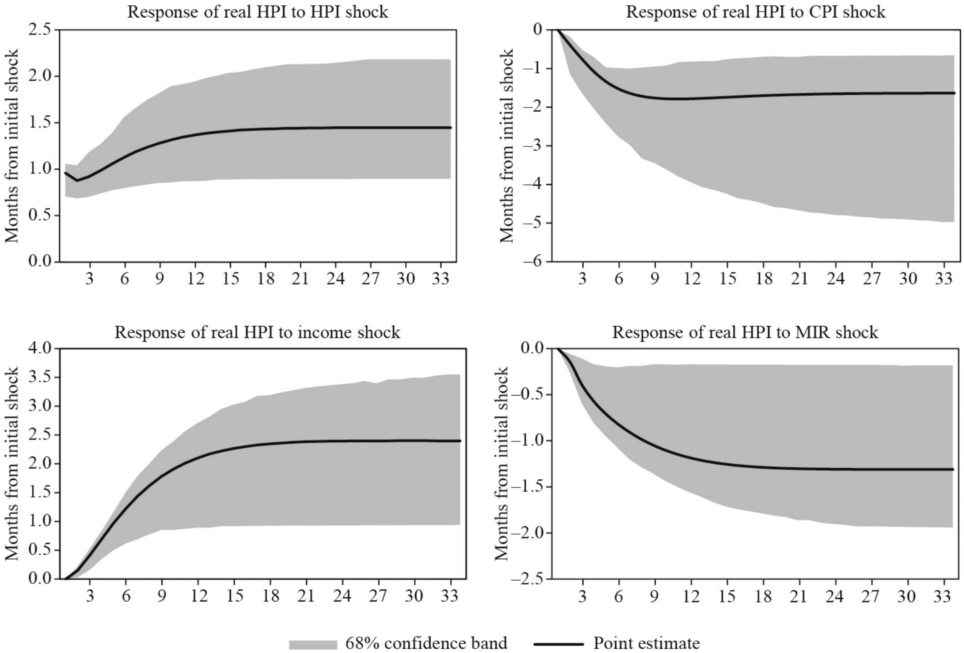
Overall, three empirical estimations (i.e., pooled cross-section, panel, and time series methods) provide robust evidence that (i) both demand- (macroeconomic variables) and supply-side (house-specific characteristics, distance, air pollution) factors are critical determinants of housing prices and (ii) the HM program's subsidized mortgage loan has affected housing prices through direct (mortgage interest rate subsidy) and indirect (household income and CPI) channels. The long-run interest rate, income, and CPI are elastic and statistically significant with theoretically consistent signs.

B. Impulse Response, Variance Decomposition, and Historical Decomposition of Real Housing Prices

To assess the dynamic behavior of the VECM of real HPI for apartments of up to $80\,\mathrm{m}^2$, we employ generalized impulse response function (GIRF) together with bootstrapped standard errors. Figure 5 reports point estimates and 68% confidence bands of the GIRFs.

The size of each shock is a 1% (or 1 percentage point for interest rate) change in the shock variable. A 1% own shock increases the real HPI by 1.5% after 36 months

Figure 5. **Impulse Responses of the Real Housing Price Index for Apartments of Up to 80 Square Meters**



CPI = consumer price index, HPI = housing price index, MIR = mortgage interest rate.
Notes: The figures show accumulated impulse responses of the first-differenced variables, which correspond to responses of the level variables. Given that the level variables are nonstationary, their responses to shocks have a permanent nature.
Source: Authors' calculations.

from the initial shock, and the response is highly persistent. A 1% increase in the CPI decreases real HPI by 1.6%–1.7% after 6 months. The response of real HPI to the income shock gradually increases over time. A 1% increase in real household income pushes up real HPI by 2.2%–2.4% after 12 months from the initial shock. Because of the HM program (interest rate subsidy), the average mortgage interest rate immediately fell by 7 percentage points. According to the response of real HPI to the MIR shock, the policy intervention has increased real HPI by 6%–9% for the next 36 months from the initial shock (i.e., June 2013).

Though impulse response functions show the transmission and effect of structural shocks, they do not provide evidence regarding their significance in HPI fluctuations. Variance decomposition, on the other hand, shows the significance of each identified shock in the fluctuations of the variables of interest. Table 5 presents

Table 5. **Forecast Error Variance Decomposition of the Real Housing Price Index for Apartments of Up to 80 Square Meters (in %)**

Forecast Horizon (Months)	HPI Shock	CPI Shock	Income Shock	MIR Shock
3	90.4	1.3	3.0	5.3
6	71.5	2.9	12.5	13.0
9	63.6	2.4	18.5	15.4
12	60.2	1.8	21.6	16.3
15	58.6	1.4	23.3	16.7
18	57.6	1.2	24.3	17.0
21	57.0	1.0	24.9	17.1
24	56.5	0.9	25.4	17.2
27	56.2	0.8	25.7	17.3
30	56.0	0.7	25.9	17.3
33	55.8	0.7	26.2	17.4
36	55.6	0.6	26.3	17.4

CPI = consumer price index, HPI = housing price index, MIR = mortgage interest rate.
Notes: The table shows the variance decomposition of real HPI, which determines how much of the forecast error variance of the level variable can be explained by the identified shocks (HPI, income, CPI, and MIR shocks). The columns give the proportion of forecast error in real HPI accounted for by each identified shock.
Source: Authors' calculations.

the results of the forecast error variance decomposition (Cholesky decomposition) of real HPI for apartments of up to 80 m^2.

The total variance of the HPI is decomposed in each period of the forecast horizon and we measure the percentage of this variance that each shock can explain. For the first three quarters, the highest explanatory power is attributed to HPI's own shocks (90% of the variance). However, 3 years after the shock, real household income and the mortgage interest rate shock account for the significant variation (26.3% for income shock and 17.4% for mortgage interest rate shock) in the HPI. The CPI shock accounts for a small portion (less than 3%) of the HPI variation for all forecast horizons. Another observation is that house prices are rigid, particularly in short horizons, and the importance of household income and mortgage interest rate shocks in explaining the HPI variance increases over time. These results are robust regardless of the ordering of variables used in the Cholesky decomposition.

Next, we explore which factors (structural shocks) drove the recent boom and bust in the Mongolian housing market. Historical decompositions provide an interpretation of historical fluctuations in the modeled time series through the lens of the identified structural shocks. The estimated VECMs are used to analyze the historical decomposition, which describes the variation of real HPIs over time in terms of the structural shocks. The historical decomposition is always backward-looking and treats everything as observed. Therefore, having estimates of the model's impulse response parameters and the history of structural shocks is sufficient information to calculate the historical decomposition.

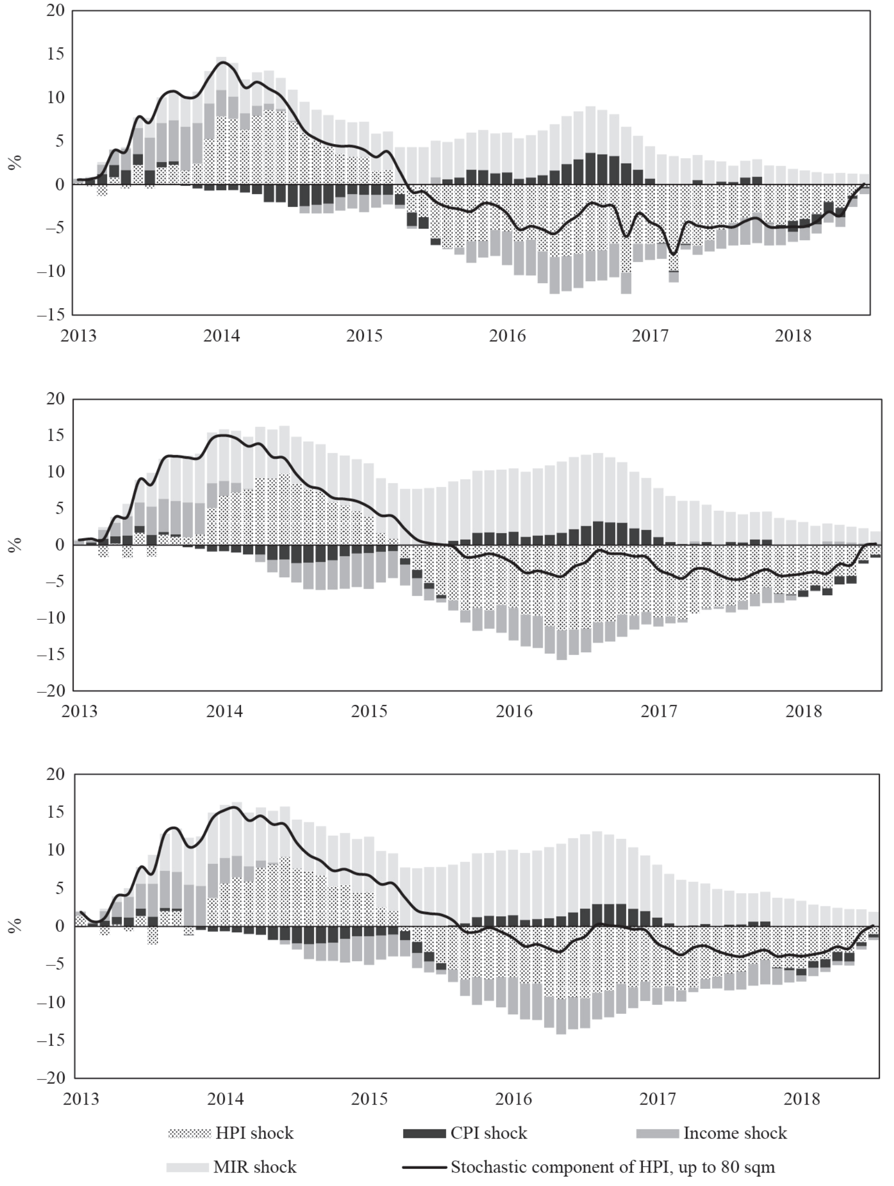
Historical decompositions are estimated using the generalized approach proposed by Pesaran and Shin (1998). Unlike the traditional (i.e., recursive or Cholesky) approach, the generalized approach does not require orthogonalization of shocks and is invariant to the ordering of the variables in the VECM. Figure 6 displays the generalized historical decomposition of real HPIs by focusing on the contributions of each shock (HPI, real income, and mortgage interest rate shocks) over the period January 2013 to September 2018. The historical decompositions of different HPIs are qualitatively the same because the contribution of each shock moves all HPIs in the same direction, but quantitatively different in the sense that the magnitude of the contribution explained by a certain shock varies among different HPIs.

Mortgage interest rates and HPI own shocks were the main contributors to the 2013–2014 housing price boom. Under the HM program, the mortgage interest rate was subsidized starting June 2013, and the average mortgage interest rate immediately fell by over 7 percentage points. Over 35,000 borrowers took mortgage loans of MNT1.5 trillion (equivalent to 16% of the money supply) with a subsidized interest rate (8% per annum) between June 2013 and March 2014. Over the period, total mortgage loan outstanding doubled, reaching MNT2.2 trillion, and its annual growth exceeded 125% for the period September 2013 to March 2014.

Figure 6 shows that the mortgage interest rate shock drives more than half of the HPI for residential properties of up to 80 m^2, which are properties that can be bought by the mortgage loan with a subsidized interest rate. The finding indicates that the massive policy intervention in the mortgage market has led to the housing price boom in Mongolia. As the mortgage interest rate subsidy continued under the HM program, mortgage interest rate shocks continued to have a positive contribution to real housing prices over time.

Even as the subsidized mortgage rate was temporarily reduced from 8% to 5% in 2016, the interest rate shock's positive contribution increased in the same year. As the volume of subsidized mortgage loans decreased from the end of 2016, the contribution of the interest rate shock gradually shrunk.

Figure 6. **Historical Decomposition: Stochastic Components of the Real Housing Price Index**



CPI = consumer price index, HPI = housing price index, MIR = mortgage interest rate, sqm = square meter.
Note: The figures show the historical decompositions of the real HPIs, which provide an interpretation of historical fluctuations in the level variables through the lens of the identified shocks (HPI, income, CPI, and MIR shocks).
Source: Authors' calculations.

Though we use the assumption that each structural shock identified from the VECM has a zero mean, the contribution of the mortgage interest rate shock on the HPI has been positive for the whole sample period. This can be explained by the fact that in the VECM, dependent variables are modeled in a first-difference form, and structural shocks are identified from the specification.

In line with the estimates of VECM's impulse responses, the contribution of a structural shock to a level variable is calculated as the cumulative sum of the differenced variable's contribution. The empirical estimates of highly persistent impulse responses and values of the mortgage interest rate shock result in the positive contribution of the shock for the sample period.

Real household income shocks had a positive contribution to the housing price boom during the years of double-digit growth. Own shocks of housing prices also played a significant role in the housing price dynamics since the end of 2013. In the VECM, the expectation effects are reflected in housing price shocks. As highlighted by Lambertini, Mendicino, and Punzi (2013) and Kanik and Xiao (2014), own shocks of housing prices strongly amplified the housing price boom in Mongolia during the period September 2013 to March 2014. Initially, the contribution of own shocks was positive since market participants had formed an expectation that the housing price will rise further as subsidized mortgage loans rapidly increased. The expectation of large price increases had a strong impact on housing demand because people believed that housing prices were unlikely to fall. Some policy makers' statements may have also influenced housing price expectation by promoting the view that buying a house is a long-term investment, with substantial financial benefits as house prices increase.

The housing price bust started in March 2014, and CPI and real household income shocks initially drove the bust. As real housing prices started to fall, market participants' expectations reversed in the direction that the price will keep declining. Therefore, HPI shocks had a negative contribution to housing prices during this period. Together with real household income shocks, own shocks were the primary reason why the housing bust lasted several years. Overall, our analysis suggests that the HM program (i.e., mortgage interest rate subsidy) led to the boom, and the deterioration of macroeconomic fundamentals (household income and CPI shocks) and changes in expectations triggered the bust in the housing market.

VI. Conclusion

This paper has examined the effect of a mortgage interest rate subsidy on booms and busts in the housing market. Using the HM program implemented by the

Government of Mongolia as a representative case study, we quantify the effects of the HM program in housing price dynamics.

Several vital results stand out. First, we find that the most recent housing boom from Q2 2012 to Q1 2014 resulted in a 17.7% above-trend increase in real house prices, while the subsequent housing bust from Q1 2014 to Q1 2018 saw real house prices decline by 33.2% from peak to trough. Second, all estimation results based on pooled cross-sectional, panel, and time series data provide robust evidence that both demand (macroeconomic variables) and supply-side (house specific characteristics, distance, air pollution) factors are vital determinants of housing prices. The DiD estimation suggests that the HM program led to significant increases in real housing prices. The district-level panel estimation results reveal that air pollution and location of residential property (i.e., distance from the city center) are also important determinants of real house prices. Third, the estimated long-run mortgage interest rate, income, and CPI elasticities are elastic, robust, and statistically significant with theoretically consistent signs, implying that a mortgage interest rate subsidy and macroeconomic policies have direct and indirect (via their impacts on credit and income) effects on real housing price. The mortgage interest rate semielasticity and the real household income elasticity for Mongolia are estimated as -3 and 1.4, respectively. Fourth, dynamics analysis (GIRF and variance decomposition) reveals that real household income and mortgage interest rates are critical variables in forecasting housing prices in Mongolia. Real household income and mortgage interest rate shocks respectively account for 26% and 17% of the forecast error variance of real housing price. Fifth, the generalized historical decompositions based on the estimated VECMs show that the recent housing boom was mainly driven by the mortgage interest rate, real household income, and HPI own shocks, and that real household income and HPI own shocks played a significant role in prolonging the recent housing bust. The analysis reveals that the HM program drove the recent housing boom in Mongolia.

The evidence suggests that policy interventions in the mortgage market such as nontargeted and significant subsidies on the mortgage interest rate can lead to a housing boom. Therefore, an optimal policy mix (i.e., targeted subsidy or setting a limit on subsidized mortgage loan amount; macroprudential measures such as limits on loan-to-value and debt-to-income ratios; and policies supporting the supply of apartments, construction materials, and related infrastructure, etc.) must be implemented to prevent housing prices from rising excessively.

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Appendix

Table A.1. **Summary Statistics of Variables in Pooled Cross-Sectional Data**

Variable	Number of Observations	Mean or Proportion	Standard Deviation	Min	Max
Housing price (MNT)	272,799	130,000,000	144,000,000	20,300,000	6,160,000,000
Log (real housing price)	272,799	18.436	0.612	16.739	22.505
House characteristics					
Age (years)	272,799	9.634	13.791	0.000	82.000
Area (square meters)	272,799	60.489	30.574	12.000	395.500
Parking	272,799	0.612	0.487	0.000	1.000
Garden	272,799	0.529	0.499	0.000	1.000
Distance (kilometers)	272,799	4.615	5.135	0.200	143.000
Construction type					
Concrete frame	272,799	0.722	0.448	0.000	1.000
High-density concrete	272,799	0.039	0.194	0.000	1.000
Iron Caracas	272,799	0.003	0.055	0.000	1.000
Brick apartment	272,799	0.057	0.231	0.000	1.000
Wooden and brick apartment	272,799	0.005	0.071	0.000	1.000
Prefabricated apartment (base)	272,799	0.174	0.379	0.000	1.000
District					
District 1	272,799	0.240	0.427	0.000	1.000
District 2	272,799	0.330	0.470	0.000	1.000
District 3	272,799	0.006	0.075	0.000	1.000
District 4 (base group)	272,799	0.136	0.343	0.000	1.000
District 5	272,799	0.089	0.285	0.000	1.000
District 6	272,799	0.173	0.378	0.000	1.000
District 7	272,799	0.027	0.162	0.000	1.000
Macroeconomic variables					
Mortgage interest rate	272,799	10.476	1.680	7.717	17.007
ln(real income)	272,799	13.818	0.064	13.722	13.959
ln(CPI)	272,799	4.618	0.075	4.388	4.740

CPI = consumer price index, MNT = togrog.
Source: Real estate agency survey conducted by Tenkhleg Zuuch LLC.

Table A.2. **Augmented Dickey–Fuller Test for Unit Root**

H_0: The Variable Has a Unit Root	**Test for Level Variable**		**Test for Differenced Variable**	
	***t*-Statistic**	**Prob**	***t*-Statistic**	**Prob**
ln(real overall HPI)	−2.090	0.542	−7.748	0.000***
ln(real HPI for properties of up to 80 square meters)	−2.403	0.375	−7.241	0.000***
ln(real HPI with time dummy)	−2.473	0.340	−7.134	0.000***
Mortgage interest rate	−2.957	0.152	−6.939	0.000***
ln(CPI)	−1.887	0.651	−4.857	0.000***
ln(real income)	−0.725	0.967	−4.415	0.001***

CPI = consumer price index, HPI = housing price index.
Notes: ***denotes level of significance at 1%. Tests for levels data are computed from regressions with a constant and trend, while differenced data are computed from regressions with only a constant term.
Source: Authors' calculations.

Table A.3. **Lag Selection Criteria**

Lag	**LogL**	**LR**	**FPE**	**AIC**	**SBIC**	**HQIC**
Sample: Jan 2013–Sep 2018						
(i) VAR with ln(real overall HPI), ln(CPI), ln(real income), and MIR						
1	565.983	NA	3.07e–13	−17.460	−16.916*	−17.246
2	594.398	49.615	2.08e–13	−17.854	−16.765	−17.426*
3	610.693	26.381	2.09e–13	−17.863	−16.230	−17.221
4	629.280	27.734	1.98e–13	−17.945	−15.768	−17.090
5	649.776	27.979*	1.79e–13*	−18.088*	−15.367	−17.018
6	658.701	11.049	2.41e–13	−17.864	−14.598	−16.579
(ii) VAR with ln(real HPI for residential properties of up to 80 square meters), ln(CPI), ln(real income), and MIR						
1	576.757	NA	2.18e–13	−17.802	−17.258*	−17.588
2	609.892	57.854	1.27e–13	−18.346	−17.257	−18.038*
3	636.416	42.944	9.24e–14	−18.680	−17.047	−17.918
4	655.189	28.010*	8.69e–14*	−18.768	−16.591	−17.912
5	671.608	22.413	8.97e–14	−18.781*	−16.060	−17.711
6	680.428	10.921	1.21e–13	−18.553	−15.288	−17.269
(iii) VAR with ln(real HPI constructed with time dummy), ln(CPI), ln(real income), and MIR						
1	570.412	NA	2.67e–13	−17.600	−17.056*	−17.386
2	602.224	55.544	1.62e–13*	−18.102	−17.014	−17.674*
3	616.355	22.879	1.75e–13	−18.043	−16.410	−17.401
4	634.171	26.582*	1.69e–13	−18.101	−15.924	−17.244
5	651.280	23.355	1.71e–13	−18.136*	−15.414	−17.066
6	664.587	16.475	2.00e–13	−18.050	−14.785	−16.766

AIC = Akaike information criterion, CPI = consumer price index, FPE = final prediction error, HPI = housing price index, HQIC = Hannan–Quinn information criterion, LR = sequentially modified likelihood ratio test statistic (each test at 5% level), MIR = mortgage interest rate, SBIC = Schwarz Bayesian information criterion, VAR = vector autoregression.
Note: * indicates lag order selected by the criterion.
Source: Authors' calculations.

Table A.4. **Johansen Cointegration Test Results**

	Cointegration Equation Includes Constant			
	Trace Test		**Eigenvalue Test**	
H_0: Number of CE(s)*	**Statistics**	**Critical Value (At 5%)**	**Statistics**	**Critical Value (At 5%)**
(i) VECM(1) with overall HPI: ln(real overall HPI), ln(CPI), ln(real income), and MIR				
None	55.452*	47.856	28.937*	27.584
At most 1	26.516	29.797	18.428	21.132
At most 2	8.088	15.498	6.709	14.267
At most 3	1.379	3.842	1.3791	3.842
(ii) VECM(1) with HPI for properties of up to 80 m^2: ln(real HPI for properties of up to 80 m^2), ln(CPI), ln(real income), and MIR				
None	63.965*	47.856	36.715*	27.584
At most 1	27.250	29.797	17.886	21.132
At most 2	9.364	15.495	7.650	14.265
At most 3	1.714	3.842	1.714	3.842
(iii) VECM(1) with HPI with time dummy: ln(real HPI with time dummy), ln(CPI), ln(real income), and MIR				
None	62.537*	47.856	36.072*	27.584
At most 1	26.465	29.797	18.024	21.132
At most 2	8.440	15.495	6.833	14.265
At most 3	1.607	3.841	1.607	3.842

CE = cointegration equation, CPI = consumer price index, HPI = housing price index, MIR = mortgage interest rate, VECM = vector error correction model.
Notes: For all three versions, both trace and maximum eigenvalue tests indicate one cointegrating equation(s) at the 0.05 level. * denotes rejection of the hypothesis at the 5% level.
Source: Authors' calculations.

Table A.5. **Testing for Weak Exogeneity of Variables**

(i) VECM(1) with overall HPI: ln(real overall HPI), ln(CPI), ln(real income), and MIR

H_0: The variable is weakly exogenous

	ln(real overall HPI)	**ln(CPI)**	**ln(real income)**	**MIR**
LR test statistics	$\chi^2(1) = 8.69$	$\chi^2(1) = 0.75$	$\chi^2(1) = 4.35$	$\chi^2(1) = 0.72$
[p-value]	[0.003]	[0.388]	[0.049]	[0.398]

(ii) VECM(1) with HPI for properties of up to 80 square meters: ln(real HPI for properties of up to 80 square meters), ln(CPI), ln(real income), and MIR

H_0: The variable is weakly exogenous

	ln(HPI properties of up to 80 square meters)	**ln(CPI)**	**ln(real income)**	**MIR**
LR test statistics	$\chi^2(1) = 13.59$	$\chi^2(1) = 0.16$	$\chi^2(1) = 4.45$	$\chi^2(1) = 1.79$
[p-value]	[0.000]	[0.692]	[0.035]	[0.181]

Continued.

Table A.5. *Continued.*

(iii) VECM(1) with HPI with time dummy: ln(real HPI with time dummy), ln(CPI), ln(real income), and MIR

H_0: The variable is weakly exogenous

	ln(HPI time dummy)	**ln(CPI)**	**ln(real income)**	**MIR**
LR test statistics	$\chi^2(1) = 13.31$	$\chi^2(1) = 0.12$	$\chi^2(1) = 4.00$	$\chi^2(1) = 1.65$
[*p*-value]	[0.000]	[0.734]	[0.046]	[0.199]

CPI = consumer price index, HPI = housing price index, LR = likelihood ratio, MIR = mortgage interest rate, VECM = vector error correction model.

Note: The *p*-values in brackets represent the probability of the null hypothesis.

Source: Authors' calculations.