The policy-driven boom and bust in the housing market: Evidence from Mongolia

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Abstract

This paper examines the effects of a mortgage interest rate subsidy on boom and bust in the housing market by exploiting the Housing Mortgage (HM) program implemented in Mongolia. Main results are (i) the recent housing boom occurred from 2012Q2 to 2014Q1, while the housing bust lasted four years, (ii) both house-specific factors and macroeconomic variables have a significant influence on the housing price dynamics, (iii) mortgage interest rate semi-elasticity and real household income elasticity for Mongolia are estimated as -3.0 and 1.4, respectively, and (iv) dynamic analysis of the estimated VECMs suggests that the policy intervention in the mortgage market (i.e., introducing an interest rate subsidy on mortgage loans for buying residential properties with below 80 square meters) has driven the recent housing boom in Mongolia.

JEL classification: C53, D14, E32, E51, G21, R21, R31

Keywords: House prices, Booms and busts, Mortgage interest-rate subsidy, Mongolia

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1. Introduction

Global Financial Crisis (GFC) has revived interest in what determines the housing price dynamics and how macroeconomic policies should respond to booms and busts 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 policymakers and homeowners. Several papers (i.e., McQuinn and O'Reilly 2008, Agnello and Schuknecht 2011, Lambertini et al. 2013, Tu et al. 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 key determinants of housing prices. As a housing sector development requires adequate financing scheme, governments implement programs that subsidize interest rates on mortgages. Recent studies relied on the credit view (i.e., Favara and Imbs 2015, Di Maggio and Kermani 2017, Mian et al. 2017a, Justiniano et al. 2019) show that booms and busts in housing markets are due to changes in credit supply driven by looser lending constraints in the mortgage markets. In contrast, some papers (i.e., Case and Shiller 2003, Lambertini et al. 2013, Kanik and Xiao 2014, Ferrero 2015, Ascari et al. 2018) argue that house price expectation and exogenous preference shock drive housing boom-bust cycles. The papers also emphasize that the other competing hypothesis, 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 (i.e., Martins and Villanueva 2006, Hofstetter et al. 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 the context, this paper empirically examines the effects of a mortgage interest rate subsidy on boom and bust in the housing market by exploiting a large mortgage program in Mongolia called Housing Mortgage (HM program). The HM program was launched in 2013 as a part of quasi-fiscal operations implemented by the government and Bank of Mongolia (BOM) that provide a mortgage interest rate subsidy to individuals who wanted to purchase an apartment financed by a mortgage loan. The HM program also allows individuals to refinance existing retail mortgage loans with subsidized 8% interest rate. Under the HM program, the BOM also provides cheap mortgage-targeted financing to banks, leading to a rapid mortgage credit growth as well. As at the end of 2018, subsidized mortgage loan outstanding reached 3.32 trillion tugrug, equivalent to 10.2% of gross domestic product (GDP). Though the HM program initially aims to reduce Ulaanbaatar's air pollution through the development of the housing sector and support young couples with low-income, it also leads to rapid increases in apartment prices during the period 2013-2014. Evidence and lessons from the case of Mongolia would be of high relevance to avoid policy-driven boom and busts in housing markets and design adequate mortgage financing schemes for developing countries. 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 data sets, such as pooled cross-section, 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 in analyzing underlying forces of housing prices. Studies focused on demand-side factors are primarily rely on interest rates and availability of credit. The literature on the user cost model of housing services (i.e, Poterba 1984, Díaz and Luengo-Prado 2008) highlights the relationship between interest rate and housing prices. When interest rate increases, a housing investor (including owner-occupiers) prefer to invest in a bank deposit (and earning the interest rate) compared to purchasing a home (and earning the rental yield). There is a vast literature (i.e., Abraham and Hendershott 1992, Goodhart and Hofmann 2008, Iossifov et al. 2008, Adams and Fuss 2010, Berlemann and Freese 2013, Nneji et al. 2013, and DeFusco and Paciorek 2017) showing that (i) a negative relationship exists between interest rates and housing prices, and (ii) low real interest rate have major effects on housing price dynamics. These studies also find that other demand-side factors, such as inflation, GDP, fiscal deficit, current account deficit, money supply, credit, non-performing loan, employment, unemployment, total population, active population, construction cost, industrial production and housing stock, are associated housing prices using panel and time series regression analyses. Moreover, 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 price and current account. Supply-side factors can also matter. The well-established AMM model of Alonso (1964), Muth (1969) and Mills (1967), and formalized by Wheaton (1974) suggest that a range of supply-side factors such as a shortage of appropriately zoned land, driving up development costs (the value of land), poor transport infrastructure (cost of transport) and frictions increasing the cost of new housing development affect the cost of new housing and reduce its supply, which could be expected to have also increased the price of the existing stock of housing. These factors also explain how housing prices are differentiated across space.

As working with macro variables, several papers (i.e., Sutton 2002, Tsatsaronis and Zhu 2004, Iacoviello 2005, Iacoviella and Minetti 2008, Bjørnland and Jacobsen 2010, Kanik and Xiao 2014, Panagiotidis and Printzis 2016, Mian et al. 2017b, Justiniano et al. 2019) also examine the relationship among interest rates, credits and housing prices using quantitative macroeconomic models such as vector autoregression (VAR), vector error correction model (VECM) and dynamic stochastic general equilibrium (DSGE) 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 housing 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 et al. 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; however, stabilizes supply shocks. Iacoviella 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 et al. (2017b) find that a shock to household debt leads to large and immediate increases in house prices, followed by substantial mean reversion four years after the initial shock. Justiniano et al. (2019) argue that the focus of discussion should shift from constraints on borrowing to lending constraints when it comes to understanding of 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 et al. (2011) find that house-specific factors, such as year of construction, presence of garden, presence of parking, and macro factors including the long-term real interest rate, unemployment rate, and dependency ratio (ratio of population aged 65+ to population aged 15-64) significantly affect housing price dynamics. Zhang and Yi (2018) show that the location of the house, surrounding environment, housing characteristics such as the number of bedrooms, the size of the living area, and the floor are important 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 quite scarce. In the case of Mongolia, Gan-Ochir (2007) finds that house specific and surrounding environment factors play an important role in determining apartment prices in Ulaanbaatar using hedonic regression analysis. Based on the VECM, Enkhzaya (2013) shows that household income, concrete prices and mortgage loan are key drivers of apartment prices.

The remainder of this paper is structured as follows. Section 2 provides an overview of the macroeconomic environment, mortgage market development, including the details of the HP program in Mongolia. The section also identifies boom and bust episodes in the housing market. Section 3 presents the model set-up of housing prices and discusses the estimation techniques. Section 4 describes the data and reports empirical results, including the estimations of income and interest rate elasticities and the contribution of the mortgage interest rate subsidy in the boom and bust in housing price for the period 2013-2014. Finally, Section 5 concludes the paper with policy implications.

2. Overview of housing and mortgage markets in Mongolia

2.1 Housing and mortgage markets: The HM program

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

In response to the adverse external shocks, the politically driven expansionary policies have been 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 the budget revenue growth gradually slowed in the midst of declining FDI and the weakening export revenues, the currency issuance power of the central bank was seen as a reliable financing source 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 particularly high with the PSP, including the Housing Mortgage (HM) program[2].

Public willingness for affordable housing has been growing in Mongolia as household's average income is relatively low compared to housing prices. As a result, housing has been a political issue in Mongolia. Government intervention in the construction sector, a way of boosting the economy, has been constantly implemented in Mongolia for the past 20 years. Government housing policies in Mongolia were oriented towards both large-scale housing construction programs and subsidized mortgage loan programs. In 2004, the government initiated the four-year '40,000 apartment program' to promote the housing supply and provided financing of 32.7 billion MNT (government bond of 28.3 billion MNT and ADB project financing of 4.4 billion MNT) to participant banks, which lend the financing to participant construction companies. In 2009, the new government formed based on the June 2008 parliamentary election implemented another '4000 apartment program' to support the construction sector to sell their apartments and public servants to buy apartments. Under the program, public servants who work for the public sector not less than three years took (up to) 20 years mortgage loans of (up to) 40 million MNT at 8% (annual) interest rate to buy apartments hold by banks as collaterals of construction companies' loans. In 2010 and 2012, the government approved the '100,000 apartments program' (75000 apartments in Ulaanbaatar and 25000 apartments in provinces) to stimulate the housing supply and 'Regulation on 6% subsidized mortgage loan' to promote housing affordability, respectively. The 6% subsidized mortgage loan program is continued for only five months until the June 2012 parliamentary election, and about 1000 individuals took (up to) 20 years mortgage loans of (up to) 50 million MNT at 6% (annual) interest rate to buy apartments, which are less than 55 square meters and built under the '100,000 apartments program'.

Though several government housing programs were implemented before 2013, their results were not enough compared to the existing public willingness for affordable housing. Moreover, mortgage market development was weak. For instance, as the end of 2012, total mortgage loan to GDP ratio was only 5.1%, which was seven times lower than the ratio in Hong-Kong and Japan and more than ten times lower than advanced economies, 29.9 thousand borrowers took mortgage loans, and the share of mortgage loan in the total loan outstanding was 12.1%. 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 306.8 thousand of Ulaanbaatar households, 39% of 119.7 thousand households were living in apartments.

[2] 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 the price stability. The exceptionally large monetary and quasi-fiscal stimulus provided through various programs risks ratcheting up inflation, increasing public debt, adding to BOP pressures, and heightening banking sector vulnerabilities. Loose monetary and fiscal policies to buffer the economy from the external shocks supported the economic growth for a while, but at the cost of economic vulnerabilities.

Preoccupation with the presumed adverse effects of high inflation and high public demand for affordable housing has led the newly appointed government to initiate the PSP, aiming to introduce sustainable housing financing schemes and stabilize domestic prices, not only of food and petroleum but also of import raw materials for construction. The PSP started in October 2012 when the government and the BOM signed a memorandum of understanding on 'Joint implementation of the medium-term program to stabilize prices of key commodities and products.' The implementation of the PSP is approved by the parliament as it is included in 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, having a mandate of ensuring price stability, in the quasi-fiscal operations raised a concern about central bank independence.

Along with the supply-side stimulus program, the BOM launched a sub HM program within the PSP to stimulate housing demand that provided 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 the supply and demand of housing, increase housing affordability, and provide people with a safe and healthy environment of living. The whole 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 will be on-lent to households at an 8% interest rate with up to 20-year maturity. Since late 2013, some of the subsidized mortgages have been securitized into residential mortgage-backed securities issued by the Mongolian Ipotek Corporation (MIK), which was purchased by the BOM to refinance banks' funding sources for further housing mortgage loans. Loan eligibility criteria set a limit on the apartment size at maximum 80 square meters (the subsidized mortgage loan is only given for buying apartments) and required that loan applicants' minimum monthly income must exceeds MNT 1 million (defined from debt-to-income ratio of 45%). The down payment is 30% of the purchased apartment's value. Commercial mortgage businesses were substituted by the subsidized mortgage program. Existing commercial mortgage borrowers switched to the subsidized loan program, and new mortgage loan demand was almost fully absorbed by the subsidized program. In March 2016, the BOM made further amendments on HM program: (i) 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 re-development plans and rural areas of 21 provinces, and (ii) the maturity of the mortgage loan was extended from 20 years to 30 years.

As the end of 2018, the commercial banks had issued mortgage loans of 4.43 trillion MNT (equivalent to 14% of GDP) to 93865 borrowers, and out of total mortgage loan outstanding, 75% (3.32 trillion MNT) was financed under HM program to 69529 borrowers (Figure 1 and Figure 2). Mortgage loan growth sharply increased after the introduction of the HM program for the period 2013-2014, but then gradually declined. The subsidy to the mortgage interest rate boosted mortgage loans by about 150% in 2013. As market demand is started to be fulfilled, the mortgage loan growth has been reduced since 2014. After a new government formed based on June 2016 parliamentary election, the government and the BOM have stopped the PSP, except for the HM program. However, the BOM's financing for HM program loans was significantly reduced.

Figure 1. Mortgage loan outstanding

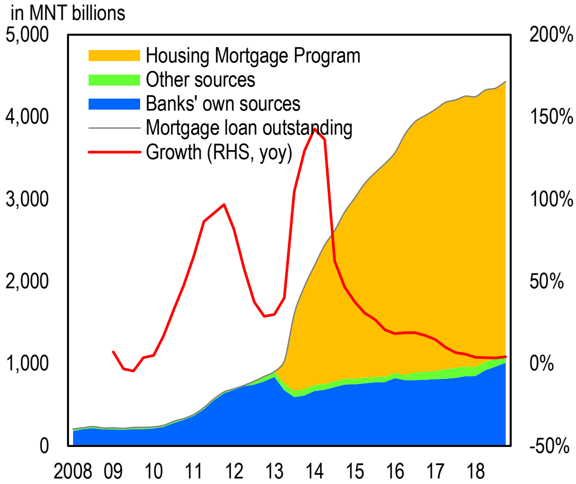
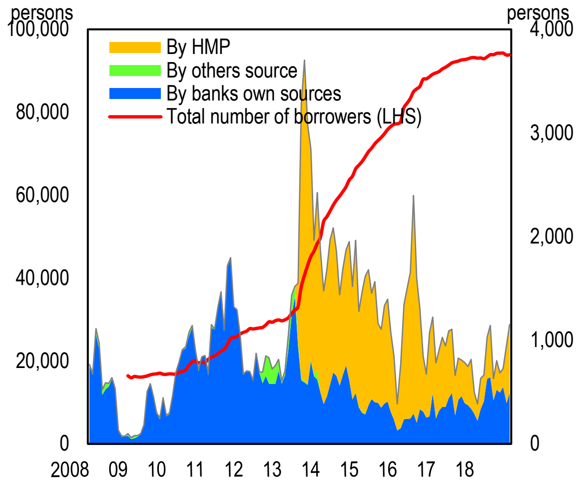


Figure 2. Number of borrowers



Source: Bank of Mongolia

In the first half of 2013, an average mortgage interest rate (weighted average rate of market and subsidized interest rates) was 16.6%, and after introducing HM program (i.e., starting the interest rate subsidy on mortgage loans), the average interest rate reduced to 9.2%. The initial subsidy shock in mortgage interest rate was 7.4 percentage points. The mortgage interest rate was 9.9% on average for the period 2013M6-2016M3. After introducing the 5% mortgage loan, the weighted average mortgage rate is decreased to 8.5%. As the supply of HM program loan was slashed, the weighted average mortgage rate of interest started to increase for the period 2017-2018. Starting from the fourth quarter of 2016, the BOM stopped to finance the HM program financing by expanding its balance sheets, instead financed the HM program using the repayment of the existing mortgage loan.

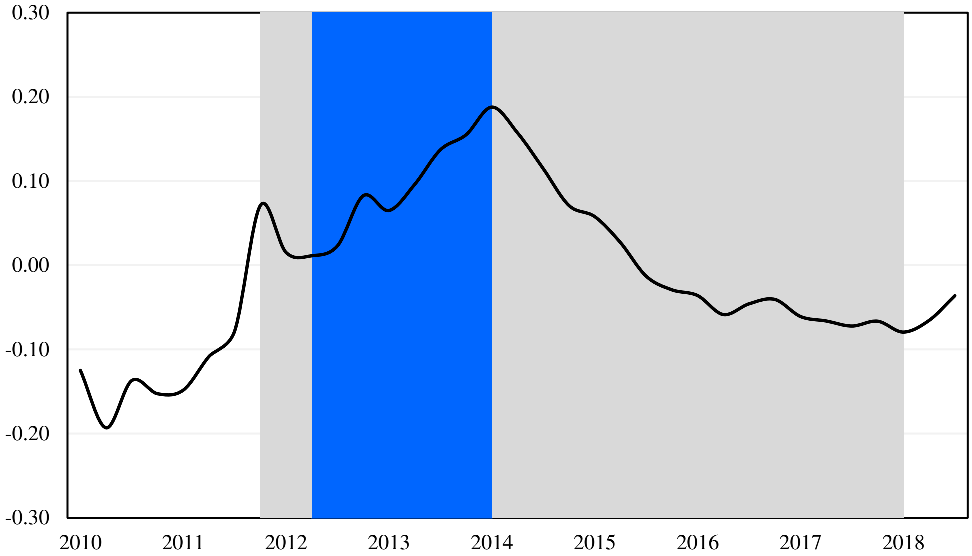
2.2 Booms and busts in the housing market

This section identifies booms and busts in housing prices. The analysis is based on real housing price quarterly data over the period 2010-2018[3]. The real housing price is measured as the ratio of nominal housing price index to CPI, and the housing price index is calculated by Tenkhleg Zuuch, one of the largest real estate data hubs in Mongolia. Following Agnello and Schuknecht (2011), we use a simple statistical approach and define booms-busts in real housing prices as major, persistent deviations from long term trends. The approach builds on the heterodox methodology that requires 'de-trending' the level of the observed variable before employing a turning-point definition of the cycle. First, we identify the housing price cycle by ore-filtering housing price series. To measure major and persistent deviations from long-term deviations, HP-filter on ex-post data is employed instead of the recursive HP-filter. We also set a very high smoothing parameter ($\lambda = 10000$) to reflect the fact that housing price

[3] Tenkhleg Zuuch real estate agency started calculating monthly housing price index (HPI) based on hedonic regression methods since January 2013. Before that, 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 have made back-casting of the HPI based on quarterly growth of NSO's HPI.

cycles are much longer than typical business cycles. Second, we define the characteristics of the cyclical phases of the housing market using Eviews's BBQ add-in that implements 'triangular methodology' proposed by Harding and Pagan (2002).

Figure 3. Real housing price gaps and boom-bust phases



Note*:* Shaded dark (blue) areas denote boom phases while the light one (grey) indicates the bust phase. Housing price gaps are computed as the deviations of the real housing prices from the trend obtained using the HP filter ($\lambda = 10000$).

The persistence is computed as the temporal distance between turning points in the de-trended real housing prices series. The magnitude is measured as the size of the changes in levels of the series from the peak (P) to through (T) and through (T) to peak (P).

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

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 5.

3. Determinants of housing prices and estimation methodology

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

3.1 Driving factors of 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 non-housing composite good to maximize his 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 the 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) the households also face a borrowing constraint 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 well in Tu et al. (2018).

In the model, a household tries to get 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 house price and the real spending on the composite good, respectively, m and n are the elasticities of intertemporal substitution and housing price, and a_1, a_2 are preference-related parameters.

The representative household maximizes lifetime utility

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

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 house price; Y_t represents real income; i_t is the mortgage interest rate; γ is a constant. Equation (3) implies that the household's income (Y_t) is spent on composite good (C_t) and to pay a periodic amount to repay the loan and the associated interest (γL_t). The 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: $(1 + i_t)L_t = \theta P_{h,t}$, where θ captures 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 equation (3) and equation (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 $c_0 = \left(\frac{a_2}{a_1}\gamma\theta\right)^{\frac{1}{n}}$. As higher income stimulates consumer demand, it is assumed that the household determines t spending on the composite good by income:

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

where a_0 and μ are parameters.

Combining (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-term using aggregate price (P_t), we reach the empirical equation of the real housing price

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

where $P_{h,t}^r = \frac{P_{h,t}}{P_t}$ is real house price, $Y_t^r = \frac{Y_t}{P_t}$ is real income, $\alpha_0 = ln\left(c_0 (a_0)^{\frac{m}{n}}\right)$, $\alpha_1 = \mu \frac{m}{n}$, $\alpha_2 = \frac{1}{n}$ 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 the empirical studies (i.e., Baffoe-Bonnie 1998 for USA, Assenmancher-Wesche and Gerlach 2008 for 17 countries, Lee 2009 for Australia, Andrews 2010 for OECD countries, Panagiotidis and Printzis 2016 for Greece). Intuitions of the determinants are as follows. First, higher household income allows taking more debt and spending a larger share of income on housing and related debt service. Hence, higher income is positively associated with a higher probability of a housing boom (Goodhart and Hofman 2008). Second, the mortgage interest rate affects household debt financing conditions (i.e., decreases in the cost of borrowing encourages housing demand), and a decrease should increase the probability of a boom (Andrews 2010). Third, higher aggregate prices may lead the higher housing investment motives (because of the decreasing real user cost after taxes), hence they are positively associated with a higher housing price (Poterba 1984, Panagiotidis and Printzis 2016).

Since we have only annual data for population and demographic in the case of Mongolia, these variables not included in our monthly estimations. The specification (8) can fit the real Mongolian situation and the main interest of the paper in the sense that the mortgage interest rate captures the effect of interest rate subsidy under the HM program, and effects of quantity 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 (i.e., Kulish et al. 2012), such as transportation cost and cost of new housing are considered in the empirical analysis. Because of available 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 proxy for the cost of housing. Building on the existing studies (i.e., Galati et al. 2011, Zhang and Yi 2018), other house-specific factors such as age, living space, parking and a garden of the house are also added in pooled cross-sectional and panel data estimations.

3.2 Estimation methodology

To examine determinants of hosing prices in Mongolia, we attempt to use all available information including pooled cross-section, panel, and time series data sets. For instance, pooled cross-section data allows us to study the effect of house-specific factors and analyze the effect of the HM program using difference in difference (DiD) method. District-level panel data is used to check robustness of pooled cross-section results and to assess effect of air pollution on housing prices as Ulaanbaatar is one of the heavily polluted capital cities. The time series data helps 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 section and panel data analysis, their results also provide robustness check for macroeconomic determinants obtained from the time series analysis. Therefore, these empirical methods (i.e., pooled cross-section, panel, and time series methods) complement each other and help to understand full of picture about the determinants of housing prices and robustness of the interest income elasticities.

For each data set, we employ different estimation methods. For instance, difference in difference (DiD) method, pooled ordinary least squares (POLS) and generalized least squares (GLS) are used to pooled cross-sectional data. Static POLS and GLS for district and time fixed effects are employed for the panel data. The vector error correction model (VECM), providing a framework studying the long-run economic relations, is used for time series data. The features of the methods are described below.

Difference-in-difference (DiD)

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:

$$ln(P_{it}) = \beta_0 + \beta_1 \cdot D_i + \beta_2 \cdot Post_t + \gamma \cdot (D_i \cdot Post_t) + \boldsymbol{H_i} \cdot \beta_{3,X_i} + \boldsymbol{Z_t} \cdot \beta_{4,Z_t} + \varepsilon_{it} \tag{9}$$

where i and t indicate individual houses and time, respectively. P_{it} is the real housing prices; D_i is dummy variable, where $D_i = 1$ if the living space is less than 80 square meters (under the MH program, interest rate subsidy only applies for houses with below 80 square meters), and $D_i = 0$ if the living space is higher than 80 square meters; $Post_t$ is also a binary variable, where $Post_t = 1$ for the MH program period, and $Post_t = 0$ otherwise, and the product, $D_i \cdot Post_t$, is the dummy variable used for measuring the treatment effect of the HM program. $\boldsymbol{H}_i$ is set of house specific variables such as year of construction, living space, presence of parking and garden, and $\boldsymbol{Z}_t$ is a set of macroeconomic variables, including log of real income, nominal mortgage rate, and log of CPI. Coefficients have the following meanings: β_0 is a constant term, β_1 is the treatment group-specific effect, β_2 is time trend common to control and treatment groups, β_{3,X_i} is the vector of parameters capturing effects of house specific variables,

β_{4,Z_t} is the vector of parameters capturing effects of macroeconomic variables, γ captures the effect of the HM program, and ε_{it} is the disturbance term.

POLS and GLS estimator

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:

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

where P_{it} is real housing prices, 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 BLUE 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) $E(u_{it}^2\mathbf{H}'_{it}\mathbf{H}_{it}) = \sigma^2 E(\boldsymbol{H}'_{it}\mathbf{H}_{it}), t = 1,2, \ldots T$, where $\sigma^2 = E(u_{it}^2)$, and $E(u_{it}u_{is}\mathbf{H}'_{it}\boldsymbol{H}_{is}) = 0$, $t \neq s$ $t, s = 1,2, \ldots T$. 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 2010). The 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 efficient than POLS.

Vector Error Correction Model (VECM)

VECM is employed in estimating the long-run housing prices 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 $\mathrm{mds}(\Sigma_\varepsilon)$) with finite fourth moments. Since each of the variables in the system are 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 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 $r = rank(\Pi)$, 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 $w_{t-1} = (\delta'\delta)^{-1}\delta'\left[\Delta y_t - \sum_{i=1}^{p-1} \Phi_i \Delta y_{t-i} - \varepsilon_t\right]$, 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, 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.

4. The data

In this paper, we employ three types of data sets, including pooled cross-sectional data, panel data, and times series data. Descriptions of the data sets are detailed below.

4.1 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 housing price index using hedonic regressions on the monthly survey data, which only includes apartments. The pooled cross-sectional data covers the period January 2013-September 2018, and the total number of observations is 272799. House specific variables in pooled cross-sectional data and their descriptions are shown in Table 1.

Table 1. Description of house specific variables

Variable	Description
House prices	Asking house prices collected from surveys conducted by Tenkhleg Zuuch
Real house prices	House price is adjusted for the consumer price index (CPI)
House characteristics	
Age (in years)	Year from construction at the time of survey (in years)
Living space (square meter)	Square meters of the houses
Living space squared	Size of the house squared
Parking	Dummy: 1 if the apartment has parking, 0 otherwise
Garden	Dummy: 1 if the apartment has a garden, 0 otherwise
Distance (in km)	How far 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
Preabricated apartment	Construction dummy: 1 if construction type is prefabricated houses, 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

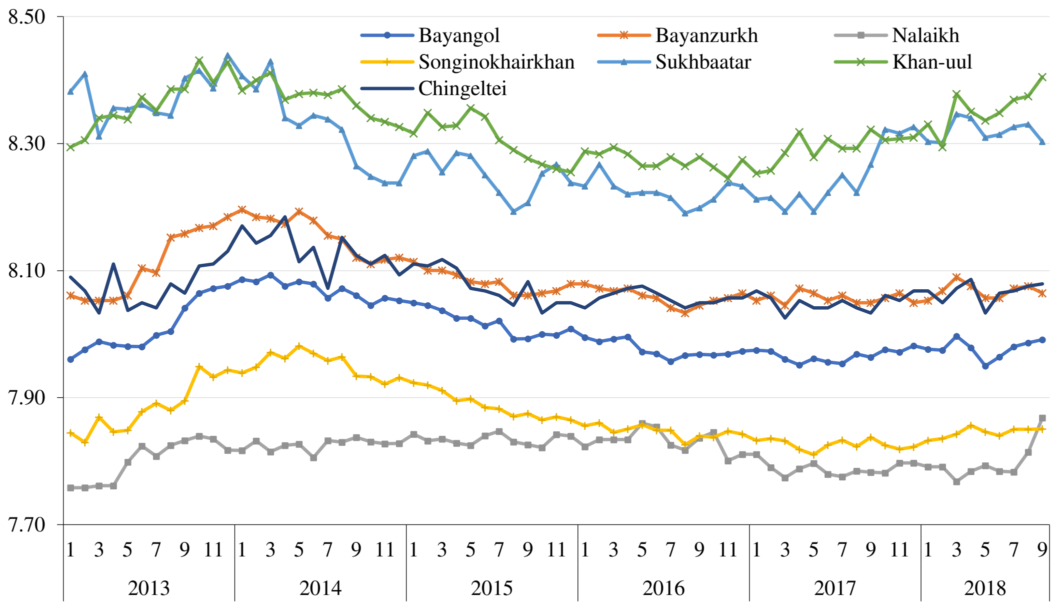
Because of data limitation, only asking housing prices are available to collect in Mongolia. The statistical characteristics of the variables are shown in Table A.1 of the appendix. The average year of construction at the time of the survey is 9.62 years, and the average living space of apartments is 60.48 square meters. Two-thirds of apartments have parking, almost half of them have a garden, and 72% of them are built by a concrete frame. The average distance from the center of the city is 4.6 km.

In addition to the data shown in Table 1, the pooled-cross sectional data estimation also consists of macroeconomic variables ($\boldsymbol{Z_t}$) such as mortgage interest rate, the natural logarithm of real household income, and the natural logarithm of CPI for the period January 2013-September 2018. Mortgage interest rate is taken as the weighted average interest rate of mortgage loans (i.e., weighted average of the market and the subsidized interest rates) and collected from Statistical Bulletin of the Bank of Mongolia. Real household income is measured as ratio of nominal household income and 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 Household Socio-Economic Survey (HSES) conducted by National Statistical Office (NSO) of Mongolia. CPI is the nationwide CPI and taken from the NSO.

4.2 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-September 2018 for Ulaanbaatar districts is used to examine how house specific factors and macroeconomic variables affect the housing price. Newly constructed average residential property prices of districts are shown in Figure 10. The average house prices of the districts have co-movements over time.

Figure 4. Average prices of residential properties by seven districts, in natural logarithm



House characteristics and macroeconomic variables (mortgage interest rate, real household income, CPI) are also included in the panel estimation. For the panel data, house characteristic variables (i.e., living space, age and distance) are measured as average of houses within each district at certain period. As air pollution has been a big issue in Ulaanbaatar and air quality differs among districts, we assume that it is a key factor affecting house buyer's choice. Since each district's time series data of air pollution is reported, we include the variable in the panel estimation. Each district's air pollution measured by NO_2 is collected from the database of Ministry of Environment and Tourism. Macroeconomic variables are same as in pooled cross section data.

4.3 Time-series data

Data used in the VECM estimation includes the monthly time series of four variables for the period January 2013-September 2018. These variables include 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 National Statistical Office (BOM) of Mongolia. The mortgage interest rate (weighted average rate of mortgage loans issued in the reporting month) and overall housing price index (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 modelling 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 property with below 80 square meters, which can be bought by a mortgage loan with a subsidized interest rate subsidy under the MH program. The time dummy variable method originally developed by Court (1939) is used to build a HPI, which is an alternative to the overall HPI. In constructing new HPIs, we use the same databases of Tenkhleg Zuuch used in constricting 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 property with below 80 square meters grows faster than the other two overall HPIs during the boom phase (i.e., period 2012Q2-2014Q1) identified in Section 2.3.

5. Empirical results

5.1 Estimation

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 the real housing prices, particularly the effects of the HM program on the housing prices. The DiD estimation covers the period January 2013-December 2013, and the first five months are classified as the pre-HM program period, while the last seven months are considered as 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 garden increases the real housing prices. For each one км distance from the center of the city, real housing prices are reduced by over 2%. Housing types significantly affect housing prices. In the case of housing type (quality), the omitted variable is chosen as prefabricated apartments. The estimation shows that high-density concrete, iron Caracas and wooden and brick houses are more expensive, while concrete frame and brick houses are cheaper compared to prefabricated houses. In the case of district, the omitted variable is district 4 (Songinokhairkhan) since housing prices in the district is the lowest.

All macro variables, such as mortgage interest rate, real household income, and CPI have a significant impact on the real housing price. The estimated interest rate elasticity is about 2.5, and elasticities of the real household income and CPI are close to 1. The estimated elasticities are in line with the results of studies surveyed by Iossifov et al. (2008).

Table 2. Estimation results of POLS, GLS and DiD model

	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***
	Macroeconomic variables		
Mortgage interest rate (MIR) (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 ($D_i \times Post_t$)			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

Notes: * p<0.10, ** p<0.05, *** p<0.01. Standard error in parenthesis.

The DiD regression is estimated only for the period January 2013-December 2013, reflecting the fact that the HM program starts in June 2013 and our sample starts from January 2013[4]. The real housing prices increased by 3.7% on average (β_2) during the first seven months of the HM program (i.e., between June 2013 and December 2013). Prices for residential properties with the living space of less than 80 square meters grew by 7.8% on average (β_1) during 2013. The coefficient (γ) on the product ($D_i \times Post_t$), capturing the effects of the HM program on the housing price is estimated at 0.032. The estimation implies that the HM program potentially lead 3.2% increases in the real housing prices for the period June 2013-December 2013.

Panel data regression analysis

To examine the effects of house specific and macroeconomic variables on the 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.

Table 3. Estimation results of POLS and fixed effect (FE) estimator

	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 (MIR)	-0.016***	-0.019***	0.026
	(0.00)	(0.00)	(0.07)
ln (CPI)	-0.862***	-0.785***	-0.54
	(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***	27.6
	(1.31)	(0.93)	(30.9)
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

Notes:***, **, * indicate that the null hypothesis of non-causality is rejected at 1%, 5%, and 10% levels, respectively. The standard error in parenthesis. # coefficients for time dummies are not shown in the table.

The house specific factors except for distance have statistically significant effects on the real housing prices. The result was robust for all estimation methods. Signs of the estimated parameters are the same as discussed in the pooled cross-sectional data analysis. As a novel result, the real housing prices intend to be cheaper for houses located in areas with higher air pollution measured by Nitrogen dioxide (NO2). According to the static POLS estimation, apartments are cheaper if they are in more distance from the city center.

For static POLS and FE (district) methods, the interest rate elasticity and income elasticity are statistically significant at the 1% significance level and estimated as 1.6-1.9 and 0.65-

[4] Since maximum pre-treatment period is 6 months, post-treatment period is chosen as 6 months in the regression.

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 have been estimated as statistically insignificant since the method controls for 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, FDI, cash transfers etc.), not included in the estimation.

Time series analysis

As there is no time series data of supply-side factors (and micro-housing attributes), we estimate the VECM model for demand-side determinants as specified in equation (8). As the HPI only includes apartments (not single-family homes, semi-detached or terraced houses), we assume that in the segment, prices are determined by these macro variables. Before estimation, univariate unit root tests are conducted, and Augmented Dickey-Fuller (ADF) test is applied for testing stationary of these variables. ADF test statistics are summarized in Table 2.A of the appendix.

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). For instance, the null hypothesis that the series in level has unit root is not rejected, and the null hypothesis that the first difference of the series has unit root is rejected at the 1% significance level.

Before the co-integration test and estimation, the appropriate number of lags for the VECM model must be determined. We estimate three versions of VECM with different real HPIs, such as (i) overall HPI calculated by Tenkhleg Zuuch, (ii) HPI for residential properties with below 80 square meters, and (iii) HPI constructed with time dummy. Results of Lag selection criteria are shown in Table 3.A of the appendix. For the vector autoregression (VAR) with overall HPI, likelihood ratio (LR) test, Final prediction error (FPE) and Akaike Information Criterion (AIC) suggest five lags, however, Schwartz Bayesian Information Criterion (SBIC) and Hanan-Quin information criterion (HQIC) indicate one and four lags, respectively. For the VAR with HPI for below 80 square meters, the LR test and FPE suggest four lags, while AIC, SBIC, and HQIC information criterion indicate five, one, and two lags, respectively. For the VAR with HPI constructed with time dummy, FPE and HQ information criterion suggest two lags, while the LR test, AIC, and SC information criterion indicate four, five, and one lags, respectively. However, for three versions of VAR, only 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 Eigen-value co-integration tests are conducted to determine the number of co-integrations among the four variables in the model.

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

The weak exogeneity test is used to find the proper specification of the VECM model (i.e., system equations or a single equation). The test results are shown in Table 5.A. For all three versions, the null hypothesis that the variable is weak 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 more driven 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 weak exogenous) must be employed in estimating co-integrating vector, α'. To this end, the joint restriction $\delta_{MIR} = \delta_{CPI} = 0$ (which is not rejected by the data as LR test statistics is $\chi^2(2) = 1.41$, the p-value of LM test is 0.50 for overall HPI, $\chi^2(2) = 1.99$, the p-value of LM test is 0.37 for HPI for below 80 square meters residential properties, and $\chi^2(2) = 1.79$, the p-value of LM test is 0.41 for HPI constructed with time dummy) is imposed in the VECMs to obtain efficient estimators for the parameters of the co-integrating vector. For all three versions, the VECM with one lag and the weak 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.

Table 4. Estimation results of VECM

	Dependent variable: Δln (real HPI)		
Independent variables	Overall HPI	HPI for below 80 sq.m residential properties	HPI constructed with 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)
$\Delta\,\mathbf{ln}(\mathbf{real\ HPI}(-\mathbf{1}))$	-0.074	-0.057	-0.018
	(0.124)	(0.122)	(0.121)
$\Delta\,\mathbf{ln}(\boldsymbol{CPI}(-\mathbf{1}))$	-0.148	-0.025	-0.027
	(0.233)	(0.194)	(0.212)
$\Delta\,\mathbf{ln}(\mathbf{real\ income}\ (-\mathbf{1}))$	-0.001	-0.031	-0.043
	(0.133)	(0.113)	(0.123)
$\Delta(\boldsymbol{MIR}(-\mathbf{1}))$	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

Notes:***, **, * indicate that the null hypothesis is rejected at 1%, 5%, and 10% levels, respectively. The standard error in parenthesis.

For all three versions, each long-run elasticity of explanatory has theoretically expected sign and is statistically significant at the 1% significance level, suggesting that the real household income, mortgage interest rate, and CPI affect the real housing price. The real income elasticity is estimated as $\alpha_1 = 1.4$, which is in line with the existing results (i.e., Hofman 2005 for the Netherlands, Oikarinen 2005 for Finland, Jacobsen and Naug 2005 for Norway). The interest rate semi-elasticity is estimated at $\alpha_2 = 0.03$, suggesting that one percentage decrease in the average mortgage interest rate leads to a 3% increase in the real housing price. The estimated value of the semi-elasticity is modest and closer to the results obtained in the 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 the findings imply that mortgage interest rate subsidy and macroeconomic policies potentially have a significant effect on the real housing price.

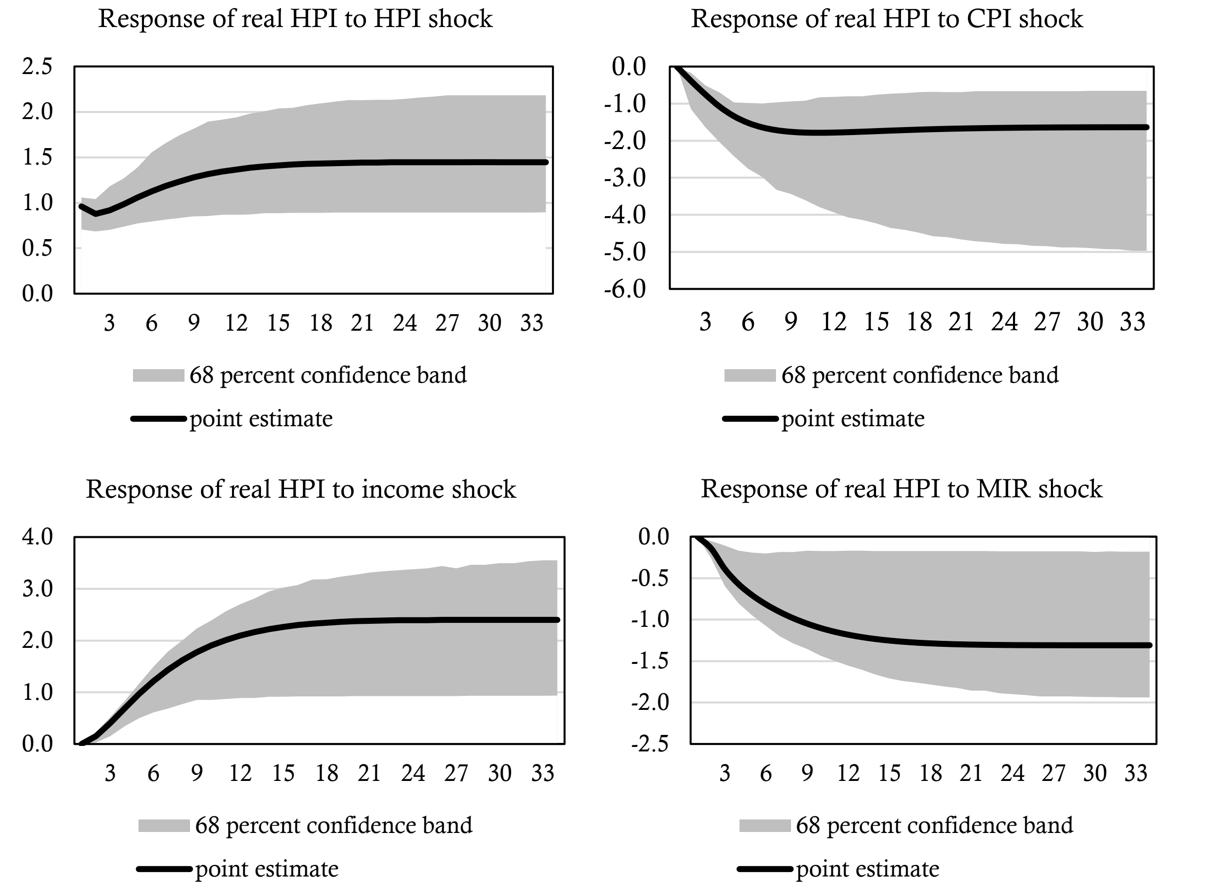
Another interesting result is that VECM feedback takes place through both real housing prices and real household income adjustments. The error correction coefficients of real housing price equation ($\delta_{HPI} = -0.13$) has expected sign. The result suggests that any deviation from the long-run equilibrium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

Overall, three empirical estimations (i.e., pooled cross-section, panel, and time series methods) provide the 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 delivering subsidized mortgage loan has affected the housing prices through direct (mortgage interest rate subsidy) and indirect (household income and CPI) channels since the long-run interest rate, income and CPI elasticities are elastic and statistically significant with theoretically consistent signs.

5.2 Impulse response, variance decomposition and historical decomposition of real housing prices

To assess the dynamic behavior of the VECM of real HPI for apartments with below 80 square meters, we employ generalized impulse responses (GIRF) together with bootstrapped standard errors. Figure 5 reports point estimates and 68% confidence bands of GIRFs. The size of each shock is chosen as one percent (or one percentage point for interest rate) change in the shock variable. One percent own shock increases the real HPI by 1.5 percent after 36 months from the initial shock, and the response is highly persistent. One percent increase in CPI decreases the real HPI by 1.6-1.7 percent after 6 six months. Response of the real HPI to income shock gradually increases over time. One percent increase in real household income pushes up the real HPI by 2.2-2.4 percent after 12 months from the initial shock. Because of the HM program (interest rate subsidy policy), the average mortgage interest rate immediately fell by 7 percentage points. According to the response of the real HPI to MIR shock, the policy intervention has increased the real HPI by 6-9 percent for the next 36 months from the initial shock (i.e., June 2013).

Figure 5. Impulse responses of real HPI for below 80 square meters



Though impulse response functions show 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 shocks in fluctuations of interested variables. Table 5 presents the result of the forecast error variance decomposition (Cholesky decomposition) of real HPI for apartments with below 80 square meters.

The total variance of the HPI is decomposed in each period of forecast horizon and we measure the percentage of this variance that each shock can explain. For the first 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 mortgage interest rate shocks account for significant variation (26.3% for income shock and 17.4% for mortgage interest rate shock) in the HPI. CPI shock accounts for 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 importance of household income and mortgage interest rate shocks in explaining the HPI variance increases over time. These results are robust regardless of what ordering of variables is used in the Cholesky decomposition.

Table 5. Forecast error variance decomposition of real HPI for below 80 square meters, in percent

Forecast horizon	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

Note: The columns give the proportion of forecast error in the HPI accounted for by each endogenous variable.

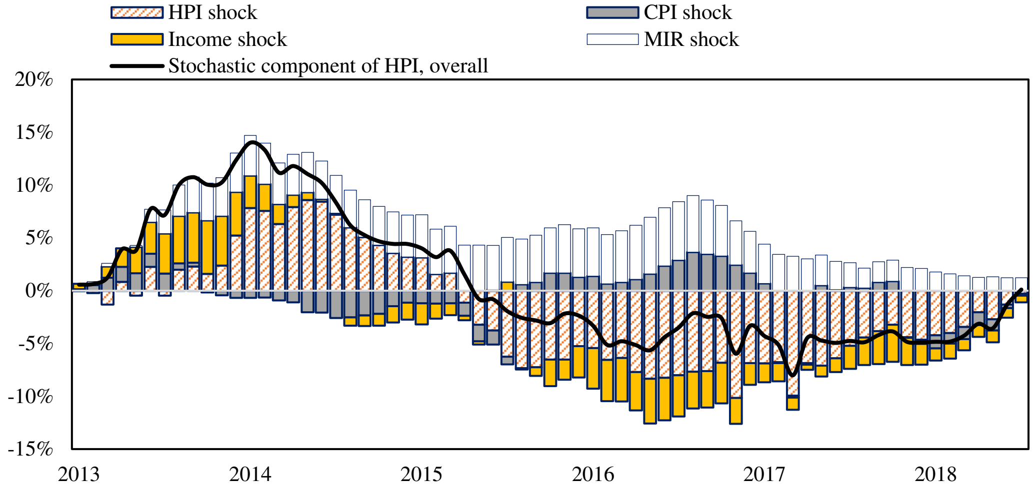
In this section, we explore which factors (structural shocks) drive the recent boom and bust in the Mongolian housing market. Historical decomposition provides an interpretation of historical fluctuations in the modelled time series through the lens of the identified structural shocks. The estimated 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 the 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 2013M1-2018M9. The historical decompositions of different HPIs are qualitatively the same as the contribution of shocks move the same directions, but quantitively different in the sense that the magnitude of the contribution explained by certain shock varies among different HPIs.

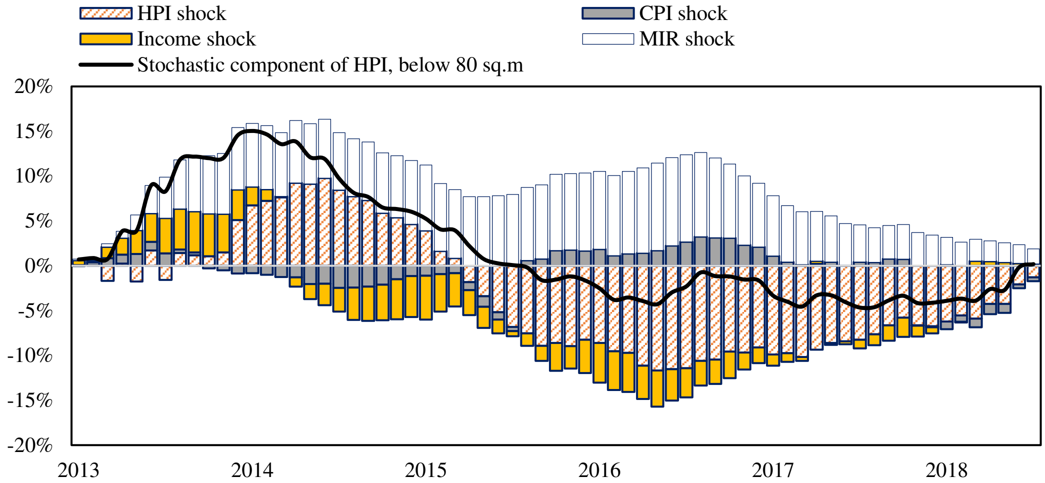
The boom of housing prices over the period 2013-2014 has been mainly contributed by mortgage interest rate and HPI own shocks. Under the HM program, the mortgage interest rate is subsidized starting from June 2013 and the average mortgage interest rate immediately fell by over 7 percentage points. Over 35000 borrowers took mortgage loans of 1.5 trillion MNT (equivalent to 16% of M2 money a) with subsidized interest rate (8% per annum) between June 2013 and March 2014. Over the period, total mortgage loan outstanding doubled reaching 2.2 trillion MNT and its annual growth exceeded 125% for the period September 2013-March 2014.

Figure 6. Historical decomposition: stochastic components of real HPIs

A. Real overall HPI



B. Real HPI for below 80 square meters



C. Real HPI constructed with time dummy

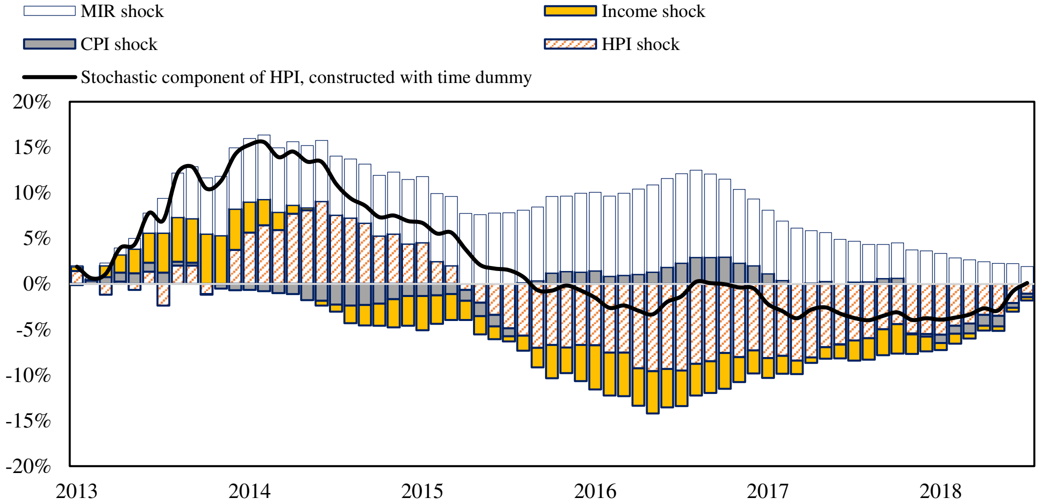


Figure 6 shows that the interest rate shock drives more than half of the HPI for residential properties with below 80 square meters, which can be bought by the mortgage loan with a subsidized interest rate. The finding indicates that the massive policy intervention in the mortgage market has led the housing price boom in Mongolia. As the mortgage interest rate subsidy continued under the HM program, the mortgage interest rate shocks have positively contributed to the real housing prices over time. As the subsidized mortgage rate temporarily reduced from 8% to 5% in 2016, the positive contribution of the interest rate shock in the same year has increased as well. As the volume of the subsidized mortgage loan has decreased since the end of 2016, the contribution of interest rate shock has gradually shrunk.

Tough 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. It can be explained as follows. In the VECM, dependent variables are modelled in 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 for a level variable is calculated as cumulative sum of the differenced variable's contribution. The empirical estimates of highly persistent impulse responses and values of mortgage interest rate shock result in the positive contribution of the shock for the sample period.

The real household income shocks also have positively contributed to the housing price boom during the years of the double-digit growth. Own shocks of housing prices have 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 et al. (2013) and Kanik et al. (2014), the own shocks strongly amplified the housing price boom in Mongolia during the period 2013M9-2014M3. Initially, its contribution was positive since market participants have formed an expectation that the housing price will rise further as the subsidized mortgage loan rapidly increased. The expectation of large price increases had a strong impact on the housing demand because people believed that housing prices are unlikely to fall. The house price expectation has been enhanced by some policymakers' statements that buying a house is a long-term investment, having huge financial benefits as housing price increases.

The housing price bust started from 2014M3. CPI and the real household income shocks have initially driven the bust. As the real housing price started to fall, market participants' expectations reversed in the direction that the price will keep declining. Therefore, HPI shocks have negatively contributed to the housing price, and together with the real household income shocks, own shocks have been the main sources of why the housing price bust lasted much longer. Overall, the exercise suggests that the HM program (i.e., mortgage interest rate subsidy) has led the boom, and deterioration of macroeconomic fundamentals (household income and CPI shocks) and changes in expectation have steered the bust in the housing market.

6. Conclusion

This paper has examined the effect of a mortgage interest rate subsidy on boom and bust 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 the housing price dynamics.

Several important results stand out. First, we find that the most recent housing boom from 2012Q2 to 2014Q1 resulted in an above-trend increase of real house prices by 17.7%, while the recent housing bust lasted four years (i.e., from 2014Q1 to 2018Q1) and real house price declined by 33.2% from peak to through. Second, all estimation results based on pooled cress sectional, panel, and time series data provide the robust evidence that both demand (macroeconomic variables) and supply-side (house specific characteristics, distance, air pollution) factors are vital determinants of the housing prices. The difference-in-difference (DiD) estimation suggests that the HM program has 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 the 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 the real housing price. The mortgage interest rate semi-elasticity and the real household income elasticity for Mongolia are estimated as -3.0 and 1.4, respectively. Fourth, Dynamics analysis (GIRF and variance decomposition) reveals that real household income and mortgage interest rate are the key variables in forecasting housing prices in Mongolia. real household income and mortgage interest rate shock respectively account for 26% and 17% of the forecast-error variance of the real housing price. Fifth, the generalized historical decompositions based on the estimated VECMs show that the recent housing boom has been mainly driven by mortgage interest rate, real household income and HPI own shocks, and real household income and HPI own shocks have played a significant role for the recent long-lasted housing bust. The analysis reveals that the HM program has driven the recent housing boom in Mongolia.

The evidence suggests that policy interventions in the mortgage market such as non-targeted and significant subsidy on mortgage interest rate can lead the housing boom. Therefore, an optimal policy mix (i.e., targeted subsidy or setting limit on subsidized mortgage loan amount, macroprudential measures such as limits on loan-to-value and debt-to-income ratios, policies supporting supplies of apartments, construction materials, related infrastructures etc.) must be expected to curtail boom probabilities.

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Appendix

Table 1.A Summary statistics of variables in pooled cross-sectional data

Variable	# of obs	Mean or Proportion	Std.dev	Min	Max
House prices-levels in togrogs	272,799	130,000,000.0	144,000,000.0	20,300,000.0	6,160,000,000.0
Log (real house price)	272,799	18.436	0.612	16.739	22.505
House characteristics					
Age (in years)	272,799	9.634	13.791	0.000	82.000
Area (square meter)	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 (in km)	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 house	272,799	0.057	0.231	0.000	1.000
Wooden and brick house	272,799	0.005	0.071	0.000	1.000
Prefabricated houses (base group)	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 (MIR)	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

Source: Real estate agency survey conducted by Tenkhleg Zuuch

Table 2.A ADF 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 below 80 sq.m2)	-2.403	0.375	-7.241	0.000***
ln (real HPI with time dummy)	-2.473	0.340	-7.134	0.000***
Mortgage rate of interest (MIR)	-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***

Notes: '***', '**'and '*' denote the level of significance at 1%, 5% and 10%, respectively. Tests for levels data are computed from regressions with constant and trend while differenced data are computed from regressions with only constant term.

Table 3.A Lag selection criteria

1) VAR with ln (real overall HPI) ln (CPI) ln (real income) MIR
Sample: 2013M01-2018M09

Lag	LogL	LR	FPE	AIC	SC	HQ
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

2) VAR with ln (real HPI for below 80sq.m^2 residential properties) ln (CPI) ln (real income) MIR
Sample: 2013M01-2018M09

Lag	LogL	LR	FPE	AIC	SC	HQ
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

3) VAR with ln (real HPI constructed with time dummy) ln (CPI) ln (real income) MIR
Sample: 2013M01-2018M09

Lag	LogL	LR	FPE	AIC	SC	HQ
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

Notes: * indicates lag order selected by the criterion, LR: sequentially modified LR test statistic (each test at 5% level), FPE: Final prediction error, AIC: Akaike information criterion, SC: Schwarz information criterion, HQ: Hannan-Quinn information criterion.

Table 4.A Johansen Cointegration test Results

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

	Co-integration Equation Includes Constant			
	Trace test		Eigen-value test	
H_0: Number of CE(s)*	**Statistics**	**Critical value (at 5%)**	**Statistics**	**Critical value (at 5%)**
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

2) VECM(1) with HPI for below 80sq.m^2: ln (real HPI for below 80sq.m^2) ln (CPI) ln (real income) MIR

	Co-integration Equation Includes Constant			
	Trace test		Eigen-value test	
H_0: Number of CE(s)*	**Statistics**	**Critical value (at 5%)**	**Statistics**	**Critical value (at 5%)**
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

3) VECM(1) with HPI with time dummy: ln (real HPI with time dummy) ln (CPI) ln (real income) MIR

	Co-integration Equation Includes Constant			
	Trace test		Eigen-value test	
H_0: Number of CE(s)*	**Statistics**	**Critical value (at 5%)**	**Statistics**	**Critical value (at 5%)**
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

Notes: For all three versions, both Trace and Max-eigenvalue tests indicate one cointegrating equation(s) at the 0.05 level. * denotes rejection of the hypothesis at the 5% level.

Table 5.A Testing for weak exogeneity of variables

1) VECM(1) with overall HPI: ln (real overall HPI) ln (CPI) ln (real income) MIR
H_0: The variable is weak 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]

2) VECM(1) with HPI for below 80sq.m: ln (real HPI for below 80sq.m^2) ln (CPI) ln (real income) MIR
H_0: The variable is weak exogenous

	ln (HPI below sq.m)	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]

3) VECM(1) with HPI with time dummy: ln (real HPI with time dummy) ln (CPI) ln (real income) MIR

H_0: **The variable is weak 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]

Notes: The p-value in bracket represents the probability of the null hypothesis.