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ABSTRACT

This paper uses a two-step procedure to analyze the long-run dynamics between real house prices and their fundamentals in Lima, Peru. In this framework, first a hedonic price index is calculated, and then used for estimating a quarterly vector error correction model over the period 1998-2014. The price determinants considered in this application are: real mortgage interest rate, real gross domestic product, and trading volume. The reduced form of the model is employed for generating alternative price forecasts. In addition, a structural decomposition of the system allows us to identify and give an economic interpretation to the permanent and transitory shocks. Finally, this analysis is also applied to different tranches of the price distribution to assess if the interrelationships in the system vary across them. Results imply that income and trading volume shocks contribute the most at explaining the dynamics in prices. Also, under reasonable assumptions for the modeled fundamentals, predictions suggest that real house prices would undergo an important deceleration during the following years. Some signs of differenced behavior throughout the price distribution in the housing market cannot be ruled out in this analysis.

JEL Classification: R21, E31, C32.
Keywords: House prices, Hedonic Index, Vector autoregression.

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1. Introduction

Real house prices in the capital of Peru, Lima, have been increasing substantially during most part of the last decade (see Figure 1). The housing price series exhibit a breaking point in 2007, and since then nominal prices have risen by over 240% while real prices accumulated an increase of over 130%.[1] The sharp upward trend raises questions about the causes and future persistence of such growth behavior. Recent developments in the housing markets-in both advanced and developing countries-suggest that significant price deviations from their demand and supply fundamentals can lead to important corrections, with negative consequences for the economy and financial stability. The goal of this paper is to, first, exploit the existing apartment dataset in order to build more reliable price indices; and then complement previous work on the housing long-term dynamics by modeling a structural model. Finally, this methodology is applied to different sections of the price distribution to see if their interrelations with the fundamentals differ across them.

There have been numerous important contributions in the empirical literature that explain real price movements in terms of their underlying determinants. This literature usually employs proxies for income, demographic and financial factors in the determination of the long-term housing demand, whereas construction costs and measures for the number of available residences help account for the effects of the housing supply. This has been carried out in a single-equation framework (see Engelhardt and Poterba, 1991; Abraham and Hendershott, 1996; Clayton, 1996; Capozza et al., 2002; among many others), and more recently in multi-equational settings (see Sutton, 2002; Klyuev, 2008; Tsounta, 2009; and Cubeddu et al., 2012). There also exists a vast literature that focuses on explaining the observed co-movement between prices and trading volume (see Stein, 1995; Berkovec and Goodman, 1996; and Genesove and Mayer, 2001).

Empirical studies in this line have already been applied to the case of Peru.[2] Cubeddu et al. (2012) and BBVA (2012) generate long-term equilibrium prices under the hypothesis of cointegration .[3] Both conclude that prices have shown overvaluation in the recent years, but the misalignment is relatively modest. Orrego (2013) uses a more diverse set of fundamentals which include variables related to demographics, terms of trade, current account deficit, institutional environment and stock market performance to find cointegration. Then, a distribution of equilibrium prices is built by resampling the cointegrating vector. His conclusions about house prices are similar to the ones in the previous studies.

This paper follows a two-step empirical procedure to assess the interactions between housing price movements and their determinants. Analysis is built upon the seminal work of Griliches (1971) and King et al. (1991). Individual applications of these techniques to housing markets are found in Meese and Wallace (2003) and Gattini and Hiebert (2010). In the first stage, hedonic house price indices are estimated using two different approaches. Second, the generated price index is used in a structural vector error correction model (SVECM) framework to analyze the way in which economic fundamentals constrain price dynamics. After considering a wide group of housing demand and supply shifters, a parsimonious system specification is found to have a meaningful relation with the evolution of prices. Besides the price index, three variables are included: income (in the form of GDP), trading volume, and a measure of long-term real interest rate.

The resulting hedonic regressions allow obtaining a constant quality price index, and overcoming matching problems typically found when comparing dwelling prices over time. A set of coefficients for

[1] Apartments have commonly been sold in dollars throughout the relevant period of analysis. Thus, the difference between nominal and real prices responds to both changes in the exchange rate and Peruvian inflation.

[2] All these studies have employed the median price index published by the Central Bank of Peru (BCRP), which only includes information on the five upper-income districts.

[3] The former only uses GDP in the set of economic fundamentals, while the latter adds a measure of housing supply and construction costs.

dwelling characteristics is estimated per each percentile of the price distribution to find that implicit prices for housing attributes vary as observed apartment prices increase.

The estimated VECM is employed for two purposes. First, the forecasting performance is evaluated, and price predictions are generated by using its reduced form. The model suggests that, under different reasonable assumptions, a deceleration period that would bring prices closer in line with their modeled determinants is expected during the following two years. Second, a structural decomposition approach is used for identification by distinguishing between permanent and transitory shocks. This enables to give an economic interpretation to the different shocks in the system. Impulse responses and forecast variance decomposition are calculated for this purpose.

The remaining part of the paper is partitioned into five parts. Section 2 summarizes the data to be used. Section 3 outlines the estimation models to be followed in each stage. Section 4 reports the empirical results. First, the findings in the hedonic regressions are presented; and, second, the forecasting performance of the reduced model as well as the properties obtained through the structural model are discussed. Section 5 presents the results of applying this analysis to different parts of the house price distribution. Finally, section 6 closes with some conclusions.

2. Data and stylized facts

House price dynamics appear to have changed since 2007, going from a slightly decreasing trend to the upward sloping trend observed afterwards. A number of ways of explaining such behavior have been proposed by the academic and non-academic circles. In particular, it is widely believed that in Lima-a city that hosts around ten million people-, land availability is steadily decreasing as population keeps on growing. Also, Peru has observed important economic growth over the past ten years, experiencing an average annual growth of 6% in this period (see Figures 2 and 3). This growth, in turn, has led to higher purchasing power of households through both higher wages and a more dynamic labor market. Additionally, financial development has granted households greater access to mortgage loans. The latest international crisis also contributed in this manner by attracting important capital inflows to the economy, part of which was channeled to facilitating the financing of houses. This meant lower real interest rates. These trends have posed an important concern to the economic authorities due to the potential underlying risks. Jordà et al. (2014) showed that for 14 advanced economies, loose monetary conditions has historically led to mortgage and house price booms. In particular, many analysts argue that this scenario in Lima would have first and more significantly boosted higher-end housing demand leading to persistent visible increases in prices in the premium market. Finally, appreciation expectations added to favorable economic conditions would have fostered the build-up of prices in the rest of the real estate market.[4] This way, Lima has undergone a booming housing market for the last 8 years. Although, during the last year, as capital inflows and economic growth seemed to have stabilized, prices have started showing some signs of deceleration.

To estimate a VECM, the first task consists on choosing the economic variables that are able to explain better house price movements. Table 1 shows the main variables that were originally considered for this purpose. In order to choose the relevant system of variables, a general to specific method was followed. In this way, while testing for the existence of cointegration, only significant regressors with an economic expected sign were kept. The procedure led to a parsimonious system containing three variables. On the demand side, real GDP (y_t) is used as proxy of household income, and real mortgage interest rate (r_t) is also thought to have meaningful impact on prices. This interest rate is constructed by weighting the mortgage interest rates in nuevos soles and dollars with the series of mortgage loan stocks in each currency. This choice of variables is in line with empirical work by Abraham and Hendershott (1996) and the theoretical model developed by McQuinn and OReilly (2007).

[4] Shiller (2007) suggests that during booming periods in the housing market, expectations can play a bigger role than fundamentals at explaining price dynamics.

On the supply side, two proxy variables for housing supply were initially taken into account: the number of housing apartments for sale (even if still in construction) and the number of finished housing apartments for sale. Both pick up the effect of entry of new dwellings. Nevertheless, they show erratic behavior yielding to poor performance in most econometric tests .[5] Another variable of interest is the trading volume (q_t) in the market. Theories proposed to explain the correlation between house prices and trading volume predict positive co-movement in the short run, and negative one in the long run.[6] Furthermore, the fact that adding real construction costs (c_t) to the system, and using mortgage loan stocks (l_t) instead of interest rates (as a proxy to capture the financial impact) leads to two cointegrating vectors, will be used later as a robustness check.

The VECM, in both settings, will be estimated using quarterly data. Information on GDP is only available quarterly. Financial variables and the cost of construction data is monthly, and simple arithmetic averages are employed. Trading volume information is obtained through a yearly census, and interpolation is used to get a quarterly series. Finally, as explained below, information on apartment prices is gotten from newspapers ads weekly; however, indices are typically calculated quarterly to avoid volatility in a very heterogeneous market such as the housing one.

Before proceeding to the analysis described above, a hedonic price index is estimated. Since 1998 the Central Bank of Peru has been collecting data, from newspaper ads, regarding apartment prices and their characteristics on: location, surface area, age of the dwelling, number of bedrooms, number of bathrooms, number of garages, whether it has a street view or not, and the floor level.[7] Two of these showed better performance when coded into categorical variables. In particular, age was coded into an indicator taking 1 for new apartments, and then grouped into tranches 1-5 (years) =2; 6-10=3; 11-20=4; 21-30=5; 31-40=6; 41-50=7 in line with suggestions by Diewert (2010). Similarly, floor level was coded to reflect the distinguished preference for lower levels, and then higher floor levels were grouped each five levels. In order to avoid the effect of outliers, most characteristics were winsorized from above at 0.5% (though results do not change if this step is omitted).The final dataset contains around 54 000 observations for the period 1998q1-2014q3.

The sample data started including information on five districts in Lima until 2006; period in which they represented most of the transactions in the housing market. As house prices began to increase, other districts started showing more dynamism in the real estate, so the sample was expanded to include five more districts. This implied reaching an average coverage of over 60% for the latter period. Due to matching problems, the Bank usually only publishes median price indices for the first five districts. Here, instead, the hedonic regression approach allows overcoming the matching problem to an important extent. Thus, the hedonic price index (p_t) to be employed includes information on the 10 districts.[8]

3. Methodology

This section is divided into three parts. The first one describes the construction of hedonic apartment price indices. The second part presents a reduced model to generate price forecasts; and, finally, a common trends approach is outlined in order to obtain a structural decomposition.

[5] This could be explained due to building regulations and bureaucratic procedures that tend to slow down the construction. The impact of these administrative barriers can differ importantly across periods generating the non-smooth behavior observed in the series. Also, statistical registry becomes more cumbersome, and it could be argued that series are not very accurate. See Matsuyama (1990).

[6] For example, De Wit et at. (2010), in line with these theories, constructs a VEC model to explain Dutch price behavior using the volume of transactions, and imposing restrictions on the long-run dynamics.

[7] A few outliers were deleted from the sample. These observations corresponded basically to apartments older than 50 years, and/or with surface areas bigger than 300 square meters or below than 30 square meters.

[8] When this index is replaced by the hedonic/median price index covering only five districts, most important results presented in this paper still hold. Specific results on these can be requested to the author.

3.1. Apartment price indices

The use of median price indices is widely popular to describe the dynamics of housing markets; however, their use can often provide inaccurate information. Median indices can be biased since the quality of dwellings changes over time. Also, the median price in different periods can belong to rather different areas of the city leading to poor indicators of price changes; this inaccuracy is aggravated when there have been changes in the composition of houses sold in the period of analysis-as it may be argued that it is the case in Lima.

Hedonic regression models provide a good attempt to address these problems.[9] This method's conceptual foundation states that heterogeneous goods can be described by a bundle of objectively measured characteristics.[10] In order to construct housing price indices in this fashion, an ample dataset describing the most relevant characteristics-for acquisition decisions-of each dwelling is required. After assessing the performance and fit of different combinations, the following attributes were chosen to be included in the regressions: surface area, age, number of rooms, number of garages and floor level. As discussed by Eurostat, it is often not necessary to include many explanatory variables to construct reliable indices if the fit is acceptably good.[11]

There are two main alternative approaches for applying hedonics to housing markets; see Diewert (2003b) (2010). The time dummy variable approach pools all the periods in the sample and includes time dummies for each period. The time dummy coefficients (τ^t) pick up the pure price variation, adjusted by the effect of quality changes. In this particular case, a log-linear specification is chosen to model total apartment prices (P_n^t), and an interaction term between the surface area and age is included to try capturing the effects of structure depreciation. This implies estimating the following panel regression:

$$lnP_n^t = \alpha + \beta rooms_n^t + \phi garage_n^t + \gamma floor_n^t + \psi age_n^t + \chi[(1 - \delta age_n^t)\, surface_n^t] + \tau^t + \varepsilon^t \qquad (1)$$

The estimation pools the 67 quarters of the sample, $t = 1, \ldots, 67$, for the $N(t)$ apartments in each quarter, $n = 1, \ldots, N(t)$. Restriction $\tau^1 \equiv 0$ is usually imposed for identification purposes. Exponentiating both sides of (1), and neglecting error terms, allows to calculate relative prices, $\exp(\tau^{t+1}) / \exp(\tau^t)$, which can in turn be used as the chain link in a price index. A pooled OLS estimation is employed, accounting for possible heteroskedasticity problems. Commonly cited drawbacks to this strategy refer to potential inaccurate parameters as the sample gets larger or when structural breaks are observed-this due to parameters being kept fixed throughout the period of estimation. In addition, as more data becomes available, the index history needs to be reviewed which can prove to be sometimes inconvenient.

A second method requires estimating independent regressions for each period; see e.g. Mark and Goldberg (1984). Then, the estimated coefficients are used to construct Laspeyres and Paasche price indices. For each quarter t, the following regression is estimated:

$$lnP_n^t = \alpha^t + \beta^t rooms_n^t + \phi^t garage_n^t + \gamma^t floor_n^t + \psi^t age_n^t + \chi^t[(1 - \delta^t age_n^t)\, surface_n^t] + \varepsilon^t \qquad (2)$$

An interesting feature of this method is the possibility to deal with the frequent matching problems in the housing market statistics. It is almost never possible to have matched dwellings in different periods (same apartments are not sold each period or, even if that were the case, depreciation and renovation activities make one same apartment not comparable over time). In order to overcome this problem, the parameters estimated using quarter $\mathrm{t} + 1$ sample are employed to price out all the apartments included in quarter t sample. This permits to generate predicted quarter $\mathrm{t} + 1$ prices for quarter t apartments, $P_n^{t+1}(t)$:

[9] This methodology was first developed by Court (1939), and later popularized by Griliches (1971).
[10] See Rosen (1974).
[11] See Residential Property Price Index Handbook (2011).

$$lnP_n^{t+1}(t) \equiv \alpha^{t+1} + \beta^{t+1} rooms_n^t + \phi^{t+1} garage_n^t + \gamma^{t+1} floor_n^t + \psi^{t+1} age_n^t + \chi^{t+1}[(1-\delta^{t+1} age_n^t)\, surface_n^t]\,; \qquad t = 1, \dots, 66; \quad n = 1, \dots, N(t) \qquad (3)$$

Once the regressions are estimated, it is possible to use these matched prices to build a Laspeyres index for consecutive quarters:

$$P_{IL}(t, t+1) \equiv \frac{\left[\prod_1^{N(t)} P_n^{t+1}(t)\right]^{\frac{1}{N(t)}}}{\left[\prod_1^{N(t)} P_n^t(t)\right]^{\frac{1}{N(t)}}}\,; \qquad t = 1, \dots, 66 \qquad (4)$$

In expression (4), a geometric average is used as to keep “consistency” with the log-linear functional form. The denominator can either use observed prices or be replaced by predicted values.[12]

Similarly, this method can be applied backwards. That is, pricing out all the apartments that appeared in quarter $\mathrm{t}+1$ by taking the parameters estimated for quarter t. The numerator can use either observed prices or predicted values. A Paasche index, then, is constructed:

$$P_{IP}(t, t+1) \equiv \frac{\left[\prod_1^{N(t+1)} P_n^{t+1}(t+1)\right]^{\frac{1}{N(t+1)}}}{\left[\prod_1^{N(t+1)} P_n^t(t+1)\right]^{\frac{1}{N(t+1)}}}\,; \qquad t = 1, \dots, 66 \qquad (5)$$

Finally, using (4) and (5), a Fisher ideal price index is constructed by taking the geometric average of both indices. This will be the index to be employed for further analysis in this paper.

In order to estimate the sixty-seven equations in (2), it is possible to employ OLS robust estimates (i.e., a mean regression). Nevertheless, house price distributions tend to be positively skewed-which possibly reflects the positive skew in income distributions and the zero lower bound on transaction prices-; henceforth, a quantile regression approach is used as well since a median regression could yield more precise results for the price tendency. This latter procedure is based on the contribution by Koenker and Bassett (1978).

3.2. Reduced form model

This subsection and next employ the notation of King, Plosser, Stock and Watson (1991). Let X_t be a vector of endogenous variables that are assumed to be individually $I(1)$, then we can write their Wold representation as:

$$\Delta X_t = \mu + C(L)\epsilon_t \qquad (6)$$

where ϵ_t is the vector of one-step ahead linear forecast errors, and assumed to be serially uncorrelated with zero mean and covariance matrix Σ_ϵ. Reduced-form representation given by (6) will be used for generating house price forecasts in section 4.2.

In order to forecast using the above error-correction representation, all the variables included in the system must be assumed to be $I(1)$. Table 3 reports the modified Augmented Dickey Fuller test proposed by Elliot, Rothenberg, and Stock (1996). The number in parenthesis is the optimal lag length determined by Schwarz’s information criterion. The results using the whole sample period indicate all variables are $I(1)$ processes. Table 4 reports Kwiatkowski et al. (KPSS 1992) test for trend stationarity, which arrives to the same conclusions.[13]

[12] When observed prices are left unchanged, it is a single imputation index; otherwise, a double imputation index.

[13] Test results are based on a lag length of eight, but conclusions do not change if more lags are employed.

Next, it is necessary to ensure that the four variables to be used exhibit a common long-term trend. Table 5 presents the trace cointegration test developed by Johansen (1988). This test can be very sensitive to both lag length and functional specification. To choose the correct specification, the procedure outlined by Pantula (1989) and Johansen (1992) is followed, which basically suggests testing sequentially a series of joint hypothesis starting with the trace statistic for no cointegration $(r = 0)$ from the most restrictive deterministic component specification to the least restrictive one; and if none is rejected, proceed to assess the trace statistics for one cointegration equation $(r = 1)$, and so on.[14] The preferred model is chosen by the first time a hypothesis is rejected. For the four variables being tested here, this procedure leads to accepting there is one single cointegration relationship.
Lag length was chosen having as reference different information criteria, as reported in table 6. The chosen model, which includes six lags for the underlying VAR, performs well under stability tests, and it rejects the hypothesis of autocorrelation in the residuals up to twelve lags (LM test).

3.3. Structural model

To better understand the sources originating fluctuations in house prices, it is helpful to consider modeling structural relationships, among the variables under analysis, that take into account economic theory. In this spirit, equation (6) can be rewritten in the form of a structural model:

$$\Delta X_t = \mu + \Gamma(L)\eta_t \qquad (7)$$

where η_t is a vector of serially uncorrelated structural disturbances with zero mean and covariance matrix Σ_η. The equivalence between the reduced and structural forms implies $\epsilon_t = \Gamma_0\eta_t$ and $C(L) = \Gamma(L)\Gamma_0^{-1}$.

The identification requires imposing enough conditions that allow to deduce the structural disturbances and matrix of lag polynomials, $\Gamma(L)$, from the reduced-form errors and matrix of lag polynomials, $\mathrm{C(L)}$. There are different alternative procedures to achieve this. In this paper, we will follow the common trends approach presented in King et al. (1991), and applied to the housing market analysis by Gattini and Hiebert (2010) and Iacoviello (2002).
King et al. (1991) propose identifying the structural VECM by making a distinction between structural disturbances with permanent and transitory effects on the levels of the variables. The permanent shocks are defined to be the source of common stochastic trends among the variables in the system. In our four variable system in analysis, there is only one cointegrating equation, so there are three permanent shocks $(4 - 1 = 3)$. This implies there will be as many transitory shocks as the number of cointegrating relations; the intuition comes from the fact that a cointegrating vector is a stationary linear combination, and shocks to a stationary system should not alter the steady state.[15]

Identification, then, is reached through restrictions on the long-run multipliers, $\Gamma(1)\,(= \sum_0^\infty \Gamma_i)$, and assuming the permanent components to be uncorrelated to the transitory ones. In practice, identification implies imposing constraints that can be given an economic interpretation.[16] After motivating the restrictions-as discussed below-, impulse responses and forecast variance decomposition can be used to infer conclusions on the dynamics between the house prices and their fundamentals. Finally, standard errors for the estimated impulse responses are calculated by using Hall bootstrap confidence intervals.

3.3.1. Permanent Shocks

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[14] Although there are five possible specifications for the test, Hansen and Juselius (1995) state it is very unusual to find data that fits either the least restrictive case (case 5) or the most restrictive one (case 1). Furthermore, the variables being used here do show trending behavior, but it would be difficult to justify the presence of a quadratic trend in the system. Hence, table 5 reports only cases 2, 3 and 4 as specified in Hansen and Juselius (1995), and denoted here by model A, B and C, respectively.

[15] By expressing equation (6) in its Beveridge Nelson MA representation, one also reaches the conclusion that the structural VECM can have at most one transitory effect in this application.

[16] Since there are four variables, $k = 4$, it will be necessary at least $k(k-1)/\,2 = 6$ restrictions.

Since there is one transitory innovation, the 4x4 matrix of long-run multipliers will contain one column full of zeros. In this study, that column corresponds to the impact of the housing demand shock which is assumed to only have transitory effects. This can be motivated by arguing that sectorial price deviations from equilibrium are corrected in the long-term, and, therefore, its impacts vanish. In this line, with the variables ordered as in $X_t = [p_t \;\; y_t \;\; r_t \;\; q_t]$, the relevant matrix is given by:

$$\Gamma(1) = \begin{pmatrix} 0 & \psi_{12} & \psi_{13} & \psi_{14} \\ 0 & \psi_{22} & \psi_{23} & \psi_{24} \\ 0 & \psi_{32} & \psi_{33} & 0 \\ 0 & \psi_{42} & \psi_{43} & \psi_{44} \end{pmatrix} \qquad (8)$$

where the coefficients are to be estimated. Each column shows the impacts of a particular shock on all the variables in the system, while each row shows the responses of each variable. Hence, for instance, ψ_{43} represents the value of the impact of a financial cost shock on the trading volume, and the response of GDP to a trading volume shock is estimated through ψ_{24}. Also, the matrix main diagonal picks up the effects on the variable shocks on their own selves.

Income shock: The second column can be thought as the effects provoked by a productivity/technological shock that affects the whole economy. It follows that it should be expected to generate permanent impacts on all the variables (i.e. $\psi_{i2} \neq 0 \; for \; all \; i$). In particular, it would lead to higher housing demand-via higher income levels-, more financial development, and more construction activity-via cost reduction or higher house prices that make housing investment more profitable-; all of which in turn would imply greater trading volume.

Financial cost shock: The third column shows its effects. A negative shock of this kind can be motivated as the consequence of financial innovations-internal source-, or important capital inflows-foreign source-that cause interest rates to fall. Although the interest rate being used here is the mortgage interest rate, since it was not possible to obtain a separate cost-of-capital proxy for the housing supply, the interest rates offered to enterprises have exhibited very similar trend.[17] Then, negative co-movement with housing demand and supply is expected. The net impact on house prices will depend on the magnitude of the effects on each curve; and similarly regarding the effects on the trading volume. It is also expected to show a positive effect on the economic activity.

Trading volume shock: Empirical literature suggests that, in the long run, the correlation between trading volume and prices is negative. Berkovec and Goodman (1996), in the framework of search models, suggest that as sales increase, the number of houses built increases importantly and, thus, in the long run the vacancy rate raises leading to higher sales time. Eventually sellers react to this trend by decreasing their ask prices.[18] Empirical studies also conclude on positive correlation among the two variables in the short run.[19]

[17] As a matter of fact, long-term wholesale banking interest rates-granted to big and medium sized enterprises-followed closely the mortgage interest rate trend. The correlation between both series increased in the period 2006-2014 (period of prices run-up), at around 0.90.

[18] In theoretical search models for housing, sellers and buyers meet randomly in the market in a scenario with incomplete information (and backward-looking expectations). Transactions occur when the buyer's reservation price is higher than the seller's ask price. Furthermore, it is usually assumed that buyers react faster than sellers, and seller's reservation prices are negatively related to the time on the market (i.e. the more time a house takes to get sold, the more willing the seller is to lower the ask price).

[19] Stein (1995) points out that for repeat buyers, the down-payment comes largely from the sale of an existing house; so as prices rise, buyers trade up leading to higher transaction volume. Berkovec and Goodman (1996) reach same conclusion in the short-run using search models. Finally, Genevose and Mayer (2001) argue that sellers exhibit loss aversion, so they will be reluctant to sell below the purchase price. The three approaches, theoretically and empirically, lead to positive co-movement in the short run.

As in De Wit et al. (2010), the shock of sales is assumed to mainly respond to the supply of apartments. It could respond to different underlying shocks such as migration, mobility within the market, flexibilization of building regulations on zoning laws and building permits, or the matching among buyers and sellers. The demand effect contained in the trading volume would be controlled, to an important extent, by the inclusion of the two demand fundamentals. This shock would then foster activity in the construction sector- and, through it, more labor demand-, which in turn means more economic growth. Understood as a supply shock, it could increase returns in the housing market and temporarily attract more investment to this sector; however, substitution among investment categories would equalize returns in the long run. Therefore, the impact on the interest rate would be non-significant in long time horizons.

3.3.2. Transitory Shocks

The housing demand shock is the only transitory one in this system. This shock would increase house prices making investment more attractive in the sector. It would also impact the appreciation expectations of households boosting temporarily housing demand, in line with Schiller (2007). The impact on activity, and income, operates through the increased activity in the construction sector and its traditional multiplier effects. Also, via higher economic growth and demand pressure, there would be a contemporaneous effect on real interest rates.
On the other hand, the short-run interaction between output and real interest rates is restricted to be null. This is motivated by the lags through which monetary policy operates. Finally, it is assumed that the trading volume does not impact real interest rates contemporaneously.

In this VEC model, the fundamentals are the income and interest rate, while the price and trading volume can be thought out as state indicators of the market. The econometric framework allows to analyze both types of variables. Shocks to the market indicators pick up impulses that cannot be accounted for by the fundamentals.

4. Results

4.1. Hedonic regressions

In this subsection, the results of applying both approaches to hedonic regressions are discussed. Figure 1 shows the median index, the Fisher ideal index and the time dummy hedonic index. It can be seen that the latter departs significantly from the two first ones since 2006; i.e. it fails more visibly at capturing accurately the observed price changes during the upswing of prices. Actually, this result is not surprising. As observed house prices started rising, the implicit prices of housing attributes also did. This method implies restricting the coefficients to be constant, so it cannot pick up these changes. Thus, the index exhibits undervaluation.

In contrast, the Fisher index follows closely the median index. Difference in the two indices would reflect the fact that the former accounts for quality change in apartments. Furthermore, the two hedonic indexes cross each other at the beginning of the sample and in 2007-period in which the run-up of prices start-; the graph shows that the undervaluation of the time dummy hedonic index accrues over time leading to larger differences in the hedonic indexes level towards the end of the sample. Table 2 reports the average for the sixty-seven sets of coefficients estimated. Surface area and the number of garages are the more significant variables in the regression, while the interaction between surface area and age (the proxy for depreciation) is not significant. Although interpreting the coefficient magnitudes in these regressions is not straightforward, the number of garages seems to be key in the determination of average house prices. All signs are expected in both the OLS and the median regressions. The bigger the surface area, the more rooms and garages, and the higher the level floor, the higher the price of the apartment. And the older the dwelling, the less expensive it is.

Housing markets are heterogeneous, and differences in the relation between house prices and their characteristics along the price distribution are expected. One way to observe this consists on estimating Fisher indices for different price percentiles as to obtain a distribution of coefficients.
Figure 4 shows the distribution for the five main attributes.[20] Results show that households getting more expensive apartments have higher valuation for larger surface areas than those purchasing cheaper ones. Also, lower-income buyers have more interest in larger number of rooms, given a surface area. People getting more expensive real estate would place more negative valuation to older dwellings. Finally, the implicit prices for the number of garages and floor level are relatively stable throughout the price distribution.
In general, these trends could reflect that more economic-constrained households –who get cheaper apartments- value more "utilitarian" attributes such as the number of rooms. As households climb in the housing ladder, attributes related to comfort start gaining importance. So, for instance, higher-end apartments are typically bigger but the number of rooms does not increase proportionally, as to provide comfortable larger rooms.

4.2. Forecasting prices in Lima

In this subsection the reduced model described by (6) is used to produce house price forecasts. The estimated VECM for this purpose is derived from the cointegration equation reported in Table 7. The cointegrating vector shows significant positive signs for the three variables. In line with the previous discussion, this reflects that more economic growth leads to higher prices via the demand curve. Trading volume and price present barely significant positive co-movement. As mentioned earlier, there is positive correlation among the both in the short-run and negative in the long-run. Possibly as the time span were longer, the sign of the coefficient would become negative. Finally, the positive sign on the real interest rate could be motivated by a dominant effect from the supply equation in line with Meese and Wallace (2003). However, comparing coefficient magnitudes and net effects of the fundamentals on house prices is a difficult task in a reduced-form model, and will be discussed in the next subsection in a structural model framework.

The forecasting performance of the VECM is assessed through rolling window forecasts, using a 12 years window, that allow obtaining out-of-sample forecast performance indicators for the period 2010q1-2014q3. The performance statistics are based on 1-step, 2-step and 4-step forecast errors. In particular, the mean error (ME), the root mean squared error (RMSE) and the mean squared error (MSE) are employed to test the performance.

Table 8 reports the performance forecast statistics. As in Gattini and Hiebert (2010), the VECM performance is compared to the errors produced by out-of-sample rolling forecasts generated by a VAR specified in levels. The authors suggest this can be used as a way to check the reliability of the cointegration relationship since the VAR can be seen as the unrestricted counterpart of the estimated VECM. Therefore, if the restrictions imposed through the error correction mechanism are not binding, the VAR is more likely to significantly outperform the VECM.
Results point towards the VECM model usually showing better forecasting performance in the five years predicted. Although, if the period is broken into two parts, the VAR shows better performance in the period 2010-2012 in shorter horizon forecasts (1-step and 2-step). The latter finding responds to the fact that in this period, prices accelerated more rapidly and would have departed more significantly from their long-run determinants. As the VECM model captures better the new trend, in the subsequent period, it is able to outperform the VAR more significantly. As an overall, results would suggest the restrictions imposed in the cointegration framework are valid.

[20] Each point in the distribution is the average of the sixty-seven coefficients estimated (for each quarter). Bootstrapped confidence intervals are also included.

Second, predictions for the following eight quarters are presented in Figure 5. Three different scenarios are considered depending on the assumptions made on the future behavior of fundamentals. Scenario B considers the annual average growth of these variables observed in the past two years; Scenario A basically differs in that it considers a sharper deceleration in real GDP and relative stagnation in the trading volume (possibly reflecting a slowdown in the housing building sector); and Scenario C reflects a situation in which real GDP picks up reaching similar growth rates to the ones experienced before the recent slowdown, and trading volume keeps increasing steadily. All three scenarios consider that real interest rates follow their recent behavior (in the context of minor capital inflows). It is important to mention that scenario A reflects a very unlikely outlook, and it is presented just to contemplate a very pessimistic case; while Scenario C seems to be more in line with the expectations of the economic media.
Scenario A implies an accumulated depreciation of real house prices by around 7% in the following two years.[21] Scenario B leads to a null growth over the same period. Lastly, the assumptions in scenario C imply an accumulated increase of less than 10%. As a reference, during the past two years real house prices grew by over 20%, and at even higher rates during 2008-2012. Thus, even the more optimistic scenario reflects an important slowdown in the price dynamics. The forecasts based on this particular set of variables are valid to the extent that omitted variables in our system do not change significantly. Furthermore, as it can be seen in the confidence intervals for scenario C, the probability of a temporary larger price deviation from its determinants cannot be discarded. However, the housing market in Lima is already showing some first signals of deceleration, and these results seem to be able to pick up such behavior. These results are in line with previous studies that suggested prices have exhibited overvaluation in the recent years; i.e., a deceleration period needs to occur eventually to bring prices back in line with their fundamentals.

4.3. Structural decomposition

Here, the results of applying the structural decomposition, described in the previous section, to (6) are presented. The estimated coefficients for the long-run matrix show signs in accordance to the assumptions outlined in subsection 3.3., and the main diagonal coefficients are very significant and positive.

4.3.1. Impulse responses

The estimated impulse response graphs for each of the four structural shocks can be found in Figures 6 to 9. The magnitude of each shock is one standard deviation of the variables in logs.

Housing demand shock: A positive shock of this type leads to a significant increase of prices for around 6 quarters, and only dies out after 5 to 6 years. This relatively long persistence is also found in Iacoviello (2002) for different countries in Europe. The real interest rate reacts positively with some important number of lags and soon later dies out in line with Gattini and Hiebert (2010). The initial impact on housing sales is positive and then turns negative, in line with theory. Finally, it also shows a relatively small but significant positive effect on real GDP, which could be motivated through a financial accelerator mechanism from the construction sector to the whole economy.

Income shock: This shock increases productivity which yields to higher income levels and, consequenly, a permanent increase in house prices due to demand pressure. As expected, it also generates a positive impact on economic growth though it is short-lived. Confidence bands widen importantly after 6 quarters making it not possible to discard a null effect since then. It also exerts a positive effect on real interest rates which could be understood indirectly through the boosted money demand, or through higher returns to capital as a result of the productivity innovation. The negative impact on the trading volume is unexpected, but it might be a consequence of higher interest rates.

[21] Considering the effective inflation rates in previous years, scenario A would traduce into relatively stable nominal prices.

Financial cost shock: The net effect of this shock on prices depends on the specific effects observed in the housing demand and supply. As seen Figure 8, the positive net impact would suggest a supply predominant response; the increase on the cost of capital would constrain more the supply than mortgage interest rates do in the demand side in the medium and long run. This can be expected in a scenario in which land prices have increased even more than apartment prices making expected building profits more sensitive to changes in the interest rates.[22] Nevertheless, the effect during the first two quarters is negative, and as time passes by, it grows positive. The latter would be in line with the fact that households react faster (to an increase in mortgage interest rates), and apartment builders react slower (since projects are considered in longer time horizons) but stronger, offsetting the initial demand response. Closely related, the trading volume would decrease as a consequence of lower supply and demand. It would operate with some lags since the supply reacts slowly. Also, unsurprisingly, it has a positive impact on real interest rates for some quarters.

Trading volume shock: The shock shows persistence on itself. The impact on house prices is negative in the long run, but positive in shorter horizons. In addition to the theories aforementioned, the initial positive effect can also be explained due to the fact that increases in housing sales build up appreciation expectations and, thus, boost the demand leading to temporary price upswings (See Clayton, 1996; Shiller 2007). The impact on interest rates is basically non-significant. Again, a negative co-movement between trading volume and income is observed.

4.3.2. Variance decomposition

For the variance decomposition analysis, Figure 10 reports the relevant graphs. House prices are strongly determined by the trading volume shocks in the short run, and its explanatory power significantly lowers as the time horizon is expanded. This shock is likely to be mainly determined by supply factors-since the other two fundamentals capture the demand influence. The supply of apartments is pretty much fixed at a given period of time (especially in a city like Lima where the construction boom has left little land to build on and building regulations usually delay construction activity). So, due to this little supply price elasticity, it would determine most of the initial price variance. After a year, the income shock becomes the most relevant factor to explain prices; and it stays at around 40% of the explained price variance. The financial cost shock increases its relevance very slowly, and only becomes a key factor after 3-4 years as the trading volume becomes less meaningful. As aforementioned, the effect of interest rates-through the housing supply-is expected to take longer. Finally, the housing demand shocks seem to play a small role explaining house prices.
On the other hand, income shocks contribute importantly to explaining real GDP initially and then reduce, as the trading volume and financial cost shocks contribution rise after one year. Lags in monetary policy transmission and slow long-term housing investments help motivate these results.
Not surprisingly, real interest rates find the most important source of variation in financial cost shocks for up to 2 years. Then, it steadily decreases as income shocks increase their explanatory power. Finally, the trading volume variance is amply explained by, first, shocks in income and, then, shocks to the sales.

4.4. Quick robustness check

It can be argued that house prices have many more fundamentals which are not included in the four-variable system in this application. One way to check the robustness of this small-scale system involves considering a different system, and assessing if results change significantly. In particular, the same common trends approach for structural decomposition is applied to a new vector which contains an added variable, construction cost (c_t), and employs mortgage loan stocks (l_t) instead of interest rates: $Z_t =$

[22] This is in line with the land price series collected, but not published, by the Central Bank of Peru. These series exhibit shaper upward trends.

$[p_t \;\; y_t \, c_t \;\; q_t \, l_t]$. After applying standard Johansen's cointegration tests, two cointegrating vectors are found.[23]
For the innovation accounting analysis, the structural long-run matrix would look like this:

$$\Gamma(1) = \begin{pmatrix} 0 & \gamma_{12} & \gamma_{13} & 0 & \gamma_{15} \\ 0 & \gamma_{22} & \gamma_{23} & 0 & \gamma_{25} \\ 0 & \gamma_{32} & \gamma_{33} & 0 & 0 \\ 0 & \gamma_{42} & \gamma_{43} & 0 & \gamma_{45} \\ 0 & \gamma_{52} & \gamma_{53} & 0 & \gamma_{55} \end{pmatrix} \qquad (9)$$

In this case, there will be two transitory shocks: housing demand shock and trading volume shock (both are market indicators, and the effects of sectorial shocks can be assumed again to be short-lived). A permanent **Construction cost shock** is expected to have an impact on all the variables in the system. It can be seen as an exogenous increase in construction sector wages or a rise in raw material prices. So, it can affect negatively the construction activity, and consequently the economic growth. The latter would also imply a slowdown in the housing demand and, hence, less mortgage loan flows. Also, now there is a **Financial shock** which is very similar in nature to the financial cost shock described previously, and it is not expected to have a meaningful direct impact on construction costs. The motivation for the income shock follows the same intuition outlined in section 3.3.

Figure 11 presents the forecast variance decomposition for house prices in this new framework. As in our previous model, the trading volume shocks starts out as the variable with higher explanatory power reaching almost 70% in both scenarios. Again, as before, after a year the income shock surpasses in importance of the housing sales, and also remains as the most important one through almost the entire horizon span. Furthermore, the financial shock exhibits growing relevance in a similar fashion to the financial cost shock in the original system. Although, its absolute relevance diminishes due to the added construction cost shock, and it operates through some lags given the slow nature of the housing building sector as discussed above. Also in line with the previous model, housing demand shocks play a minor role.
In Figure 13, the impulse responses of the different shocks to house prices are depicted. All impacts show similar dynamics as the ones observed in the other system. Income shock causes a significant permanent increase on prices, while the trading volume shock effect also turns negative after some lags. The latter effect is complemented with the negative contribution of the cost shock. The financial shock significantly increases prices after some quarters.
Thus, both exercises seem to behave similarly, in terms of quantitative impacts and lags, and arrive to the same conclusions which would validate our previous analysis.

5. Economic Strata

This section pursues two goals. First, the existence of a long-run relationship between different tranches of the housing price distribution is studied. Second, the analysis applied in section 4 is employed to determine if there are significant behavior differences across these tranches, regarding their relations with fundamentals.

5.1. Cointegration analysis

There are a number of alternative procedures to separate a total sample of houses into sub-samples or strata.[24] Basically, post-stratification refers to dividing the sample according to the values taken by one or more variables in the dataset. Given our interest in the behavior particularities among dwellings that

[23] The purpose here is to analyze the structural model properties. However, imposing some restrictions on the coefficients could allow interpreting each cointegrating equation as long-run housing demand and supply, respectively. See Bagliano et al. (1991) for a discussion on multiple cointegration interpretation.
[24] See Residential Property Price Index Handbook (2011), chapter 5.

belong to different economic strata, two stratification variables are naturally considered: location of the apartment, and its total price. The former is commonly useful if there is a homogeneous geographic distribution of dwellings according to price in the city; this is not the case in Lima. The available database contains information on the district in which the apartment is located; however, most districts have apartments with a wide range of observed prices. This makes using a location indicator not very suitable. Consequently, the total price of the dwelling is used to build price indices in two steps. First, the sample is broken into three tranches equally-sized in each quarter by using the values of the percentiles thirty-three and sixty-six. The group containing higher prices will be referred as Stratum 3 (S_3), while Stratum 2 (S_2) and 1 (S_1) refer to the middle and lower tranches, respectively. Second, as explained in section 3, a Fisher ideal index is built for each tranche.[25] The resulting indices are shown in Figure 13, and it can be seen that the Stratum 3 has exhibited a more pronounced growth since 2007 (actually the other two strata took some extra quarters before following this trend).

Next, cointegration between these series is tested using Johansen's framework. One cointegrating vector is found, and reported in Table 9. This provides evidence of long-term co-movement across different economic strata in the housing market. Specifically, the speed of adjustment parameters are positive and significant for Stratum 3 and Stratum 2 but very small. This is expected in a context where one of the variables (S_3 here) deviates persistently from the others. Although there is a catching-up trend in the other two strata, the growth difference is still significant. The results also suggest slow upward adjustment towards prices in the higher stratum; i.e. an increase in the upper-income market reinforces its own tendency, and pushes prices up in the middle-class apartments. The effect on lower-income housing markets is not so clear.

To better interpret the effects on each other, a Cholesky decomposition is employed to estimate the impulse responses in the system. As discussed in Section 2, the higher stratum can be expected to be the most "exogenous" variable in this system (appreciation expectations started in this sub-market), as well as to have a significant impact on the others. To verify this intuition, a Granger causality test is reported in Table 10. Results support the idea that Stratum 3 helps forecast the other two, and it also shows Stratum 1 Granger causes Stratum 2. According to this suggested ordering, impulse responses are presented in Figures 14, 15 and 16.[26]

To explore the effects of the shocks, it is useful to consider the different types of apartment buyers. As argued in Case and Shiller (1989), in broad terms, there are three types in the market. First, buyers who want to live in the house; second, house owners who want to trade up (e.g. to get a bigger property); and, finally, those who wish to buy and sell, as to get a profit.
A shock to the lower-income housing market has an expected positive impact on the all the sub-markets, though significance is low for the highest stratum. Expectation of further appreciation fosters first buyers to hurry their acquisition decision in Stratum 1. As these prices approach the levels observed in Stratum 2, it can be argued that some lower-income households will be willing to pay an extra premium to get a better apartment in Stratum 2.[27] This poses demand pressure on both markets and, thus, leads to higher prices. This behavior could also affect Stratum 3, through expectations; however, the wide confidence intervals do not make it possible to infer on the response. Second, a shock to mid-class real estate strangely yields non-significant effects in all strata. Finally, shocks to the higher stratum exhibit positive impacts on the rest. Price increases in expensive real state usually have more substantial effects on appreciation expectations. This would cause pressure demand from the three types of buyers, which spills over to all the strata.

5.2. Structural model results

[25] Since samples for each tranche are relatively small, the positive skew is not very relevant in this case. Therefore, OLS estimation is used instead of a median regression.

[26] However, results hold, qualitatively and quantitatively, in other alternatives of ordering.

[27] If Stratum 1 shock is big enough, it is also expected that some lower-income households consider selling their houses-profit from it-, and later buy more expensive real state.

The previous sub-section briefly outlined the interrelation among prices in different economic strata. A second step towards better understanding the sectorial dynamics involves analyzing their long-term determinants. Consistent with this notion, the structural model given by (7), including the three variables as described in section 3.3, is estimated for each price tranche.[28] Figure 17 presents the variance decomposition for each.

The trading volume shock (mainly driven by supply factors) shows the highest explanatory power across the three strata. This result is expected since land availability has reduced drastically in most areas of Lima making housing supply of apartments-given the relevant housing deficit- an important variable. The financial cost shock also contributes significantly in the three cohorts. In the two upper strata, it explains around 40%, and around 25% in Stratum 1. The income shock shows a more differenced behavior among strata. As economic growth is boosted by this shock, the higher income in households can be partially channeled to housing acquisition. Naturally, it is more relevant in the lowest stratum since the extra purchasing power might be key for accessing a mortgage loan. On the other end, higher-priced apartments usually have more appreciation expectation during economy booming periods, so the higher demand would also push prices up. Finally, housing demand shocks fail to explain much of the price variance in the three different economic strata.

In general, the determinants of the house prices seem to have different impacts on each stratum in terms of magnitude, lags and persistence. However, the brief analysis presented here has many shortcomings, and cannot be taken as conclusive First, it does not use specific fundamentals for each stratum. The dynamics of income, for example, have shown different acceleration rates in Peru along the income distribution. Also, the mortgage interest rates are different according to the household's wealth. Second, estimating an individual SVECM for each stratum is not the most efficient way to carry out this study. One alternative methodology would be to test for quantile cointegration as suggested by Xiao (2009), and model structural interrelationships in a more integrated framework. Future work on this area could undertake such endeavor.

6. Conclusions

This paper dealt first with the estimation of a hedonic house price index using transaction-level data for the city of Lima, and then the generated index was used in a vector error correction model (VECM). The second step permits to relate house prices with their determinants, which included real mortgage interest rate, real gross domestic product and trading volume. The analysis involves using the long-term relationship among these variables to better understand the important build-up of prices experienced during the past decade; and it also provides a better sense of what we could expect to observe in the coming years.

The hedonic estimation provided a price index that takes into account quality changes in the apartments over time. A specification that allows parameters to change across quarters was found to reflect the price trend more accurately. Also, the analysis suggested that the relationship between housing attributes and prices could vary throughout the price distribution. Cheaper apartments-thought to be generally purchased by lower-income households-showed relatively higher shadow prices for more "utilitarian" characteristics.

On the other hand, the reduced-form VECM showed good forecast performance during the recent period of rising prices. Moreover, under different reasonable future paths for the fundamentals, it predicts that real house prices would decelerate in the following years. House prices have exhibited an average yearly real growth of over 12% during the last 5 years. In contrast, our model, under the most optimistic scenario, suggests prices would grow by less than 5% annually. This result is consistent with previous empirical

[28] Cointegration is found among each price tranche and the fundamentals using the same VECM specification described in Section 4; however, the number of necessary lags differs. The three systems do not show either problems of autocorrelation nor stability in the period under analysis. On the other hand, using specific fundamentals for each economic strata was initially considered, but the statistics on income are only available from surveys that are not constructed to be statistically significant at that level of disaggregation, and, hence, inference becomes cumbersome. Information on real interest rates by economic strata is not published.

work for Lima's housing market that concluded on price overvaluation. Clearly, deceleration could be seen as a smooth way for prices to realign with fundamentals. In case prices would keep increasing at important rates, a more drastic correction could be expected; in consonance with Case and Shiller (1990) who suggest that larger bubbles are more likely to burst, and do so more drastically.

The structural model led to sensible results and in line with economic theory. Furthermore, results proved to be robust to variations in the model specification. Most of the price variance can be explained by shocks to the trading volume and economic growth (via its effect on income). The first component decreases in importance steadily, while the income relevance remains explaining almost half of the price variance. The effects of real mortgage interest rates become increasingly more important after a year.

Also, different tranches of the price distribution appeared to show different interrelation regarding the fundamentals. As expected, the trading volume shock-which mainly reflects underlying supply shocks-explains importantly all price strata in the short run. The effects of an income shock seem to be more relevant in the left part of the price distribution. Nevertheless, these last conclusions are drawn from a simple methodology strategy, and should be expanded by future work.

Finally, further research should focus on more sectorial dynamics. In a heterogeneous housing market, it cannot be discarded the possibility of important misalignments affecting specific economic strata in the population. Secondly, in case prices kept on deviating from fundamentals, there are no studies yet dealing with the implications of alternative policies (see Borio et al. 1994, for policy oriented literature) that could be employed to avoid the build-up of a price bubble.

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Tables

Table 1: List of Variables

Variable	Mean	Std. Dev.	Min	Max
Real house price index (Fisher hedonic index)	4.59	0.23	4.22	5.13
Real GDP in Peru	4.99	0.27	4.64	5.43
Real GDP in Lima	5.00	0.30	4.62	5.46
Income index: employed population aged 25-45 in Lima	4.79	0.12	4.62	5.06
Income index: employed population aged 46-65 in Lima	4.78	0.12	4.61	5.00
Income index: employed population in Lima	4.79	0.12	4.62	5.05
Index of employed population in Lima	4.80	0.11	4.61	4.98
Index of population aged 25-45 in Lima	4.78	0.08	4.61	4.90
Index of population aged 46-65 in Lima	4.83	0.15	4.61	5.09
Index of total population in Lima	4.78	0.09	4.61	4.91
Real construction cost index	4.71	0.08	4.58	4.85
Number of apartments transacted in Lima	6.37	0.97	4.61	7.50
Number of apartments for sale in Lima	5.46	0.51	4.60	6.13
Number of finished apartments for sale in Lima	5.37	0.57	4.44	6.12
Real mortgage interest rate	0.08	0.02	0.03	0.13
Stock of mortgage loans	5.58	0.81	4.60	7.07
Stock market index	5.84	1.13	4.27	7.21

Note: All series are quarterly with base 1998.q1=100, except for the interest rate. Variables are seasonality adjusted by using the Tramo Seats method and expressed in logs, except for interest rate that is specified as log(1+r). Source: BCRP, SBS, INEI, CAPECO and SMV.

Table 2: Hedonic Regression Estimation
Averages and standard deviations: 1998q1-2014q3

	OLS	Median	P10	P90
Surface area	0.0067	0.0071	0.0057	0.0083
	(0.0005)	(0.0007)	(0.0011)	(0.0009)
Age	-0.0301	-0.0308	-0.0262	-0.0454
	(0.0165)	(0.0219)	(0.0222)	(0.0218)
Rooms	0.0216	0.0106	0.0668	-0.0350
	(0.0146)	(0.0095)	(0.0382)	(0.0189)
Garage	0.2130	0.2168	0.2100	0.1796
	(0.0235)	(0.0281)	(0.0459)	(0.0376)
Floor level	0.0151	0.0138	0.0128	0.0162
	(0.0053)	(0.0064)	(0.0105)	(0.0086)
Age*Surface	-0.0001	-0.0001	-0.0001	0.0000
	(0.0001)	(0.0002)	(0.0003)	(0.0003)
Constant	10.3	10.3	9.9	10.6
	(0.0942)	(0.1130)	(0.1849)	(0.1488)
R2	0.70	0.72	0.64	0.68

Note: For the quantile regressions, R2 reports the pseudo R2. The second, third and fourth column present the results of hedonic regressions for the percentiles 50, 10 and 90, respectively. Standard errors are reported in parenthesis.

Table 3: GLS Augmented Dickey-Fuller Test

	Level t-stat	First Difference t-stat	Second Difference t-stat
Real house price	-0.51 (4)	-4.51 (1)*	-4.00 (3)*
Real GDP	-1.50 (1)	-1.90 (3)**	-2.62 (1)*
Real interest rate	-2.71 (3)	-5.09 (3)*	-2.23 (2)*
Trading volume	-1.95 (1)	-2.22 (1)*	-4.25 (1)*
Mortgage loans	-1.56 (2)	-2.43 (1)*	-3.70 (1)*
Real construction costs	-1.66 (1)	-4.57 (1)*	-5.38 (3)*

Note: The critical values at the 5% and 10% significant levels are -3.14 and -2.84, respectively, when there is a trend included; otherwise, the critical values are -1.95 and -1.61 , respectively. Tests do not include a trend for differences, and interest rate. Source is ERS (1996). (*) and (**) denote rejection of the null hypothesis at the 5% and the 10% significance levels, respectively.

Table 4: KPSS Test

	Level t-stat	First Difference t-stat	Second Difference t-stat
Real house price	0.22*	0,46	0,11
Real GDP	0.17*	0,36	0,19
Real interest rate	0.61*	0,10	0,07
Trading volume	0.19*	0,28	0,08
Mortgage loans	0.20*	0,42	0,13
Real construction costs	0.167*	0,16	0,22

Note: The critical values at the 5% and 10% significant levels are 0.146 and 0.119, respectively, when there is a trend included; otherwise, the critical values are 0.463 and 0.347 , respectively. Tests do not include a trend for differences, and interest rate. Source is KPSS (1992). (*) denotes rejection of the null hypothesis at the 5% significance level.

Table 5: Cointegration Trace Test – Johansen Method

	Model A (lag=6)	Model B (lag=6)	Model C (lag=6)
r=0	97.77	78.37	95.69
r=1	44.20	28.56	47.71*
r=2	20.27*	13.50*	25.88
r=3	7.36**	0.60	10.57

Note: (*) and (**) denote rejection of the null hypothesis at the 1% and 5% significance levels, respectively.

Table 6: VAR Order Selection Criteria

lag	LogL	LR	FPE	AIC	HQ	SC
0	188.21		2.30E-08	-6.24	-6.19	-6.10
1	609.97	843.52	2.40E-14	-20.00	-19.72	-19.29
2	664.08	108.22	6.70E-15	-21.29	-20.80	-20.02*
3	688.16	48.16	5.20E-15	-21.56	-20.85	-19.73
4	702.26	28.20	5.80E-15	-21.50	-20.57	-19.11
5	735.89	67.25	3.40E-15	-22.10	-20.94	-19.14
6	763.72	55.67	2.50E-15	-22.50	-21.12	-18.98
7	795.26	63.08*	1.70E-15*	-23.03*	-21.43*	-18.94
8	802.91	15.30	2.80E-15	-22.74	-20.93	-18.09

(*) indicates the lag order selected by the criterion

LR: Sequential modified LR test statistic

FPE: Final prediction error

AIC: Akaike information criterion

HQ: Hannan-Quinn information criterion

SC: Schwarz information criterion

Table 7: Cointegration Relation

Real GDP	-3.72 (1.1107)
Interest rate	-14.40 (2.9537)
Sold apartments	-0.35 (0.1792)
Speed of Adjustment	-0.020 (0.0088)

Note: Cointegrating vector is given in the form $(1, -\beta)$

Table 8: Forecast Performance

2010 - 2014

	VAR	VECM	VAR	VECM	VAR	VECM
	One-Step Ahead		***Two-Step Ahead***		***Four-Step Ahead***	
ME	0.027	-0.002	0.040	-0.004	0.066	0.025
MSE	0.004	0.005	0.008	0.008	0.019	0.013
RMSE	0.066	0.073	0.091	0.092	0.136	0.115

2010 - 2012

	VAR	VECM	VAR	VECM	VAR	VECM
	One-Step Ahead		***Two-Step Ahead***		***Four-Step Ahead***	
ME	0.024	-0.003	0.031	-0.012	0.070	0.038
MSE	0.004	0.005	0.007	0.009	0.021	0.018
RMSE	0.064	0.071	0.084	0.095	0.146	0.136

2013 - 2014

	VAR	VECM	VAR	VECM	VAR	VECM
	One-Step Ahead		***Two-Step Ahead***		***Four-Step Ahead***	
ME	0.032	0.000	0.056	0.010	0.060	0.001
MSE	0.005	0.006	0.010	0.007	0.014	0.004
RMSE	0.071	0.076	0.102	0.086	0.119	0.067

Table 9: Cointegration Relation among House Prices

Stratum 1	169.61
	(40.9229)
Stratum 2	-170.68
	(40.1662)
Speed of Adjustment S1	0.000
	(0.0014)
Speed of Adjustment S2	0.003
	(0.0015)
Speed of Adjustment S3	0.004
	(0.0017)

Note: Cointegrating vector is given in the form $(1, -\beta)$

Table 10: Granger Causality Test

Null hypothesis	F-test	p-value
S3 price does not Granger cause S1 price	3.30	0.04
S3 price does not Granger cause S2 price	3.37	0.04
S2 price does not Granger cause S3 price	0.08	0.92
S2 price does not Granger cause S1 price	0.20	0.82
S1 price does not Granger cause S3 price	0.57	0.57
S1 price does not Granger cause S2 price	2.95	0.06

Figures

Figure 1: Real Apartment Price Indices

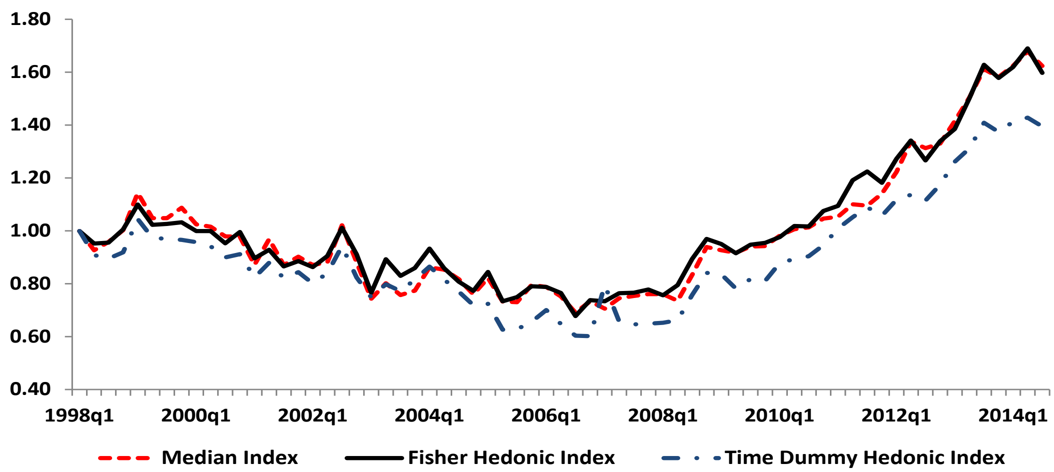
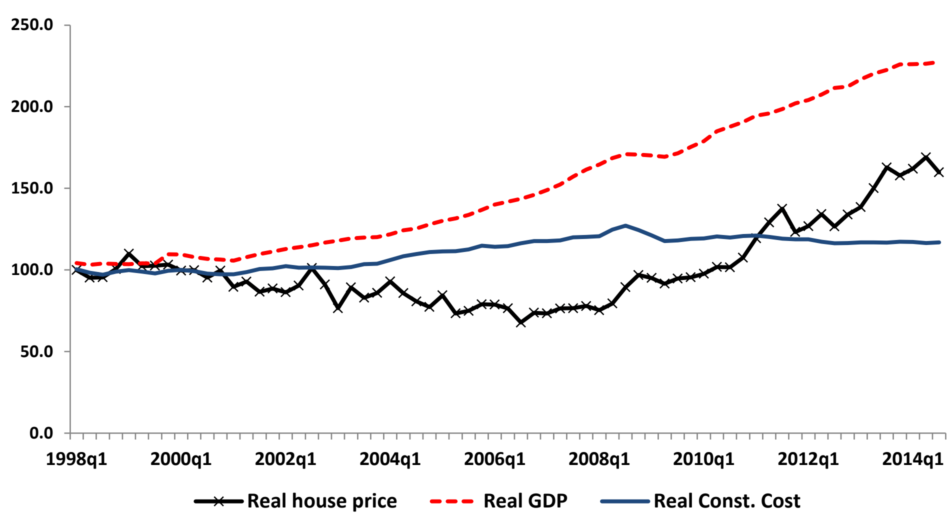


Figure 2: Evolution of Housing Market and Related Variables



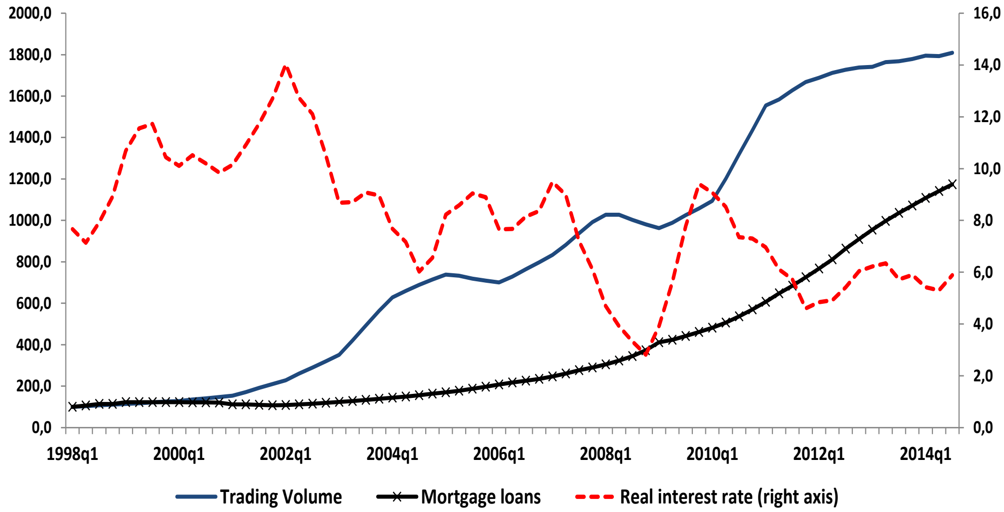


Figure 3: Fundamentals (annual growth, unless otherwise denoted)

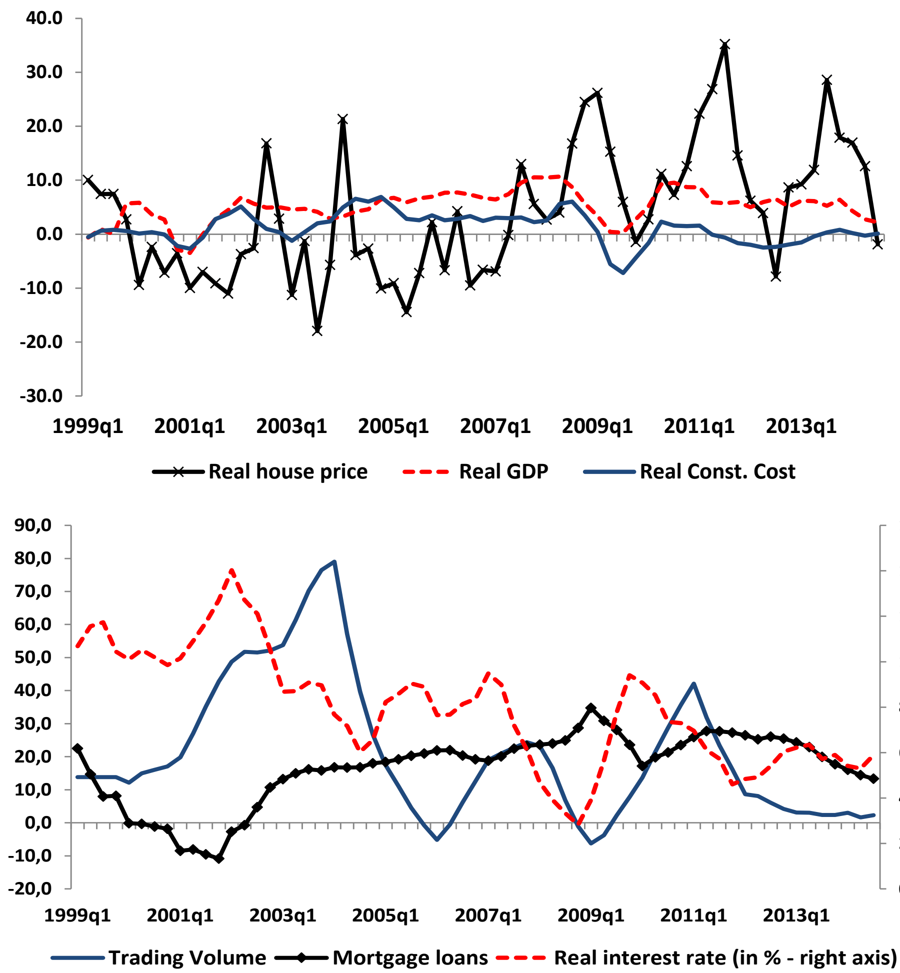
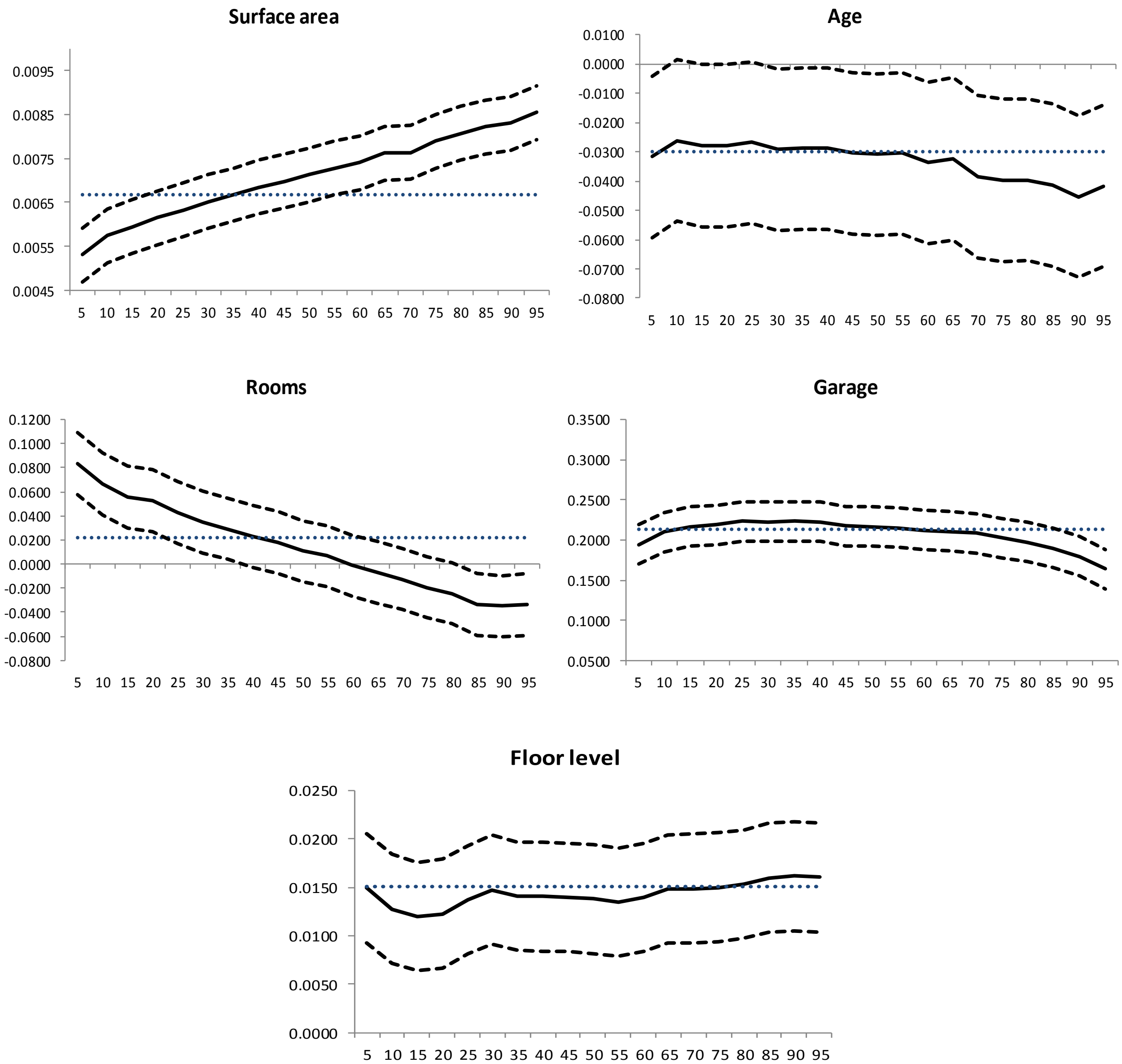
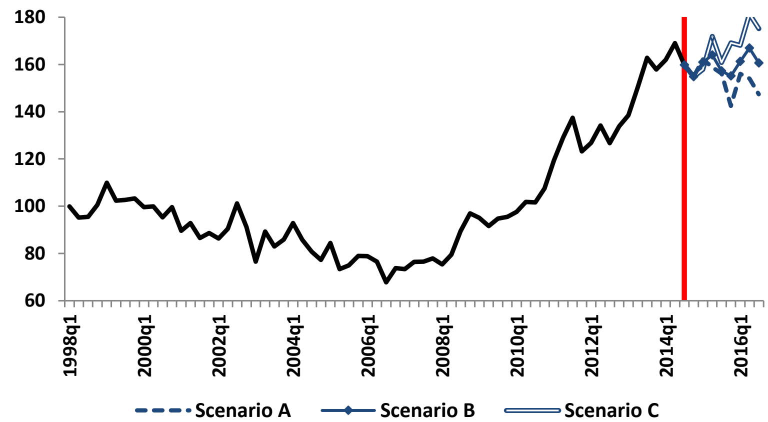


Figure 4: Quantile Regression Estimates



Note: Coefficient estimates over quantiles ranging from 0.05 to 0.95, and 90% confidence intervals. The dotted straight lines in each graph represent the OLS estimate.

Figure 5: Dynamic Forecast for Real House Prices (2014q4-2015q3)



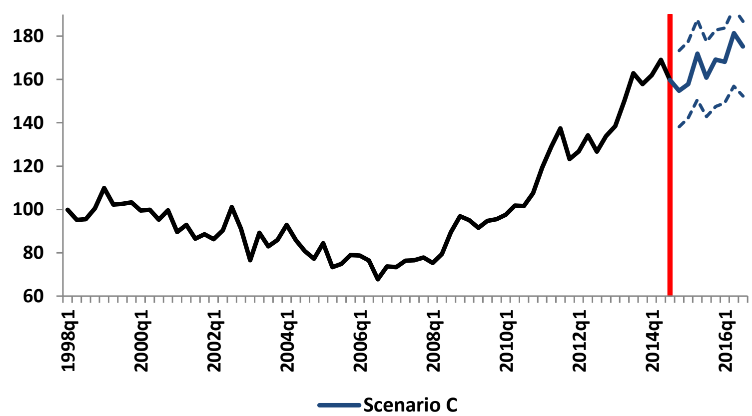
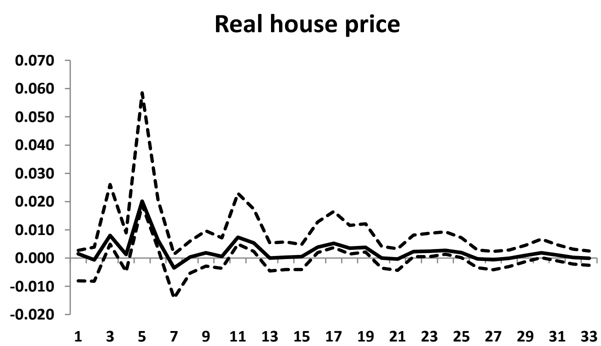
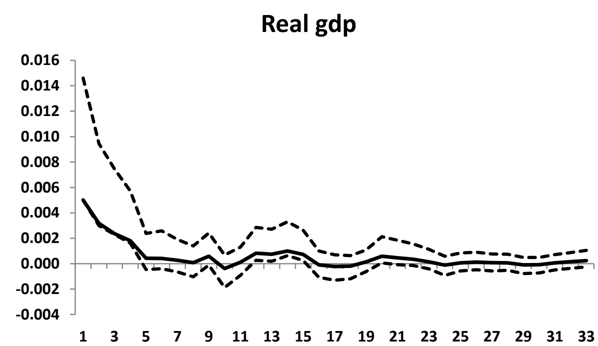
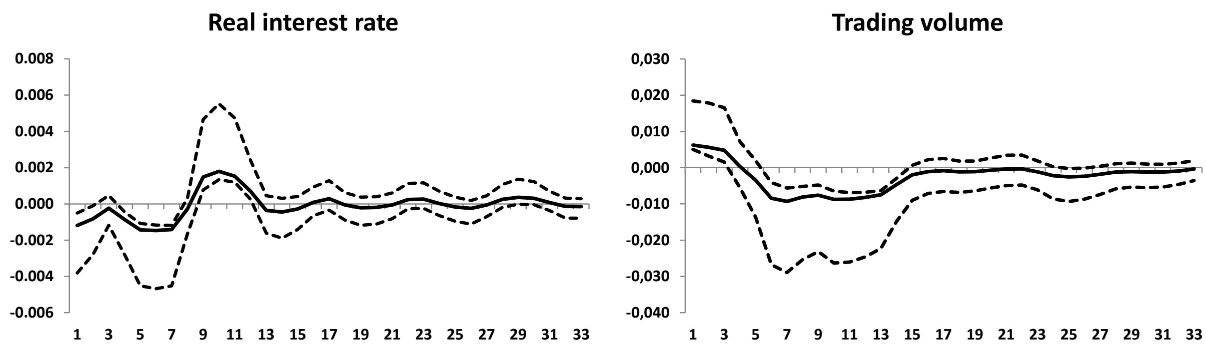


Figure 6: Impulse Response Function: Housing Demand Shock

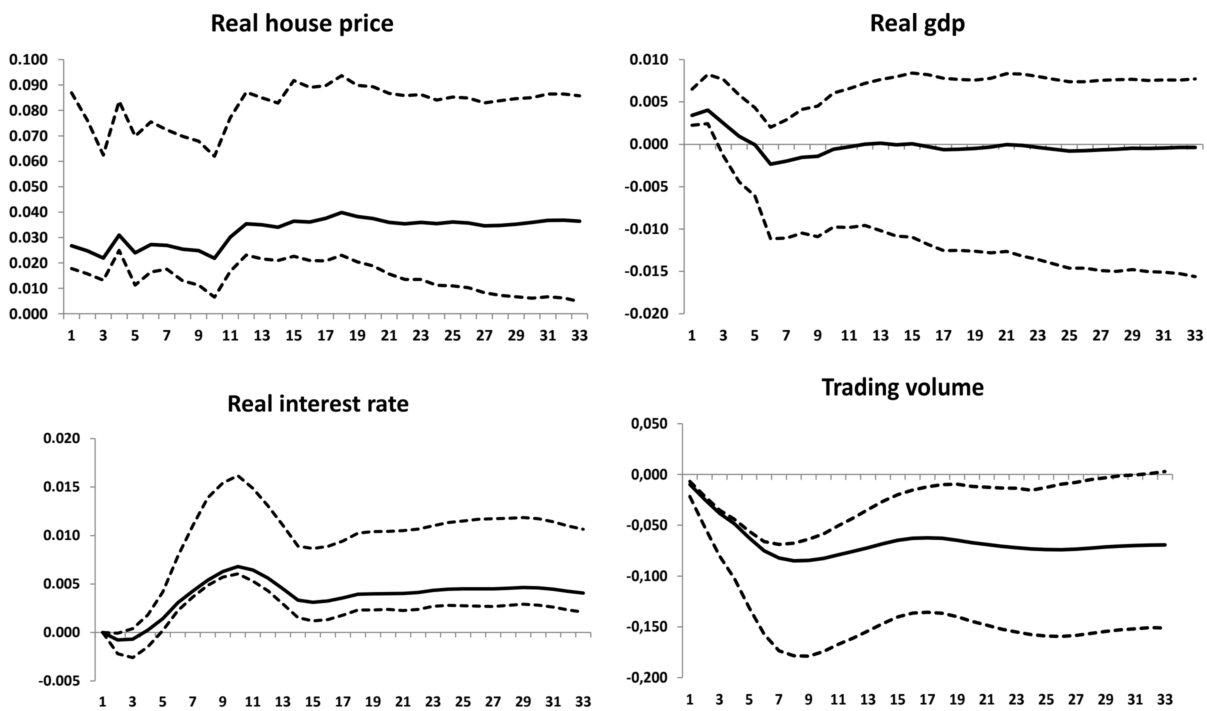






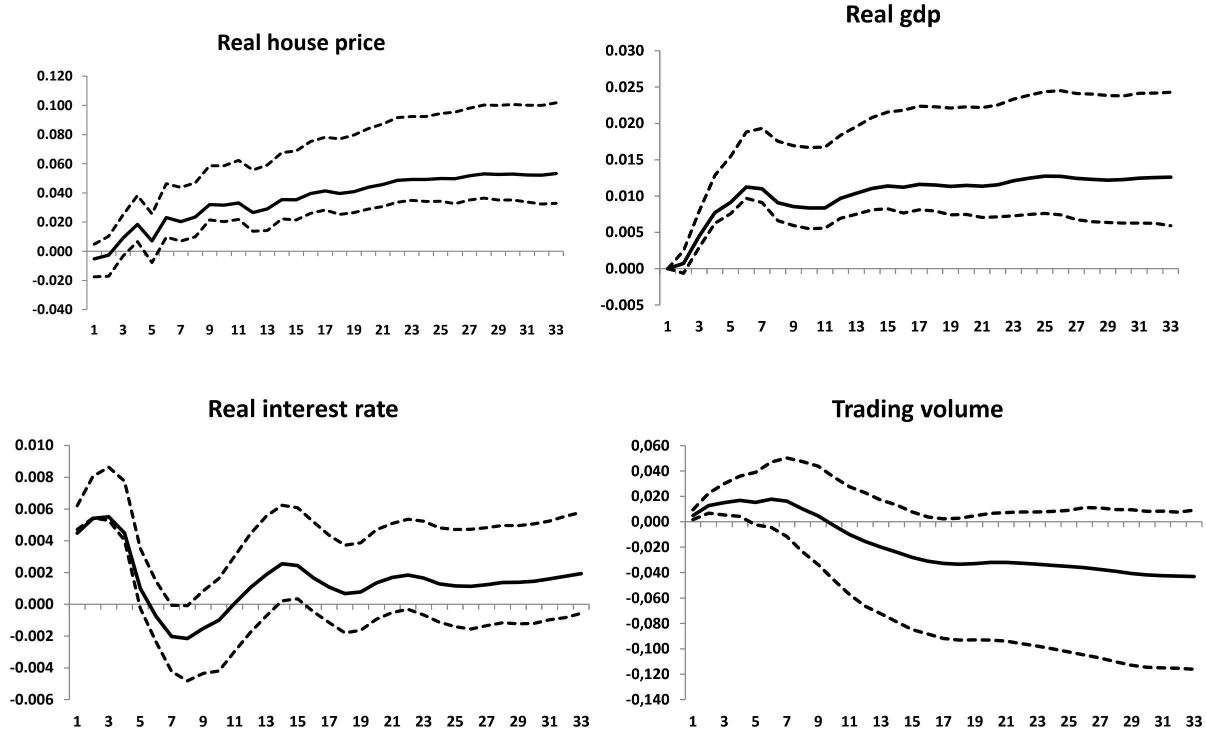
Note: Confidence intervals at 90% are boostrapped (2000 replications).

Figure 7: Impulse Response Function: Income Shock



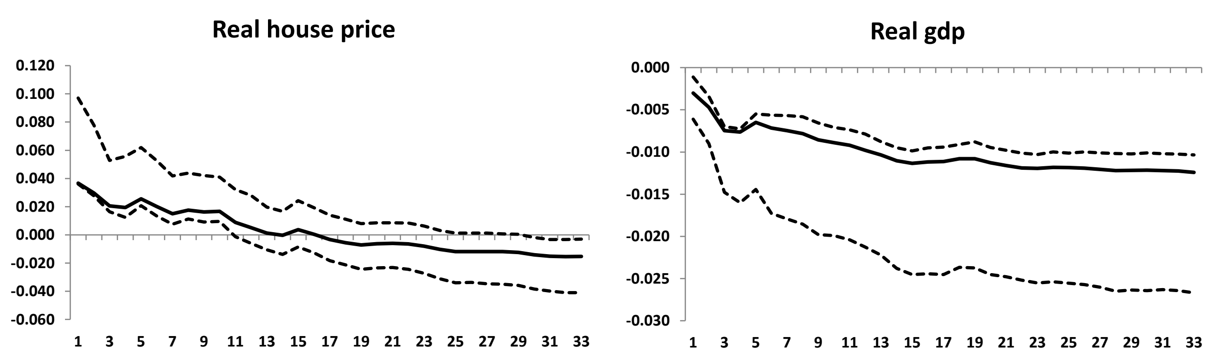
Note: Confidence intervals at 90% are boostrapped (2000 replications).

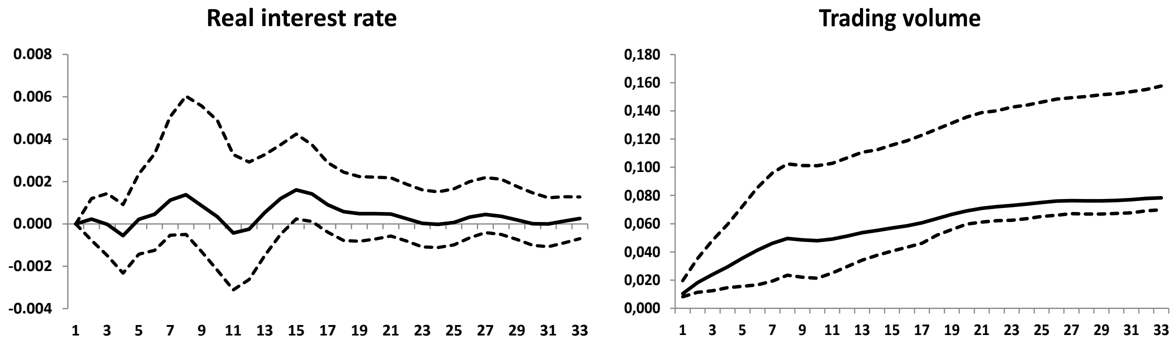
Figure 8: Impulse Response Function: Financial Cost Shock



Note: Confidence intervals at 90% are boostrapped (2000 replications).

Figure 9: Impulse Response Function: Trading Volume Shock





Note: Confidence intervals at 90% are boostrapped (2000 replications).

Figure 10: Variance Decomposition

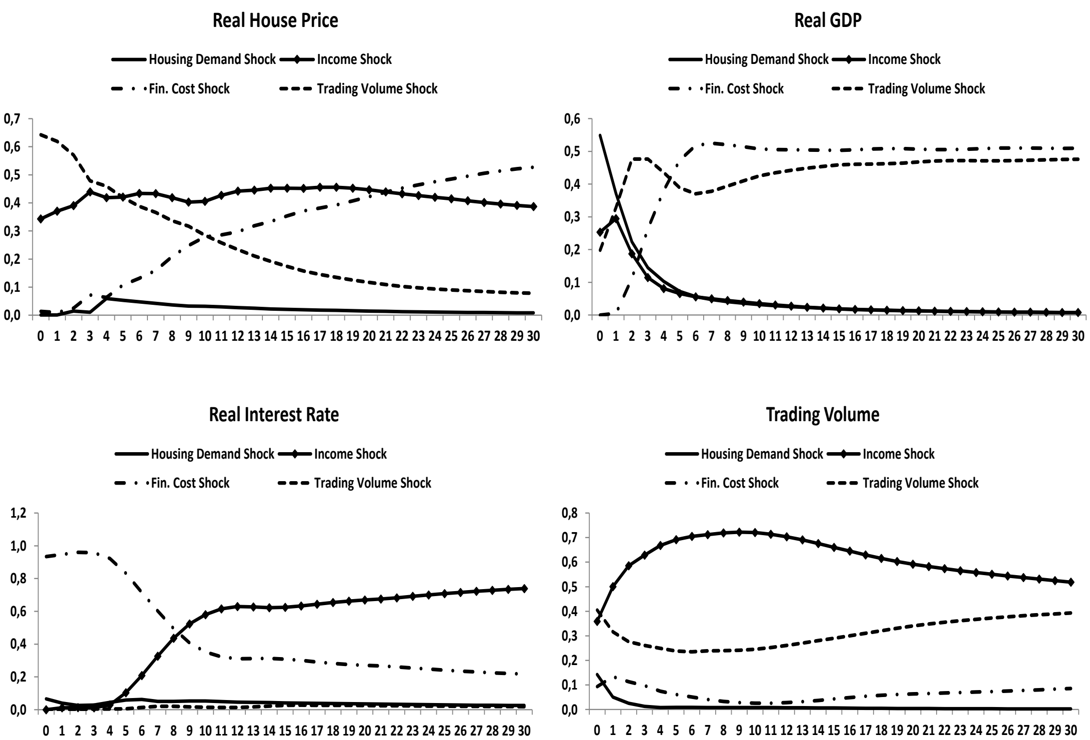


Figure 11: Variance Decomposition – Two Cointegrating Vectors

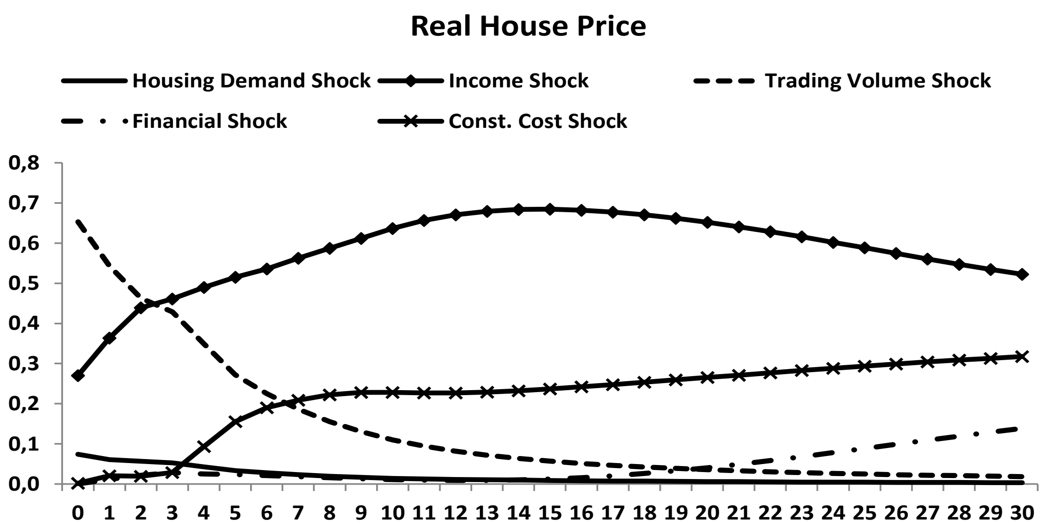
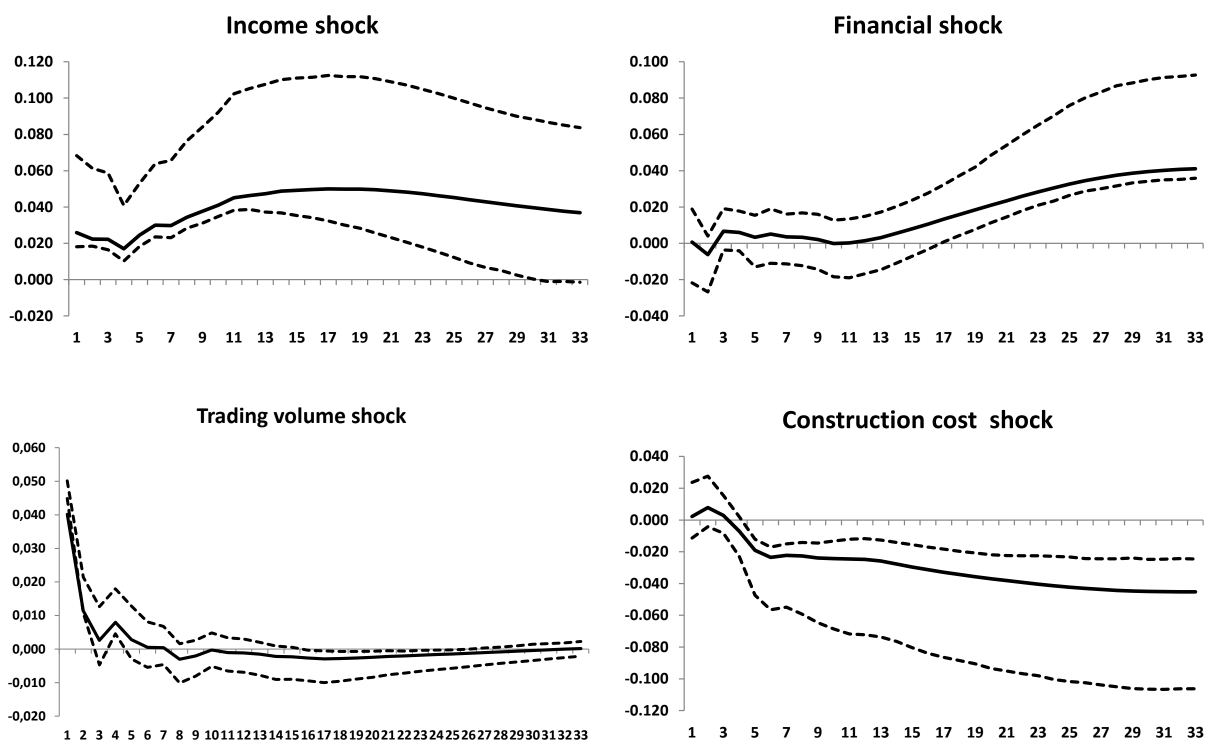


Figure 12: Real house price responses – Two Cointegrating Vectors



Note: Confidence intervals at 90% are boostrapped (2000 replications).

Figure 13: Real House Price by Economic Strata

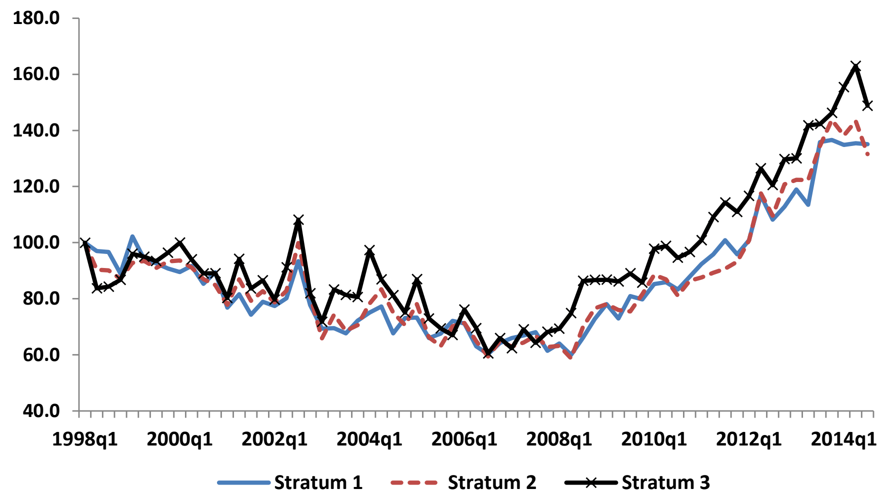
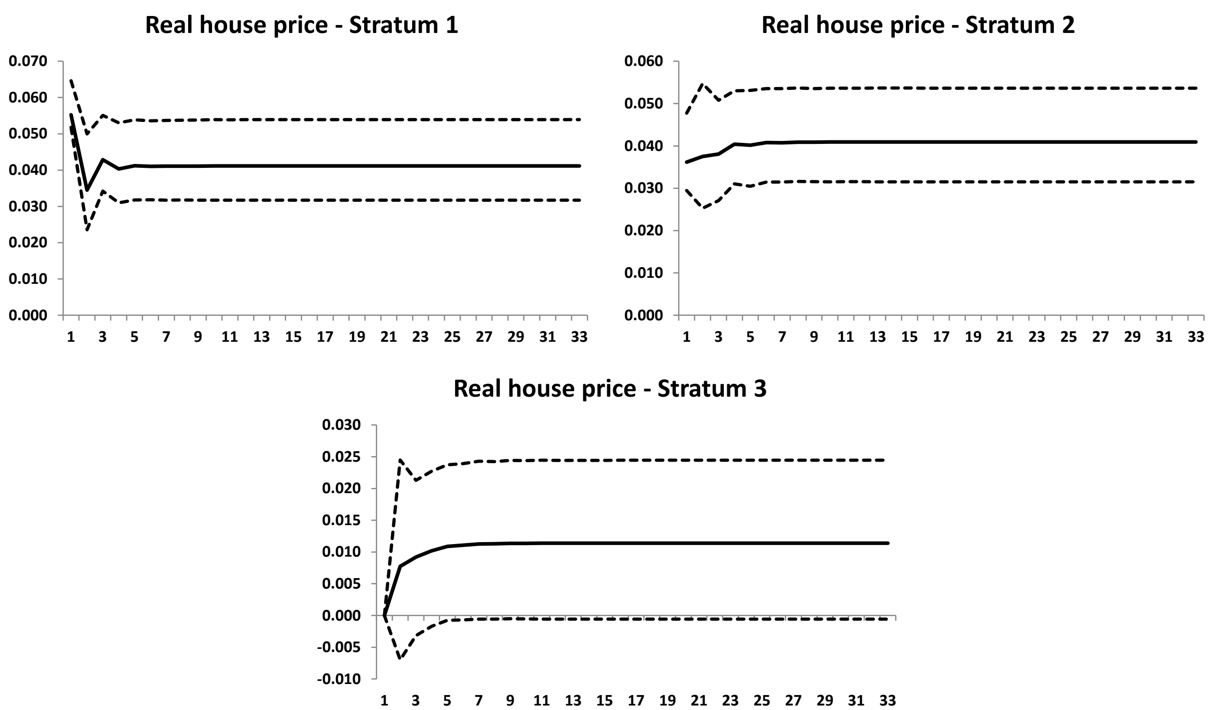
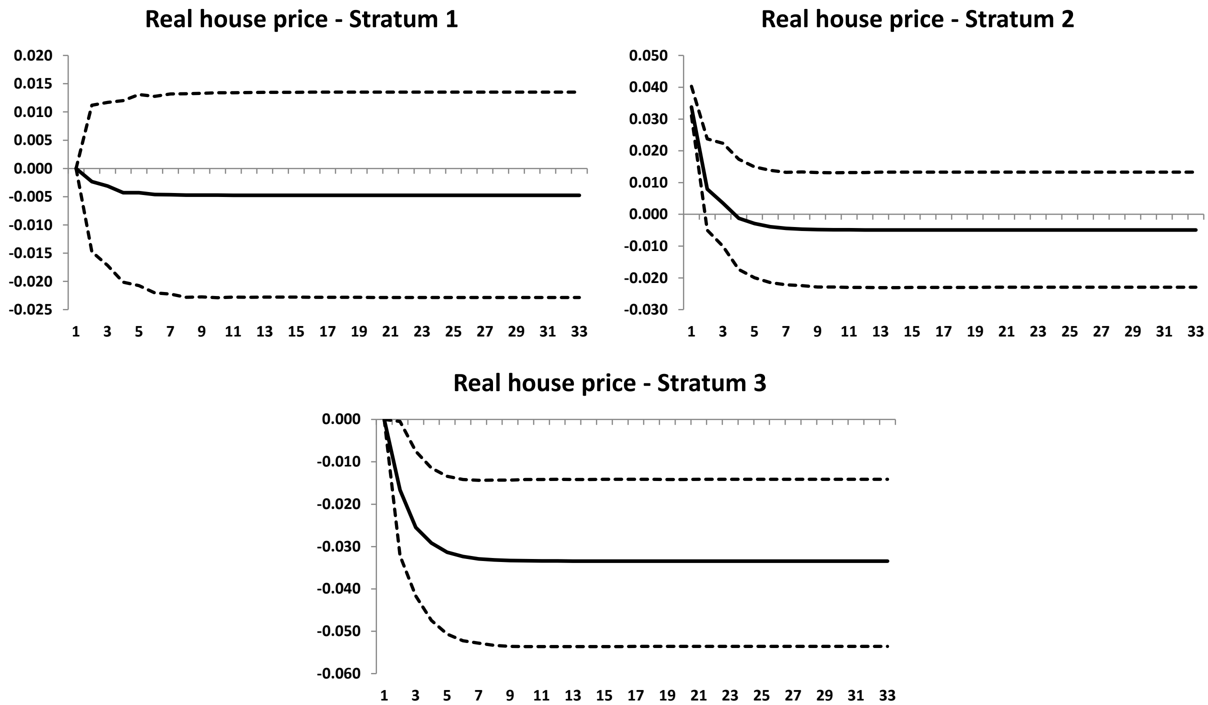


Figure 14: Impulse Responses: Stratum 1 Shock



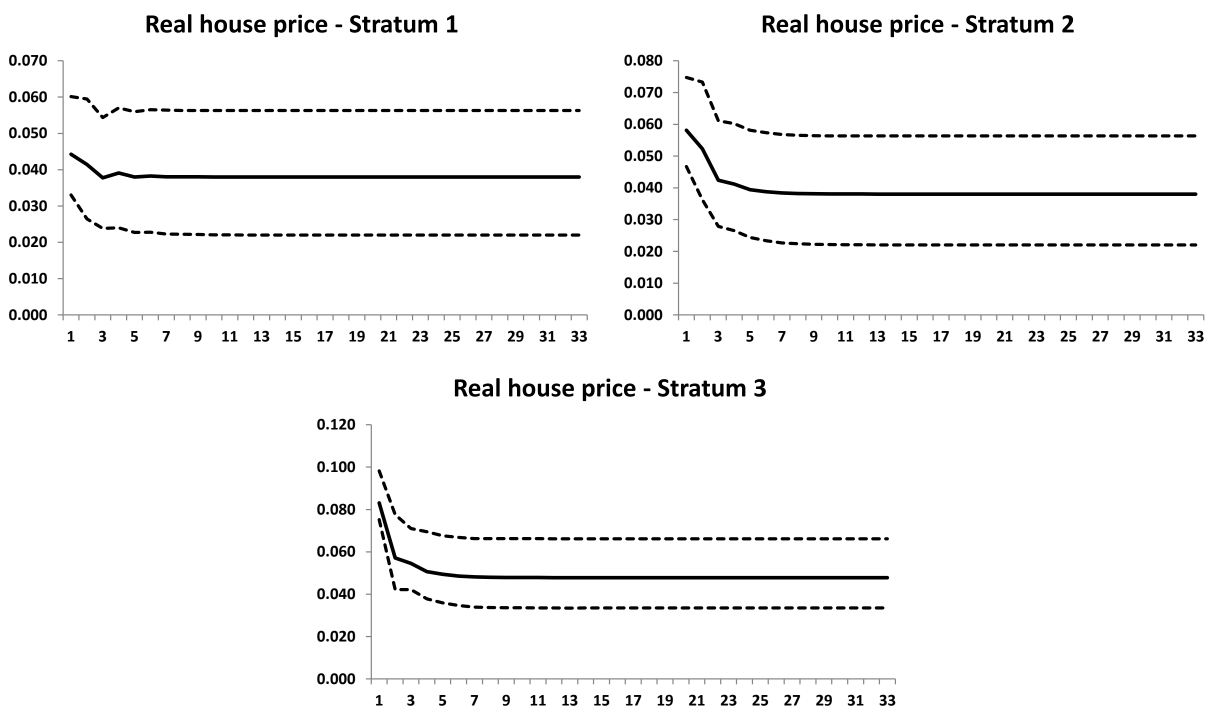
Note: Confidence intervals at 90% are boostrapped (2000 replications).

Figure 15: Impulse Responses: Stratum 2 Shock



Note: Confidence intervals at 90% are boostrapped (2000 replications).

Figure 16: Impulse Responses: Stratum 3 Shock



Note: Confidence intervals at 90% are boostrapped (2000 replications).

Figure 17: Variance Decomposition