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What Drives Housing Dynamics in China? A Sign Restrictions VAR Approach*

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Abstract

We study housing dynamics in China using vector autoregressions identified with theory-consistent sign restrictions. We study five potential drivers: 1) Population increases; 2) a relaxation of credit standards, for example, due to the shadow banking system; 3) increasing preferences towards housing, for example, due to a housing bubble or housing being a status asset to be competitive in the marriage market; 4) an increase in the savings rate; and 5) expected productivity progress. Our results show that fundamental shocks (population, credit and productivity) play a major role in the dynamics of house prices and residential investment before 2009. Preference shocks seem especially relevant in the last several years, and when the estimation uses price indices not coming from China's National Bureau of Statistics.

JEL codes: E3, F44, R21, R31

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1 Introduction

In this paper we study five drivers of housing dynamics in China. We analyze: 1) Population increases; 2) a relaxation of collateral constraints or lending standards; 3) increasing preferences over housing, for example, due to a housing bubble, or because housing has a special status in the Chinese marriage market; 4) an increase in the savings rate when a house is one of few assets in which to store value; 5) productivity increases in the tradable sectors. We discuss each of these shocks in greater length in Section 2. It is commonly argued that policy should react differently to each of them. This motivates our interest in quantifying their importance.[1]

We identify the shocks using sign restrictions on impulse responses that are consistent with the macroeconomic literature on the drivers of housing markets.[2] To do so we analyze a dynamic general equilibrium model that integrates the multiple ways in which housing markets interact with the economy (residential investment, wealth and collateral effects, imports of construction-related goods). We look for variables that react differently to each of the five shocks. For example, house prices increase when population increases because housing supply is partially inelastic and cannot satisfy the extra demand for housing. Simultaneously, a higher population decreases the marginal productivity of labor and leads to a negative wealth effect and higher per capita savings. Thus, population shocks cause a negative correlation between per capita consumption and house prices. Other shocks, like a loosening of credit conditions, induce a positive correlation. In Section 3 we discuss what restrictions allow to identify each shock. An online Appendix contains the model that formally derives the restrictions.

We compare our results for different house price indices because, as we show in Section 2, official house price indices (like the 70 cities index published by the National Bureau of Statistics) report smaller house price increases than private sector indices. Our results suggest that all the shocks play an important role in driving housing dynamics. For example, variance decompositions show that each of the five shocks contribute at least 10% to the forecast error variance for housing prices or quantities. Population and preference shocks are especially important when we use those house price indices with larger fluctuation. Historical decompositions show that population and technology shocks are the most important determinants of housing dynamics before 2009. House preference shocks become increasingly important after 2009, suggesting either a possible housing bubble in China since then, or an increase in the value of a house for

[1]For example, policymakers may not want to react to fundamentals (productivity or population increases), however they may want to dissuade housing booms driven by a bubble. If the boom is caused by non-housing reasons such as the lack of a safety net or financial repression then policies may need to focus on those causes and not on housing markets.

[2]See for example Davis and Heathcote (2005) or Iacoviello and Neri (2010) among others.

status reasons.

This paper contributes to two sets of literature. First, methodologically we add to the literature that analyzes housing markets using structural vector autoregressions (SVARs). We believe this is the first paper that derives theory-consistent sign restrictions to jointly identify each of the five shocks discussed above.[3] Second, by the topic of our study, we contribute to the literature on the determinants of China's housing boom. So far this literature has not used structural vector autoregression techniques.[4] Finally, our survey of house prices in China may be useful for future scholars interested in Chinese housing markets. We briefly survey these two literatures in the next paragraphs.

The SVAR literature on housing markets started by identifying monetary shocks using short or long run restrictions (Lastrapes 2002, Musso et al. 2011) or sign restrictions (Vargas-Silva 2008). Jarociński and Smets (2008) were the first to identify a housing demand shock using a mixture of recursive identification and sign restrictions. They impose that a housing demand shock moves residential investment and house prices in the same direction while the shock has no contemporaneous effect on other components of GDP like consumption. Andre et al. (2012) and Cardarelli et al. (2008) apply the same restrictions. These restrictions may be contradictory with the predictions of a benchmark model of housing markets. For example, in most models consumption and GDP would react immediately to housing demand shocks. Moreover, positive comovement between residential investment and house prices can be due to shocks other than housing demand, such as savings glut shocks or expected TFP. Our paper is closely connected to Gete (2014) and Sa and Wiedalek (2013) who derive sign restrictions from DSGE models. Gete (2014) decomposes a housing demand shock into a bubble shock, a population shock and a credit expansion shock and estimates housing dynamics in the OECD. Sa and Wiedalek (2013) compare savings glut shocks and monetary policy in the U.S. None of these papers jointly identify the five shocks as we do.

Concerning the literature on housing dynamics in China, several papers using panel data methods find that the main drivers are urbanization, technological progress, low mortgage rates, property taxes and the land granting system (for example, Bai et al. 2013, Glindro et al. 2011, Ren et al. 2012, Wang et al. 2011 or Wang and Zhang 2014). Wei et al. (2012) explore regional variation to show that imbalances in the sex ratio drive China's house prices due to the status associated with owning a house. Ahuja et al. (2010) and Wu et al. (2012) analyze price-to-rent ratios with the user's cost approach to suggest overvaluation in some markets.

[3] Sign restrictions, although not yet popular in studying real estate markets, have been applied to study other shocks as for example fiscal, monetary, news or technology shocks. See for example, among others, Canova and Nicolo (2002), Charnavoki and Dolado (2014), or Fratzscher and Straub (2013).

[4] Tan and Wu (2014) is an exception as they identify monetary shocks with short run restrictions.

This paper proceeds as follows. Section 2 describes housing dynamics in China and motivates the five shocks that we study. Section 3 derives the restrictions that identify each shock. Section 4 estimates vector autoregressions and imposes the sign restrictions. Section 5 discusses the results and robustness tests. Section 6 concludes. Appendix I contains the data sources. Appendix II discusses the house price indices. An online Appendix contains the model and the formal derivation of the sign restrictions.

2 What Can Explain China's Housing Dynamics?

House prices in China have increased quickly recently. Figure 1 compares real house prices in China (using the popular "70 Cities Index") with several OECD economies. Since it is often controversial whether the official house price indices are reliable we compare various housing indices. We focus on two popular indices computed by China's National Bureau of Statistics (the 70 Cities and the Average Selling Price Indices), and on two indices from other sources which display larger price fluctuations (the Centaline and the NDRC Price Indices). We describe the indices carefully in Appendix II. Figure 2 plots them. Tables 1 and 2 report their average yearly growth rates, standard deviations and correlations. There is ample heterogeneity in the dynamics of the house price indices. For example, the Centaline Index displays the largest house price increases, while the Average Selling Price and the 70 Cities Index report the lowest increases. This fact is consistent with the concerns that official statistics underestimate house price growth in China.[5] Next, we discuss the five shocks that we study.

2.1 Urbanization and Population Flows

China has had massive population flows towards urban areas. As we document in Figure 3, the share of total population living in urban areas has increased from 28% in 1994 to more than 50% in 2012. And the percentage of population in cities with more than 1 million residents has risen from merely 11% of the total population in 1994 to more than 20% in 2012. Thus, population flows are a potential major driver of housing demand, house prices, and residential investment.

[5] For example, in 2009 the 70 Cities Index suggested that nominal house prices at the national level only increased by 1.5 %, whereas many analysts claimed that the growth rate was much larger, and it seems that even China's statistics bureau admitted that their calculation "diverged significantly from the market reality" (Financial Times 2010).

2.2 Relaxation of Credit Constraints

China's financial system is highly regulated, and Chinese banks are allocated a maximum lending quota each year that they should not exceed. However, in recent years banks in China have been using financial innovations such as wealth management products to circumvent their lending quota (The Economist 2013). Chinese banks have created a large "shadow banking" sector that, at the end of 2012, may have been equivalent to 40% of GDP (The Wall Street Journal 2013). Some observers claim that much of this surge in credit has been channeled towards weaker borrowers who are usually rejected by traditional banks, and are using the new credit to buy real estate (2013 Forbes). In this regard, this expansion of credit seems similar to the credit expansions that several authors have proposed to explain the recent U.S. housing boom (see for example Favilukis et al. 2010 among others).

2.3 Productivity

China has undergone a spectacular economic transformation involving fast productivity progress. For example, Xu and Yu (2012) estimate that Total Factor Productivity (TFP) increased by an average annual growth rate of 2.2% from 1996 to 2007. Higher productivity translates into higher households' income and higher demand for housing. For example, Kahn (2008) argues that the resurgence in productivity in the U.S. that began in the mid-1990s largely contributed to the U.S. housing boom. Moreover, if productivity growth in the construction sector is slower than in other sectors, this would create upward pressure in the relative price of new houses. Several authors have documented that this is usually the case for most countries (see Sharpe 2001 for Canada, Moro and Nuno 2012 for Germany, Spain, the U.K. and the U.S.).

2.4 Preferences towards Savings

China's gross national savings as a percentage of GDP was around 35% in the 1980s, then the rate climbed to 41% in the 1990s, and accelerated in the 2000s to reach 53% in 2007. Households' savings accounted for 6–7% of GDP in the late 1970s but grew to about 22% in 2007 (Yang et al. 2011). These increases in the savings rate motivated Bernanke (2005) to talk about a "savings glut".

High savings rates create demand for assets that serve as a store of value (Chen and Wen 2013 propose a model to capture this mechanism). Real estate is among the few assets available to Chinese households given the capital controls that limit the ability to invest overseas and the non-competitive caps on banks' deposit rates. Households hold housing, gold, or bank accounts because they wish to save (Fawley and Wen 2013). Thus, the forces pushing for high savings also push for higher housing demand. These forces are the subject of an active literature (see Yang et al. 2011 for a survey). Possible causes are cultural norms, an ageing population, intensified competition in the marriage market, income inequality or precautionary savings from employment uncertainty and an incomplete social security system.

2.5 Preferences towards Housing

A housing bubble or a change in the status value of housing in marriage markets are two factors driving housing demand that can be captured in a model as an increase in preferences towards housing. Both factors have been proposed for different authors. For example, Barth et al. (2012), among many others, claim that there is a housing bubble in China. Wei et al. (2012) claim that a rise in the sex ratio accounts for 30-48% of the rise in real urban housing prices in China during 2003-2009, because households with a son try to buy houses in hopes of improving their son's odds of finding a wife. Our restrictions to identify an increase in the preferences for housing are consistent with both a bubble and with an increase in the value of housing as a status good.

3 The Sign Restrictions

We derive identification restrictions for the previous five shocks that are consistent with a standard dynamic general equilibrium model.[6] The model integrates the multiple ways in which housing markets interact with the economy (residential investment, wealth and collateral effects, imports of construction-related goods). Table 3 summarizes the restrictions.

All five shocks, when positive, lead to higher house prices although for different reasons. Population, housing preferences and higher expected TFP generate a larger demand for housing because housing is a normal good. A savings glut also increases housing demand, since housing is an asset in which to store value. The credit shock allows credit constrained households to borrow more and use the extra borrowings to buy both houses and non-housing consumption. For most of the parameters used in the literature, a credit shock would push house prices up.

We can separate the five shocks into two groups by examining the correlation between the change in consumption of tradable goods and house prices. Group 1: Housing preference and

[6] The Online Appendix contains the model and its impulse responses.

savings glut shocks imply a negative correlation between households' consumption of tradable goods and house prices. Facing a housing preference shock, households prefer housing more than they did before. For example, this could be because of a bubble or an increase in the status benefits of owning houses. Thus, non-housing consumption decreases while house prices increase. It happens similarly for savings glut shocks because when Chinese households want to save more a house is one of the few assets available to them. Group 2: Population, credit shock and TFP increases lead to a positive correlation between house prices and non-housing consumption because these shocks increase aggregate demand for all normal goods.

It is possible to separate the two shocks in Group 1 by looking at the correlation between house prices and the current account/GDP ratio. A savings glut shock leads to savings, thus an increase in the current account/GDP. On the other hand, a housing preference shock leads to a current account deficit because the domestic country imports tradable goods both to build new houses and for consumption smoothing reasons as discussed by Gete (2009).

Among the shocks in Group 2, we can identify the TFP shock because it is the only one that increases TFP while house prices go up. In order to differentiate the population shock from the credit shock, we look at per capita consumption of tradable goods. Facing a positive credit shock, per capita consumption increases as the constrained agents can borrow and consume more. However, facing a population increase, per capita consumption goes down because higher population means lower marginal product of labor and thus a negative per capita wealth effect.

4 Structural Vector Auto Regressions

4.1 Data

We start by estimating a reduced form VAR with six variables that allow us to apply the sign restriction identification discussed before. We estimate the following VAR in companion form:

$$Y_t = BY_{t-1} + u_t \tag{1}$$

$$Y_t \equiv \begin{bmatrix} \log C_t \\ \frac{CA}{GDP} \\ \log p_{h_t} \\ \log Y_h \\ \log c_t \\ \log TFP \end{bmatrix}$$

All variables are in real terms: log of aggregate consumption of nondurables (C), the current account/GDP ratio $\left(\frac{CA}{GDP}\right)$, log of house prices (p_h), log of residential investment (Y_h), log of per capita consumption of nondurables (c), and log of Total Factor Productivity (TFP). Appendix I has the data sources. We compare four house price indices. These indices start from different dates and we discuss them in Appendix II. We use the 70 Cities and the Average Selling Price Indices (quarterly data from 1999Q1 to 2012Q4) and the Centaline and the NDRC Price Indices (data available from 2007Q1 to 2012Q4). We checked different information criteria to choose lag length, and two lags were enough to adequately capture the dynamics of the data. We do not model cointegration relationships; Sims et al. (1990) have shown that the dynamics of a VAR in levels can be consistently estimated even in the presence of unit roots. We also include a constant term.

4.2 Methodology

To implement the sign restriction methodology we follow Uhlig (2005), using an efficient algorithm proposed by Rubio-Ramirez et al. (2010). Here we briefly discuss the methodology. The goal of any Structural Vector Autoregression is to map the reduced-form forecast errors (u_t) that we obtain from estimating (1) into structural shocks (ε_t) with economic meaning and orthogonal between them (their variance-covariance matrix is the identity matrix, $E(\varepsilon_t\varepsilon_t') = I$). That is, if the link between reduced-form and structural shocks is

$$u_t = A\varepsilon_t \tag{2}$$

then the objective of a SVAR is to characterize the matrix A. Once A is identified we can study the effect of the structural shocks on the economic variables of interest. The matrix A is unique up to an orthonormal transformation, i.e., wherever $QQ' = I$ then $E(u_t u_t') = AQQ'A'$.

The sign restriction methodology identifies a set of AQ matrices which is consistent with what theory says should be the sign of the reaction of the economic variables to a structural shock.[7] The impulse responses to the structural economic shocks are

$$\frac{\partial Y_{t+j}}{\partial \varepsilon_t} = B^j A \tag{3}$$

[7] We follow the algorithm of Rubio-Ramirez et al. (2010). Without loss of generality, we assume $A = chol(\Sigma)$, then we draw a matrix X, whose cells come from a standard normal distribution. Then we compute the QR decomposition of X. We normalize the diagonal of R to be positive and check if AQ satisfies the sign restrictions of Table 3. If it does, we keep AQ, if not we discard and draw again. We keep drawing until we have 100 successes.

where j is the number of period of the impulse response. In our case we use the sign restrictions discussed in Section 3 and summarized in Table 3. In the results that we present in Section 5 we imposed the restrictions for two periods. We checked the results for restrictions imposed for one, three and four periods and the results are similar. In Section 5 we follow the common procedure in the literature and show the results for the median of our set of AQ matrices (see for example Charnavoki and Dolado 2014).[8]

5 Results

Tables 4 to 7 report the percentage of the variance of the forecasting error that is attributable to the different shocks. Table 4 estimation is based on the 70 Cities Index, Table 5 uses the Average Selling Price Index, Table 6 uses the Centaline Index and Table 7 uses the NDRC Property Price Index. We report the results for real house prices and residential investment at forecast errors of 1, 3 and 5 years. These tables show that, no matter the price index used, all the five shocks play an important role in explaining both house price growth and residential investment fluctuation. Furthermore, except for savings glut shocks, all other shocks usually explain at least 10% of the variance. The tables with the NDRC and Centaline Indices highlight the importance of population and housing preferences shocks.

Figures 4 to 7 report the historical decomposition for the different house price indices. All Figures show a similar message: the shocks to fundamentals (population increases, credit relaxation and productivity growth) contribute the most up to 2009. However, after 2009, there is a major increase in the role of the housing preference shock (that captures either a bubble or the status value of housing).

6 Conclusions

In this paper we used vector autoregressions to study five shocks usually discussed as drivers of Chinese housing dynamics. We identified the shocks using sign restrictions consistent with a standard DSGE of housing markets. Variance decompositions at different forecast horizons and for different price indices show that population increases, credit relaxation, housing preferences

[8] Fry and Pagan (2005) have pointed out that this procedure may be problematic as the results reported may be coming from different AQ matrices. To overcome this problem they propose what they call "the median target method", that is, to pick the AQ matrix whose impulse responses are as close to the median values as possible. We explored this method and found pretty similar results. This is also the case in Sa and Wiedalek (2013).

and productivity growth matter for both house prices and residential investment. A savings glut is a less important but still relevant driver. Population and preference shocks are especially important drivers if we use the price indices that show larger house price increases (that is, indices not computed by China's National Bureau of Statistics). Historical decompositions show that fundamental shocks (population increases, credit relaxation and productivity growth) were the major drivers of house prices up to 2009. Since then, housing preference shocks (which capture either a bubble or the status value of housing) have been the dominant driver.

Our results suggest that Chinese policymakers should be cautious when designing policies to counteract the current housing boom, as the boom is being driven by multiple factors, some of them benign such as higher productivity and population growth. At the same time our results seem to support the IMF recommendation that China must act to prevent the risks associated with speculative demand in its real estate markets (IMF 2013).

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Appendix I. Data

1. Data for China:

a) Series from Datastream: Gross Domestic Product (CHGDP...A); Consumer Price Index (CHQCP009F); Current Account Balance (CHBPQCURA); Exchange Rate between Chinese Renminbi and U.S. dollar (CHUSDSP); Urban Population (CHURBPOP); Urban Employed Persons (CHEMPALLP); Employment in Construction (CHEMCONSP); Final Consumption Expenditure (CHCNPER); Real Estate Development - Residential Building (CHINVHRCA); Three-month Treasury Bond Trading Rate (CHOIR077R); CREIS Price Index for Beijing and Shanghai (CHHPBEJMR, CHHPSHAMR); CPI_Beijing (CHCPIBEJF); CPI_Shanghai (CHCPISHGF).

b) Series from CEIC: Residential Building Sales Volume: 3959901(CECBG); Residential Building Floor Space Sold: 3973401(CECJ); 70 Cities Property Price Index for Newly Constructed Residential Buildings: 78733801(CEACBL); NDRC 36 Cities Average Property Price: 146217501(CRKAHKA); Residential Building Sales Volume_Beijing: 3960101(CECBGAA); Residential Building Sales Volume_Shanghai: 3960501(CECBGAE); Residential Building Floor Space Sold_Beijing: 256186401(CRKAPMB); Residential Building Floor Space Sold_Shanghai: 256155301(CRKAPMK); NDRC Property Price for Beijing and Shanghai: 146217601(CRKAHKB), 146218501 (CRKAHKK).

c) Series from Wind Info: 70 Cities Property Price Index for Newly Constructed Residential Buildings (S2707404); Centaline Index_Beijing (S0109786); Centaline Index_Shanghai (S0070073); Centaline Index_Shenzhen (S0109845); Centaline Index_Guangzhou (S0109895); Centaline Index_Tianjin (S0109940); Centaline Index_Chengdu (S0179681).

d) DTZ Index for Beijing and Shanghai come from DTZ Property Times quarterly reports.

2. Data for OECD countries:

a) Series from Datastream: Real Gross Domestic Product (USYEXP03B, UKYEXP03B, FRYEXP03B, BDYEXP03B, ITYEXP03B, ESYEXP03B and ESWOGDP.A); Employment (USQLF007O, FREMPTOTO, BDQLF007O, ESESENN.O, ITESENE.O, ITQLF007O); Gross Fixed Capital Formation - Residential Building and Construction (USYGFG13B, UKYGFG13B, FRYGFG13B, BDYGFG13B, ITYGFG13B, ESESENMPD and ESYPR005P); Employment in Construction (USQLF002O, UKQLF002O, UKES9KS6O, FRQLF002O, FRESZIHVO, BDQLF002O, BDESZIHVO, ITQLF002O, ITESZIHVO, ESQLF002O and ESESZIHVO); Population (USPOPNIQH, UKESENP.O, FRESU11ZO, BDESENP.O, ITESENP.O, ESESENP.O).

b) Real House Prices come from the OECD Housing Prices Database.

3. Total Factor Productivity (TFP) is computed as

$$\log(TFP) = \log(\mathit{Real\ GDP}) - (1-\alpha)\log(\mathit{Employment})$$

where α is the capital share of output assumed to be 0.36. Real GDP and employment are from the data mentioned above.

Appendix II. House Price Indices in China

There are different house price indices available in China. The first three are official house price indices. Given the suspicion that these indices underestimate house price growth, some other organizations have started to build house price indices:

1) Price Indices of Newly Constructed Residential Buildings in 70 Cities ("the 70 Cities Index") published by the National Bureau of Statistics (NBS).[9] This index has been published since 1998. Until 2005 it covered 35 major cities. Since 2005 it covers 70 medium and large-sized cities and is disaggregated into newly built residential and non-residential buildings. Until July 2005, it was published quarterly and since then it is published monthly. It uses a matching approach to control for quality changes (see Wu et al. 2013 for a discussion of the methodology).[10] The accuracy of the index is controversial (Wu et al. 2013 survey several criticisms).

2) Average Selling Price of Newly Constructed Residential Buildings ("the Average Selling Price Index"). This index has also been published by the NBS since 1998. It covers all cities. The real estate developers are required by law to report every month the transaction volume (in floor space) and the price of the units of newly-built residences. These figures are aggregated and the average selling price (in Renminbi per square meter) is generated by dividing the total transaction value by the total floor space without any adjustment for quality changes. These average prices are published at the city, provincial, and national level. Before 2011, the NBS collected their data from real estate developers, who may not necessarily report accurately as discussed in Ahuja et al. (2010). Since 2011, the NBS collects data directly from local housing

[9] The link to the historical data is http://www.stats.gov.cn/english/statisticaldata/ although it is not always easy to download long time series. The NBS is building a new database website at http://data.stats.gov.cn/workspace/index?m=hgyd

[10] For each housing complex in the sample, the average transaction price is calculated in each month and compared with that of the same complex in the previous month. The monthly house price growth rate at city level is then calculated as the average (weighted by transaction volume) of all complexes' growth rates in the corresponding month.

authorities (who have all housing transaction records). Since July 2005, the NBS also publishes a price index for secondary transactions in residential buildings.

3) Average Property Prices in 36 Major Cities published by the National Development and Reform Commission ("the NDRC Property Price Index"). These indices start from 2007 and their units are in Renminbi per square meter. Since January 2012 it was split into residential and non-residential indices.

4) Since 2005 the real estate developer Centaline Group publishes its own house price indices ("the Centaline Indices") for Shanghai, Beijing, Guangzhou, Shenzhen and Tianjin based on secondary transaction data.[11]

5) Since the early 1990s, DTZ, a global real estate adviser, started to publish quarterly residential price and rental indices ("the DTZ Index") for six cities in China (Beijing, Shanghai, Guangzhou, Shenzhen, Tianjin and Dalian). The indices are calculated from secondary transaction data, based on a tracked basket of high-end residential buildings.

6) Since 2010, the China Index Academy (one of the largest Chinese property research institutions, which integrated in 2004 with several research resources, such as China Real Estate Index System (CREIS) or Soufun Research Institute) publishes monthly House Price Indices for 100 cities ("the SouFun CREIS 100 Cities House Price Index").[12]

7) Moreover, in the spirit of the U.S. Case-Shiller indices, some Chinese scholars have built their own house price indices. For example, Guo et al. (2014), using data of newly-constructed homes in Chengdu, develop a "pseudo repeat sale" quality-controlled price index. Deng et al. (2012) collect data on land sales to create land price indices for 35 cities. Wu et al. (2013) built an hedonic price indices for 35 cities from 2006 to 2010, and by aggregation a multi-city constant-quality house price index.

[11] And for Chengdu since 2012. We constructed a national index by averaging house price growth rates across different cities.

[12] http://industry.soufun.com/en/about_us.html

Figures and Tables

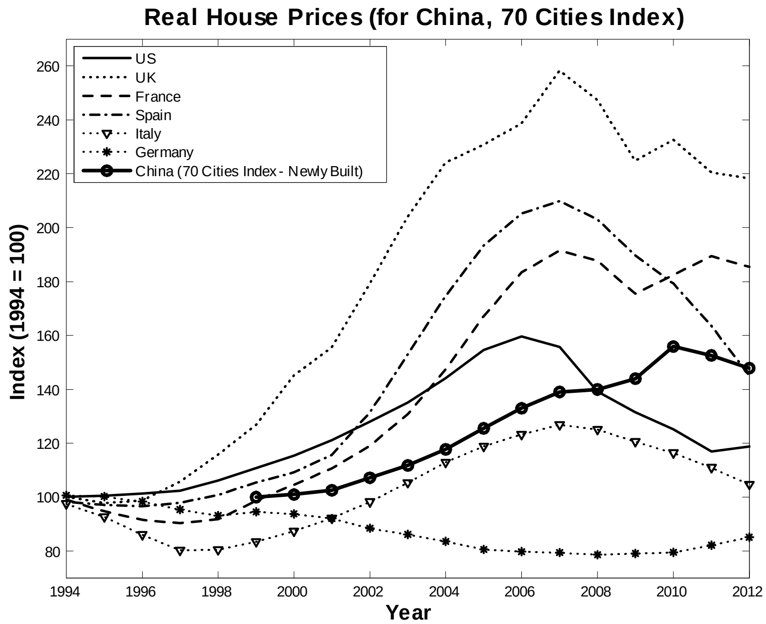

Figure 1: Real House Prices in OECD Countries and China. For data sources see Appendix I.

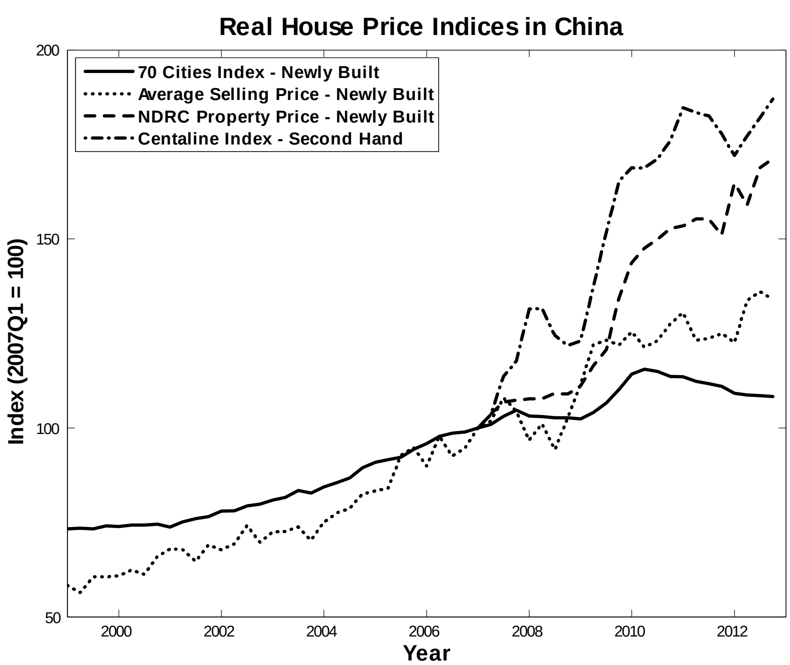

Figure 2: Real House Price Indices in China. For data sources see Appendix I.

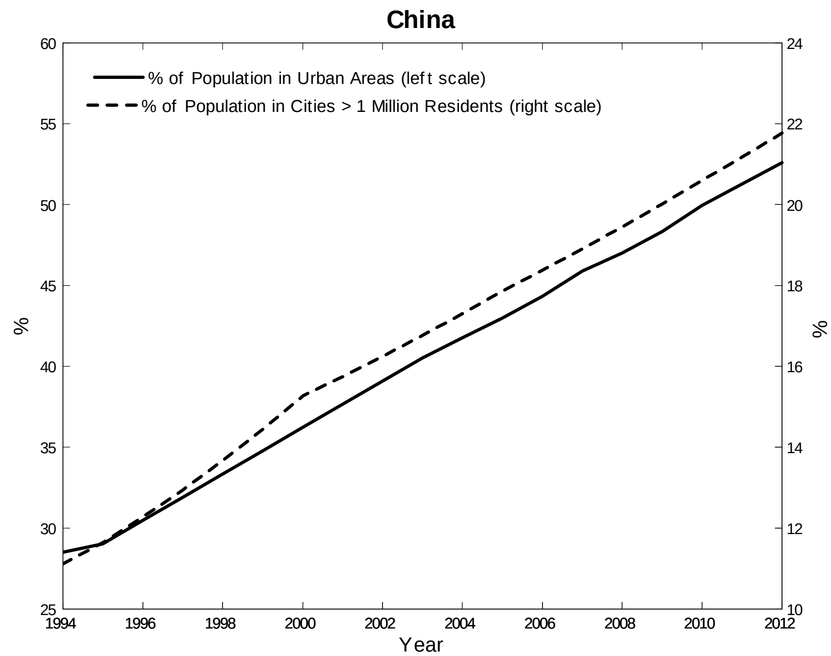

Figure 3: Population Dynamics in China. Data sources discussed in Appendix I.

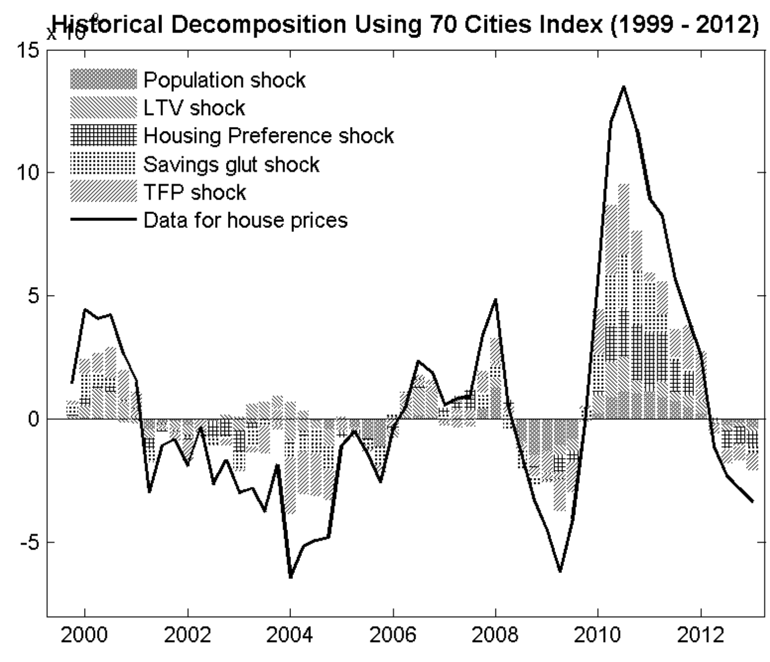

Figure 4: Historical Decomposition Using 70 Cities Index.

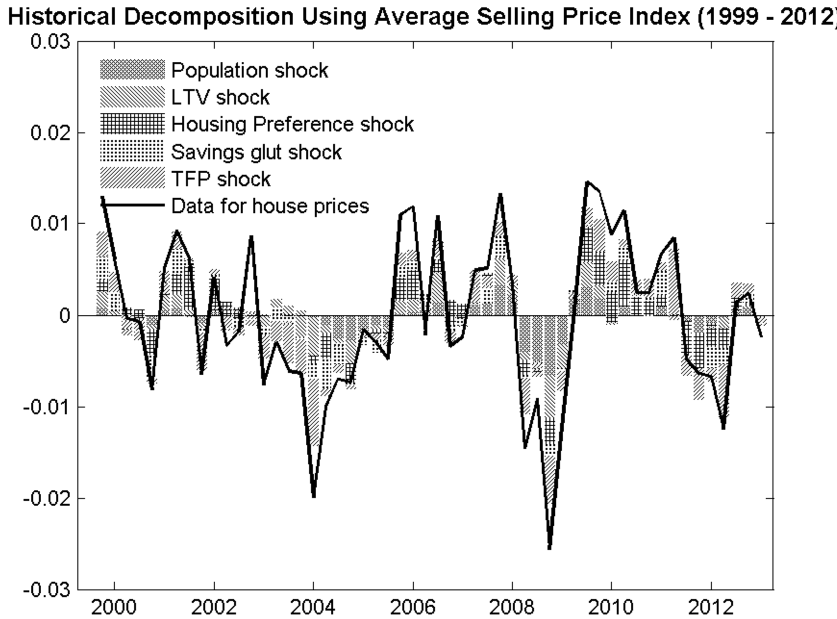

Figure 5: Historical Decomposition Using Average Selling Price Index.

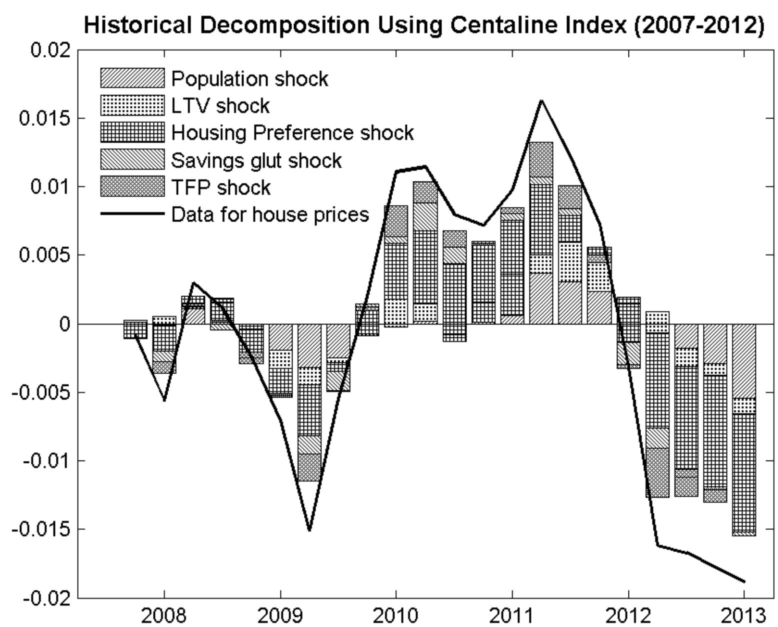

Figure 6: Historical Decomposition Using Centaline Index.

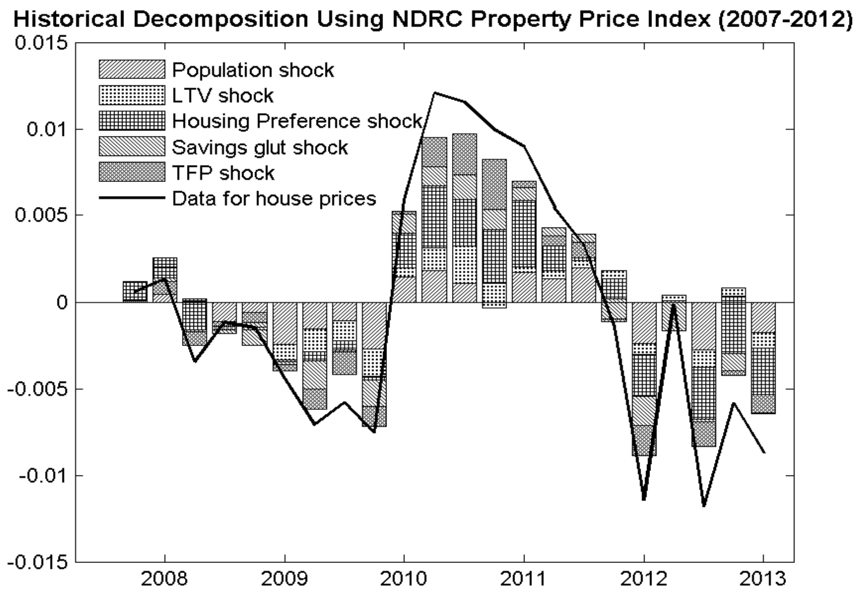

Figure 7: Historical Decomposition Using NDRC Property Price Index.

Table 1: Growth Rates of Real House Price Indices

	70 Cities Index	Average Selling Price	NDRC Property Price	Centaline Index
Average (YoY)	3.12%	6.63%	10.02%	11.35%
Standard Deviation	3.65%	7.74%	9.03%	13.54%

Note: Appendix II discusses these price indices.

Table 2: Correlation among Real House Price Indices

	70 Cities Index	Average Selling Price	NDRC Property Price	Centaline Index
70 Cities Index	1	0.967	0.809	0.874
Average Selling Price		1	0.892	0.887
NDRC Property Price			1	0.956
Centaline Index				1

Note: Appendix II discusses these price indices.

Table 3: Sign Restrictions for Positive Shocks

Variable/Shocks	Population	Credit Shock	Housing Preference	Savings Glut	Permanent TFP
Consumption	> 0	> 0	< 0	< 0	> 0
CA/GDP			< 0	> 0	
House prices	> 0	> 0	> 0	> 0	> 0
Consumption per capita	< 0	> 0			> 0
TFP					> 0

Note: Section 3 discusses the sign restrictions.

Table 4: Variance Decompositions Using 70 Cities Index

	Real House Prices			Residential Investment		
Forecast Horizon :	*1 Year*	*3 Years*	*5 Years*	*1 Year*	*3 Years*	*5 Years*
Population	7.8%	6.6%	6.4%	18.6%	18.4%	19.0%
Credit shock	11.4%	9.6%	9.2%	12.3%	11.2%	11.5%
Housing preference	11.0%	10.0%	9.6%	13.2%	13.2%	11.3%
Savings glut	10.4%	16.9%	20.9%	9.4%	8.8%	8.7%
TFP	24.2%	19.5%	17.8%	16.0%	17.1%	17.9%

Note: Quarterly data from 1999Q1 to 2012Q4.

Table 5: Variance Decompositions Using Average Selling Price Index

	Real House Prices			Residential Investment		
Forecast Horizon :	*1 Year*	*3 Years*	*5 Years*	*1 Year*	*3 Years*	*5 Years*
Population	11.3%	11.4%	12.0%	17.5%	19.2%	21.3%
Credit shock	15.9%	18.0%	18.5%	11.9%	10.4%	11.3%
Housing preference	13.3%	14.6%	13.7%	24.0%	23.2%	19.7%
Savings glut	10.5%	9.9%	10.8%	7.9%	11.1%	14.0%
TFP	25.2%	24.2%	24.4%	15.5%	17.1%	17.5%

Note: Quarterly data from 1999Q1 to 2012Q4.

Table 6: Variance Decompositions Using Centaline Index

	Real House Prices			Residential Investment		
Forecast Horizon :	*1 Year*	*3 Years*	*5 Years*	*1 Year*	*3 Years*	*5 Years*
Population	31.0%	22.8%	22.6%	21.4%	21.7%	20.4%
Credit shock	12.8%	11.9%	12.1%	13.1%	11.2%	11.8%
Housing preference	19.0%	25.8%	28.3%	23.5%	26.2%	30.2%
Savings glut	4.3%	5.8%	5.4%	5.7%	6.1%	5.9%
TFP	8.8%	9.0%	8.3%	9.2%	8.1%	7.8%

Note: Quarterly data from 2007Q1 to 2012Q4.

Table 7: **Variance Decompositions Using NDRC Property Price Index**

	Real House Prices			Residential Investment		
Forecast Horizon :	*1 Year*	*3 Years*	*5 Years*	*1 Year*	*3 Years*	*5 Years*
Population	21.4%	15.7%	14.0%	20.2%	12.1%	11.0%
Credit shock	9.0%	13.1%	11.9%	17.9%	11.9%	11.4%
Housing preference	20.7%	23.1%	26.1%	12.9%	27.8%	29.9%
Savings glut	5.1%	5.6%	5.9%	5.4%	4.2%	4.7%
TFP	15.9%	15.0%	13.9%	16.7%	10.9%	10.5%

Note: Quarterly data from 2007Q1 to 2012Q4.

On-Line Appendix Not for Publication

In this Appendix we present the model we use to derive the identifying restrictions for the five shocks discussed in the paper. We use sign restrictions that are robust across different parameterization. The model is based on Gete (2009) and integrates the multiple ways in which housing markets interact with the economy.

1 Model

There are two countries (domestic and foreign) in the model. We focus on China as the domestic country. In both countries there is a non-tradable housing sector and a tradable goods sector. The traded good is the same good for both countries, thus all trade between countries is intertemporal. The model is real and the traded good is the numeraire. The domestic country is composed of two types of households (patient and impatient) and only impatient households are credit-constrained. We work the perfect foresight version to incorporate unexpected and expected shocks. Figure 1 illustrates the structure of the model.

1.1 Domestic Households

At period t there is a mass $N_{d,t}$ of infinitely lived domestic households who can be patient or impatient. These two types differ in three dimensions: 1) The discount factor for the patient households is larger than for the impatient households ($\beta^p > \beta^i$). This is a standard technique to have credit relations in a model as the impatient households borrow from the patient ones. 2) The impatient households face a collateral constraint that limits their borrowings to a fraction of the discounted expected value of the houses they own. 3) Patient domestic households have access to two types of one-period bonds: an international bond $\left(\hat{B}\right)$ with real interest rate $\hat{R}$ to borrow or lend to the foreign households; a domestic bond (B) with real interest rate R to lend to the domestic impatient households. A non-arbitrage condition governs the relation between these two types of bonds. The domestic impatient households can only borrow from the domestic patient. This is a simplifying assumption without loss of generality. As we will discuss, the domestic impatient can borrow from the foreign households via the domestic patient households, who in that regard behave as a financial intermediary.

Both types of domestic households enjoy consumption of housing and tradable goods without any consumption home bias. Both types supply labor inelastically in the domestic country. The parameter ϕ controls the share of impatient households over the total domestic population, as well as their share in the income of the domestic country. In every period in the domestic country there are $(1-\phi)\,N_{d,t}$ patient households and $\phi N_{d,t}$ impatient households. The total population of the domestic country $(N_{d,t})$ can change over time.

1.1.1 Domestic Patient Households

There is a representative domestic patient household who maximizes the expected utility of her members

$$E_0 \sum_{t=0}^{\infty} \left(\beta_{dt}^{p}\right)^t (1-\phi)\, N_{d,t} u\left(c_{d,t}^{p}, h_{d,t}^{p}\right) \tag{1}$$

where $c_{d,t}^{p}$ and $h_{d,t}^{p}$ are the per capita consumption of tradable goods and housing. β_{dt}^{p} is a time-varying discount factor to capture changes in the desire for savings. These changes affect both patient and impatient households.

The flow of housing consumption is equal to the per capita stock of housing. Preferences are constant relative risk aversion over a constant elasticity of substitution aggregator of housing services and tradable goods consumption

$$u\left(c_{d,t}^{p}, h_{d,t}^{p}\right) = \frac{\left[\left[(1-\theta_{d,t})\left(c_{d,t}^{p}\right)^{\frac{\varepsilon-1}{\varepsilon}} + \theta_{d,t}\left(h_{d,t}^{p}\right)^{\frac{\varepsilon-1}{\varepsilon}}\right]^{\frac{\varepsilon}{\varepsilon-1}}\right]^{1-\frac{1}{\sigma}}}{1-\frac{1}{\sigma}} \tag{2}$$

where σ is the elasticity of intertemporal substitution (IES) as well as the inverse of the coefficient of relative risk aversion, ε is the static or intratemporal elasticity of substitution (SES) between housing and tradable goods consumption, and $\theta_{d,t} \in (0,1)$ is a country-specific parameter that affects the share of consumption of housing services. A bubble, or an increase in the value of owning a house in marriage markets, can be captured with changes in this parameter. In both cases households value housing more relative to goods consumption.

Multiplying per capita values by the number of patient households we obtain the aggregates for the domestic patient households:

$$C_{d,t}^{p} = (1-\phi)\, N_{d,t} c_{d,t}^{p} \tag{3}$$

$$H_{d,t}^{p} = (1-\phi)\, N_{d,t} h_{d,t}^{p} \tag{4}$$

$$B_{d,t}^{p} = (1-\phi)\, N_{d,t} b_{d,t}^{p} \tag{5}$$

$$\hat{B}_{d,t}^{p} = (1-\phi)\, N_{d,t} \hat{b}_{d,t}^{p} \tag{6}$$

where $\hat{b}^p_{dt}$ are the patient households' per capita holdings of the international bond, and $b^p_{d,t}$ the per capita holdings of the domestic bond.

The budget constraint for the representative domestic patient household is:

$$C^p_{d,t} + B^p_{d,t} + \hat{B}^p_{d,t} + q_{d,t}\left(H^p_{d,t} - (1-\delta)\,H^p_{d,t-1}\right) + (1-\phi)\,N_{d,t}\frac{\psi_B}{2}\left(\hat{b}^p_{d,t} - \bar{b}_d\right)^2 =$$
$$= R_{t-1}B^p_{d,t-1} + \hat{R}_{t-1}\hat{B}^p_{d,t-1} + (1-\phi)\,I_{d,t} \tag{7}$$

where $q_{d,t}$ is the price of a domestic house in terms of tradable goods, δ is the house depreciation rate, R_t is the domestic gross interest rate, $\hat{R}_t$ is the international gross interest rate, $I_{d,t}$ is households' income to be defined below, ψ_B is the parameter that controls the adjustment cost in the holdings of international bonds and $\bar{b}_d$ is the per capita steady state holdings. We use the adjustment cost to insure that there is a unique steady state; this is a standard technique to close international models with incomplete markets (Schmitt-Grohe and Uribe 2003, Boileau and Normadin 2008).

From the first order conditions of the domestic patient households, we can derive the non-arbitrage restriction between the return of the two bonds:

$$R_t\left[1 + \psi_B(\hat{b}^p_{d,t} - \bar{b}^p_d)\right] = \hat{R}_t \tag{8}$$

When the adjustment cost goes to zero both bonds offer the same return $\left(R_t = \hat{R}_t\right)$.

1.1.2 Domestic Impatient Households

The representative domestic impatient household maximizes the expected utility of her members

$$E_0\sum_{t=0}^{\infty}\left(\beta^i_{dt}\right)^t \phi N_{d,t} u(c^i_{d,t}, h^i_{d,t}) \tag{9}$$

$$u\left(c^i_{d,t}, h^i_{d,t}\right) = \frac{\left[\left[(1-\theta_{d,t})\left(c^i_{d,t}\right)^{\frac{\varepsilon-1}{\varepsilon}} + \theta_{d,t}\left(h^i_{d,t}\right)^{\frac{\varepsilon-1}{\varepsilon}}\right]^{\frac{\varepsilon}{\varepsilon-1}}\right]^{1-\frac{1}{\sigma}}}{1-\frac{1}{\sigma}} \tag{10}$$

where all variables are as defined for the patient household but now they have the superscript of the impatient household. We assume that

$$\beta^i_{dt} = \zeta\beta^p_{dt} \tag{11}$$

with $\zeta \in (0,1)$. Thus, $\beta^i_{dt} < \beta^p_{dt}$. The aggregate variables are

$$C^i_{d,t} = \phi N_{d,t} c^i_{d,t} \tag{12}$$

$$H^i_{d,t} = \phi N_{d,t} h^i_{d,t} \tag{13}$$

$$B^i_{d,t} = \phi N_{d,t} b^i_{d,t} \tag{14}$$

The behavior of domestic impatient households is summarized by a representative agent who chooses per capita housing, tradable consumption, and domestic bond holdings $\left(b^i_{d,t}\right)$ to maximize $(9-10)$ subject to the aggregate budget constraint:

$$C^i_{dt} + B^i_{dt} + q_{dt}\left(H^i_{dt} - (1-\delta)\, H^i_{dt-1}\right) = R_{t-1} B^i_{d,t-1} + \phi I_{d,t} \tag{15}$$

Impatient households also face a borrowing constraint such that their borrowings have to be collateralized with housing:

$$b^i_{dt} \geq \frac{-m_t E_t\left(q_{d,t+1} h^i_{dt}\right)}{R_t} \tag{16}$$

That is, impatient households per capita borrowings cannot be larger than a fraction m_t of the discounted future value of their current houses. The variable m_t controls the loan-to-value (LTV) ratio. Shocks to m_t are referred to in the macro-housing literature as credit standards shocks.

1.2 Domestic Firms

Firms use labor to produce tradable goods $(Y_{Td,t})$. They use labor and land (L_d) to produce non-tradable housing structures $(Y_{sd,t})$. Then firms use housing structures and housing appliances $(Y_{ad,t})$ to produce new houses $(Y_{hd,t})$. Tradable goods $(Y_{Td,t})$ can be used for consumption by households in both countries or as housing appliances. That is, a share of $Y_{Td,t}$ can be used as $Y_{ad,t}$. The production functions are:

$$Y_{Td,t} = A_{Td,t}\left(N_{Td,t}\right)^{\alpha} \tag{17}$$

$$Y_{sd,t} = \left[A_{sd}\left(N_{sd,t}\right)^{\alpha}\right]^{\gamma} L_d^{1-\gamma} \tag{18}$$

$$Y_{hd,t} = \min\left(Y_{sd,t}, \tau Y_{ad,t}\right) \tag{19}$$

where α, γ, τ and L_d are constants. $N_{Td,t}$ and $N_{sd,t}$ are the domestic labor allocated to tradable goods and housing sector respectively.

Equation (18) captures that land plays a role in the production of housing. Equation (19) captures that housing is produced using both tradable and non-tradable goods. The Leontief assumption in (19) captures the complementarities between tradable and non-tradable goods in producing houses. In equilibrium,

$$Y_{sd,t} = \tau Y_{ad,t} \tag{20}$$

Firms' decision is to allocate labor across two sectors. In equilibrium the value of one unit of labor must be equal across sectors. Since the households own the firms and the land, we can define households' income as the total revenues of the firms:

$$I_{d,t} = q_{d,t} Y_{hd,t} + Y_{Td,t} - Y_{ad,t} \tag{21}$$

1.3 Foreign Country

To simplify, we assume there are only patient unconstrained households in the foreign country. Their representative agent maximizes the expected utility of her members

$$E_0 \sum_{t=0}^{\infty} \left(\beta_f^p\right)^t N_{f,t} u(c_{f,t}, h_{f,t}) \tag{22}$$

$$u(c_{f,t}, h_{f,t}) = \frac{\left[\left[(1-\theta_f) c_{f,t}^{\frac{\varepsilon-1}{\varepsilon}} + \theta_f h_{f,t}^{\frac{\varepsilon-1}{\varepsilon}}\right]^{\frac{\varepsilon}{\varepsilon-1}}\right]^{1-\frac{1}{\sigma}}}{1-\frac{1}{\sigma}} \tag{23}$$

As before, we define the aggregate variables as

$$C_{f,t} = N_{f,t} c_{f,t} \tag{24}$$

$$H_{f,t} = N_{f,t} h_{f,t} \tag{25}$$

$$\hat{B}_{f,t} = N_{f,t} \hat{b}_{f,t} \tag{26}$$

The representative foreign household chooses per capita consumption of tradable goods, non-tradable foreign housing and international bonds $\left(\hat{b}_{f,t}\right)$ to maximize (22) – (23) subject to her aggregate budget constraint:

$$C_{f,t} + \hat{B}_{f,t} + q_{f,t}\left(H_{f,t} - (1-\delta) H_{f,t-1}\right) + N_{f,t} \frac{\psi_B}{2} \left(\hat{b}_{f,t} - \bar{b}_f\right)^2 = \hat{R}_{t-1} \hat{B}_{f,t-1} + I_{f,t} \tag{27}$$

Foreign firms have the same technology as domestic firms:

$$Y_{Tf,t} = A_{Tf,t} \left(N_{Tf,t}\right)^{\alpha} \tag{28}$$

$$Y_{sf,t} = \left[A_{sf} \left(N_{sf,t}\right)^{\alpha}\right]^{\gamma} L_f^{1-\gamma} \tag{29}$$

$$Y_{hf,t} = \min\left(Y_{sf,t}, \tau Y_{af,t}\right) \tag{30}$$

where N_{Tft} and N_{sft} are the labor allocated to tradable goods and housing sector in the foreign country.

The income of foreign households is the total revenue of the firms:

$$I_{f,t} = q_{f,t} Y_{hf,t} + Y_{Tf,t} - Y_{af,t} \tag{31}$$

1.4 Market Clearing and Shocks

Labor is mobile within the sectors of each country but not internationally:

$$N_{Td,t} + N_{sd,t} = N_{d,t} \tag{32}$$

$$N_{Tf,t} + N_{sf,t} = N_{f,t} \tag{33}$$

The increase in the housing stock of each country is the new houses produced minus the depreciation:

$$H_{f,t} - (1-\delta) H_{f,t-1} = Y_{hf,t} \tag{34}$$

$$H^i_{d,t} + H^p_{d,t} - (1-\delta)\left(H^i_{d,t-1} + H^p_{d,t-1}\right) = Y_{hd,t} \tag{35}$$

Tradable goods are consumed by households in the two countries, they also serve to pay the portfolio adjustment costs

$$\begin{aligned} &C^p_{d,t} + C^i_{d,t} + C_{f,t} \\ &= Y_{Td,t} - Y_{ad,t} - (1-\phi) N_{dt} \frac{\psi_B}{2}\left(\hat{b}^p_{d,t} - \bar{b}^p_d\right)^2 + Y_{Tf,t} - Y_{af,t} - N_{f,t}\frac{\psi_B}{2}\left(\hat{b}_{f,t} - \bar{b}_f\right)^2 \end{aligned} \tag{36}$$

The net supply of domestic bonds between the patient and impatient households equals zero:

$$B^p_{d,t} + B^i_{d,t} = 0 \tag{37}$$

The net supply of international bonds between the two countries equals zero.

$$\hat{B}_{d,t}^{p} + \hat{B}_{f,t} = 0 \tag{38}$$

We can define the trade balance and the current account in the domestic country as

$$TB_{d,t} = Y_{Td,t} - Y_{ad,t} - C_{d,t}^{p} - C_{d,t}^{i} - (1-\phi)\, N_{d,t}\frac{\psi_B}{2}\left(\hat{b}_{d,t}^{p} - \bar{b}_{d}^{p}\right)^2 \tag{39}$$

$$CA_{d,t} = \hat{B}_{d,t}^{p} - \hat{B}_{d,t-1}^{p} \tag{40}$$

2 Parametrization

Table 1 summarizes our benchmark parametrization. Some parameters are directly obtained from microeconomic evidence, some other parameters are selected to match certain steady state ratios. We assume that one period in the model is one year and divide the parameters in two groups:

1) Parameters in households' problems: as in most of the real business cycle literature we assume an Intertemporal Elasticity of Substitution $\sigma = 0.5$, which under CRRA preferences implies a value for risk aversion of 2. Our sign restrictions are robust to different values. The value for intratemporal elasticity of substitution ε is under open debate, as discussed in Ferrero (2013). We choose $\varepsilon = 0.4$, implying complementarity between tradable goods and houses. We select $\theta = 0.15$ to match a 10.5% share of consumption of housing services over total expenditure. The parameter $\tau = 2$ is selected to match the fact that housing appliances take up 17% of the value for new houses (Siniavskaia 2008).

Domestic and international patient households share the same discount factor in steady state; this parameter pins down the real interest rate in steady state. We set a value $\beta_f^p = \beta_d^p = 0.97$ to target a 3% annual real return. We will give transitory shocks to $\beta_{d,t}^p$ as discussed later. Given our numerical solution method, the impatient households' discount factor (β^i) needs to be small enough to guarantee that the borrowing constraint (16) is always binding (for a discussion of these technicalities see Iacoviello and Neri 2010). Punzi (2013) chooses a relatively large $\beta^i = 0.98$ for her quarterly model; Iacoviello (2005) chooses a smaller $\beta^i = 0.95$ in a quarterly model. Ferrero (2013) argues that the choice of β^i depends on the change in the loan-to-value ratio and, in a quarterly model, he chooses $\beta^i = 0.96$ when m changes from 0.75 to 0.99, and a smaller $\beta^i = 0.89$, when m changes from 0.85 to 0.95. We choose the ratio of discount factors between domestic impatient and patient households to be $\zeta = \frac{0.85}{0.97}$, which is within the range of values used in the literature.

There is no consensus in the literature among the share of households who are borrowing constrained. As we discuss below this is an important parameter which could alter the sign of the reaction of some variables to shocks. In the standard life-cycle buffer-stock model with one risk-free asset, (Heathcote et al. 2009 provide a survey) the fraction of constrained households is very small (usually below 10%) under parameterizations where the model's distribution of net worth is in line with the data. On the other extreme, Ferrero (2013) works with 100%. Iacoviello estimates that the wage income share of the patient households is 0.64. Kaplan and Violante (2012) look at the 2001 U.S. Survey and Consumer Finances for households who hold sizeable amounts of illiquid wealth, yet consume all of their disposable income during a pay-period. They find that between $\frac{1}{4}$ and $\frac{1}{3}$ of US households fit this profile. Lusardi et al. (2011) show that almost half of US households would be probably or certainly unable to "come up with $2,000 within a month". Justiniano et al. (2013) also identify the impatient households with liquidity constrained. They use the 1992, 1995 and 1998 Survey of Consumer Finances and estimate an average share of 61% in the population and they account for 46% of labor income. They control for the progressivity of the tax/transfer system and end up with a ratio between the total income of the borrowers and savers of 0.52. We assume that 50% of the domestic households are impatient and we do robustness analysis. The loan-to-value ratio in most of the literature ranges from 0.75 to 0.85, (e.g. Iacoviello 2005, Ferrero 2013 and Justiniano et al. 2013). We set as steady state $m = 0.9$.

2) Parameters in firms' problems: We normalize the steady state productivity in tradable goods and housing sector to 1 $(A_s = A_T = 1)$. In the Cobb-Douglas production functions for the goods sector, we select the standard labor intensity $\alpha_T = \frac{2}{3}$. For the choice of α_s, some literature like Punzi (2013) argues that there is higher degree of labor intensity in the housing sector. But we assume that the labor intensity in two sectors are equal: $\alpha_s = \alpha_T = \frac{2}{3}$. As argued in Iacoviello and Neri (2010), in response to shocks, larger land intensity increases the volatility of housing prices. To better match data, we pick $\gamma = 0.8$ to make land intensity in the housing sector equal 0.2. We assume that the per capita supply of land is $\frac{L_d}{N_d} = \frac{L_f}{N_f} = 0.0001$, reflecting the scarcity of land resources (still can not find good justification). For the annual house depreciation rate we set it at $\delta = 0.045$, to match the fact that around 7% of the population works in the housing sector. And our choice of house depreciation rate is within the range of values the literature: in quarterly models, Iacoviello and Neri 2010 chooses 1%, while Punzi (2013) chooses 1.5%.

3 Deriving Sign Restrictions

3.1 Exogenous Shocks

Figure 2 reports the five exogenous shocks that we feed into the model. The population, credit and TFP shocks are empirically motivated. We assume that population grows at 2% per year for 10 years. This is a middle ground between the average 1% population growth of OECD countries and the 4% at which urban population grows in China. Concerning the credit shock, we assume that the LTV ratio rises from 0.9 to 1 within 10 years. This is slightly a larger change that what Duca et al. (2011) documented for the U.S. They show that the LTV ratio for first time home-buyers rose from 85% in the late 1990s to 95% in the late 2000s. We checked that the size of the population or LTV shocks have no effect on the sign of the restrictions. Concerning TFP the shape of the shock is crucial for the response. If TFP is expected to decay the households try to save, while they try to borrow and consume if they expect future productivity to raise their incomes. We assume that the productivity progress in China is increasing and study a TFP pattern that grows at 2% for 10 years until achieving a permanently higher level.

Housing preference and savings glut shocks are more difficult to measure. Thus we resort to the standard transitory shocks. Moreover, domestic savings glut shocks have to be transitory to have a well defined steady state if we do not assume that all domestic households are impatient (an issue raised by Lucas and Stokey 1984). We increase domestic preference towards housing ($\theta_{d,t}$) to match a 10% immediate increase in the house prices. Then the value of $\theta_{d,t}$ falls towards the initial level within 10 years. The savings glut shocks are captured with a temporary increase in discount factors for both domestic households (the ratio is still governed by equation 11) to match a reduction in the real interest rates of 0.6% relative to the steady state rate.

3.2 Impulse Responses

Figures 3 to 5 report the dynamics of consumption of tradable goods, current account/GDP and house prices facing the five positive shocks. They support the identification scheme we discussed in Section 3 of the paper. Group 1 shocks: Housing preference and savings glut shocks imply a negative correlation between households' consumption of tradable goods and house prices. Group 2 shocks: Population, credit shock and TFP increases lead to a positive correlation between house prices and non-housing consumption. It is possible to separate the two shocks in group 1 by looking at the correlation between house prices and the current account/GDP ratio. A savings glut shock leads to savings, thus an increase in the current account/GDP. On the other hand, a housing preference shock leads to a current account deficit.

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4 Tables and Figures

Table 1: Benchmark Calibration

Description	*Parameters*	*Value*
Steady state patient households' discount factor	β^p	0.97
Ratio of domestic impatient to patient discount factor	ζ	$\frac{0.85}{0.97}$
Share of impatient households in domestic country	ϕ	0.5
Intertemporal Elasticity of Substitution	σ	0.5
Intratemporal Elasticity of Substitution	ε	0.4
Housing depreciation rate	δ	0.045
Ratio of housing appliances over structures	$\frac{1}{\tau}$	1/2
LTV parameter	m	0.9
Share of housing in utility functions	θ_d, θ_f	0.15
Steady state TFP in housing sector	A_s	1
Steady state TFP in tradable goods sector	A_T	1
Labor intensity in housing sector	α_s	2/3
Labor intensity in tradable goods sector	α_T	2/3
Land share in housing production	$1-\gamma$	0.2
Steady state domestic population	N_d	1
Steady state foreign population	N_f	1
Domestic land supply per capita	$\frac{L_d}{N_d}$	0.0001
Foreign land supply per capita	$\frac{L_f}{N_f}$	0.0001
Adjustment cost on international bond	ψ_B	0.008

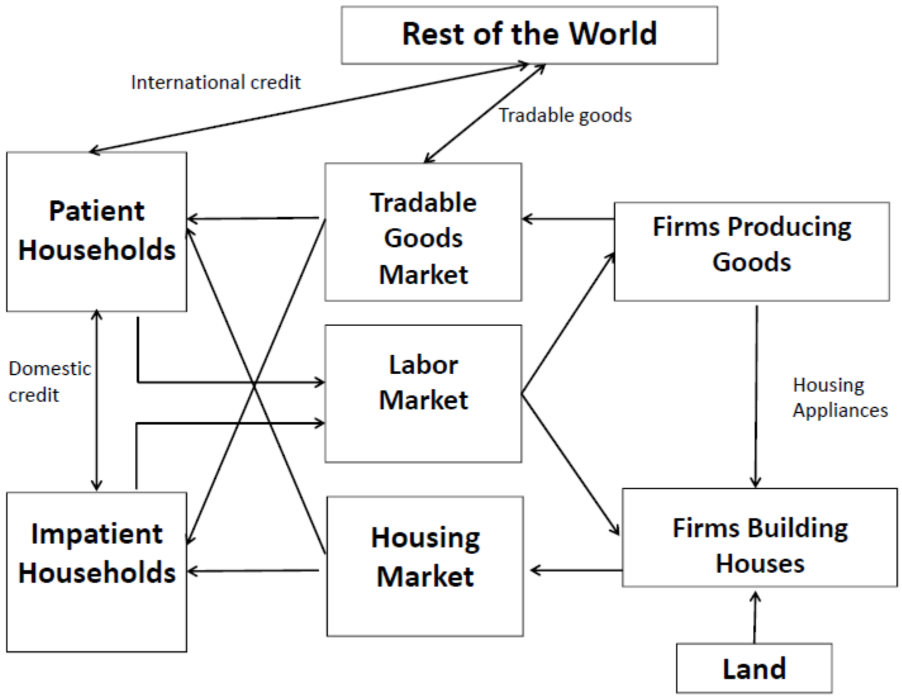

Figure 1: Structure of the DSGE Model.

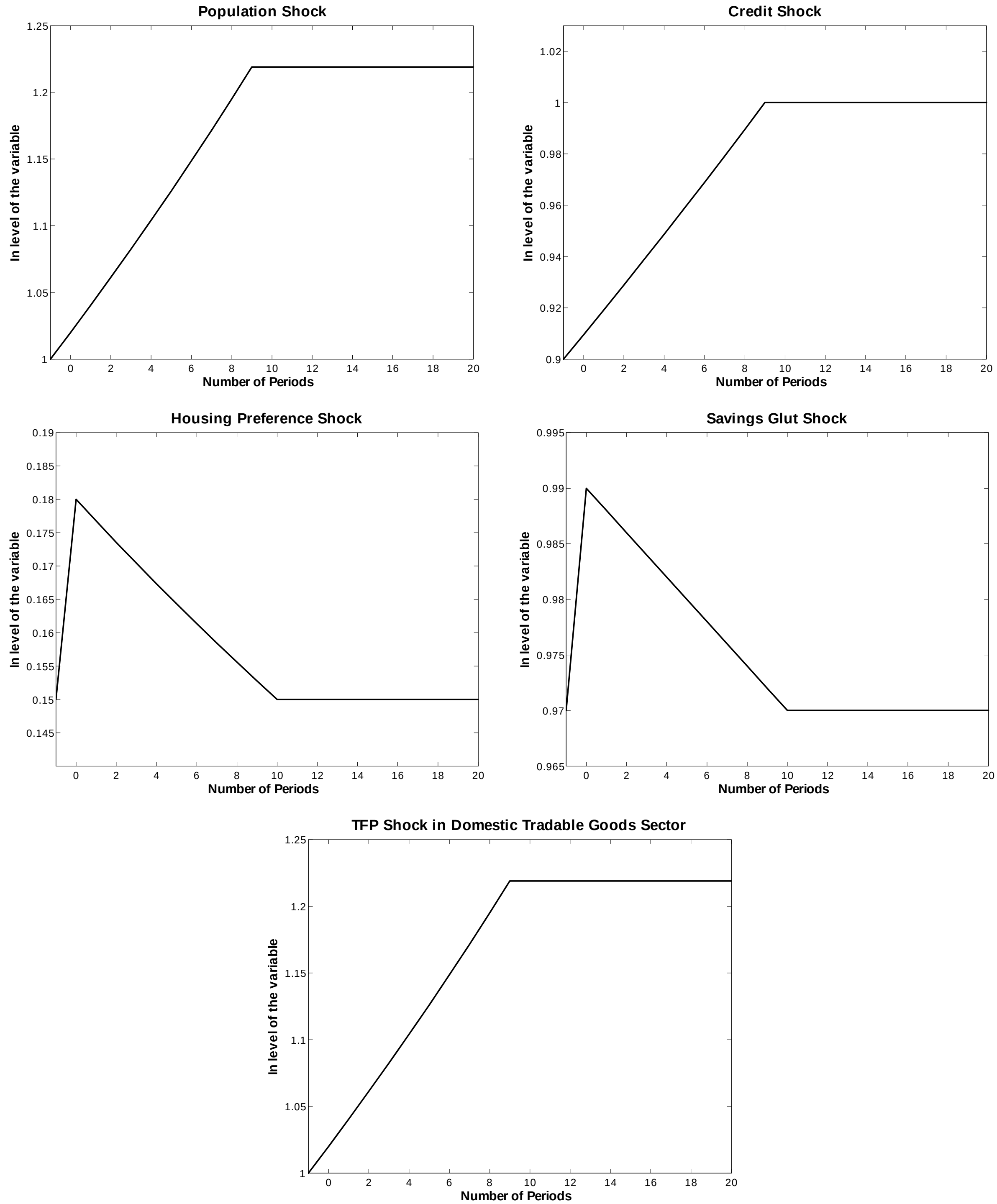

Figure 2: Exogenous Shocks. This figure plots the exogenous shocks that we feed into the model.

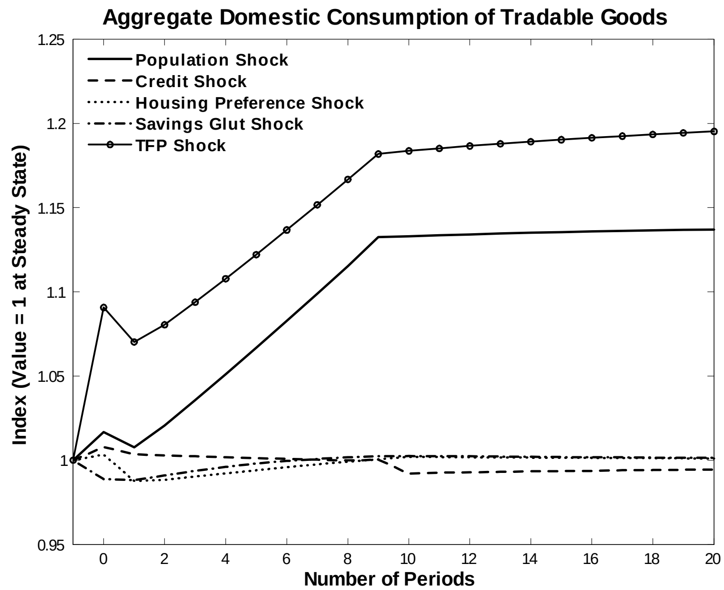

Figure 3: Aggregate Domestic Consumption of Tradable Goods. This figure plots the aggregate domestic consumption of tradable goods in the model after each of the five exogenous shocks.

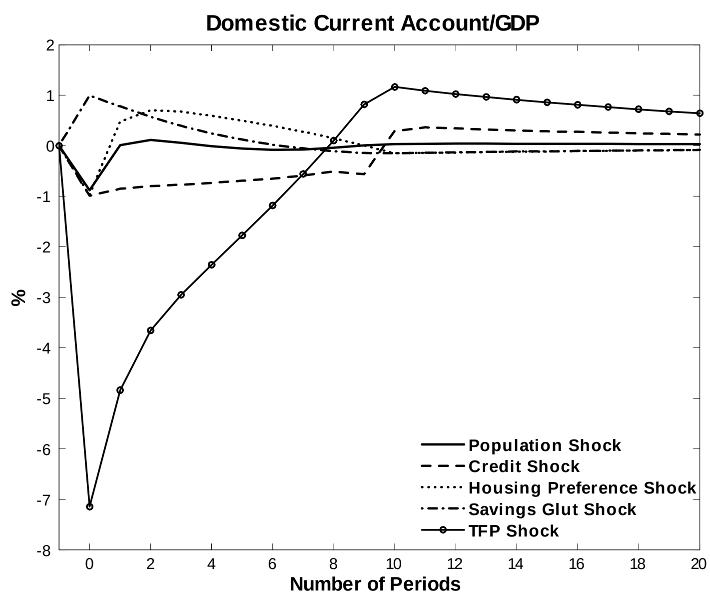

Figure 4: Domestic Current Account/GDP. This figure plots the domestic current account/GDP ratio in the model after each of the five exogenous shocks.

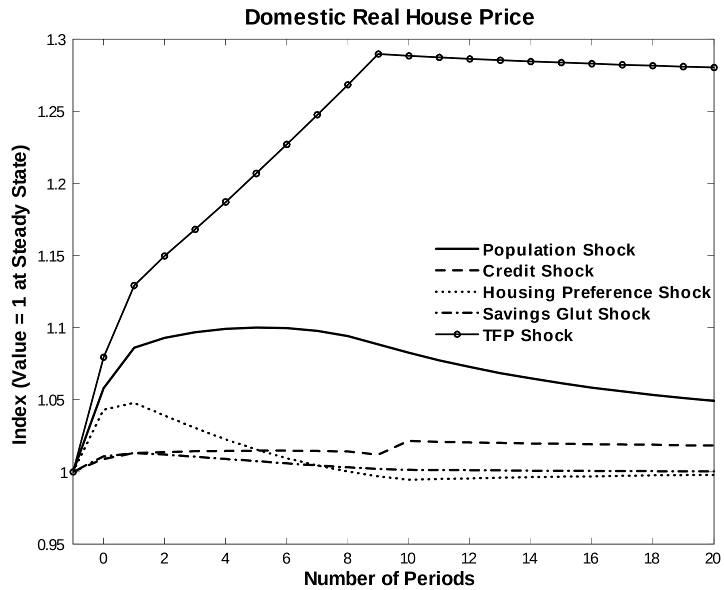

Figure 5: Domestic Real House Price. This figure plots the domestic real house price in the model after each of the five exogenous shocks.