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

Timothy Yang Bian* and Pedro Gete†

This Draft: August 2015

Abstract

We study housing dynamics in China using vector autoregressions identified with theory-consistent sign restrictions. We study seven 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 to housing being a status asset in the marriage market; 4) an increase in the savings rate; 5) expected productivity progress; 6) changes in land supply; and 7) tax policy, a proxy for policy stimulus. Our results show that, even if all shocks play relevant roles, productivity, savings glut, and policy stimulus have been the dominant drivers. When the sample is closer to 2014, housing preferences and credit shocks increase their importance to explain house prices and volume, while population shocks explain a larger share of the dynamics of residential investment. The results show some differences if we use house price indices constructed by the government or by private sources. The official indices show smaller increases in house prices and assign a smaller role to credit and preference shocks.

Keywords: Vector Autoregression; Sign Restrictions; China; House Prices

JEL Classification: C3, E3, R2.

*University of International Business and Economics. Huixin Dongjie, Chaoyang District, Beijing, 100029 China. Email: biantim@uibe.edu.cn

†Corresponding author. Georgetown University, GCER and IE Business School. 37th and O Sts., NW Washington, DC, USA 20057. Email: pg252@georgetown.edu

1 Introduction

Given China's importance for the world economy and the rapid rise in its house prices, with increases larger than those seen in the U.S. before the recent financial crisis, there is a lot of interest in academia and in policy circles about what drives housing dynamics in China. It is especially important for policy design to disentangle the role played by fundamentals, like population or technology growth, from other potential drivers, like bubbles, stimulus policies or financial repression.

We analyze seven potential drivers of housing dynamics in China using structural vector autoregressions (SVARs) identified with theory-consistent sign restrictions. 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 households can store value; 5) productivity increases in the tradable sectors; 6) changes in land supply; and 7) tax policy, a proxy for policy stimulus.[1] We use house prices from multiple sources because the accuracy of the official Chinese house price indices (such as the 70 cities index published by the National Bureau of Statistics) is controversial. Wu et al. (2013) survey several criticisms.

Our identification procedure exploits sign restrictions on impulse responses that are consistent with the macroeconomic literature on the drivers of housing markets.[2] To derive them, we analyze a dynamic general equilibrium model that integrates the multiple ways in which housing markets interact with the economy (i.e. residential investment, wealth and collateral effects and imports of construction-related goods). We look for variables that react differently to each of the seven shocks. For example, we can disentangle population increases from loosening of credit conditions because population shocks cause a negative correlation between per capita consumption and house prices, while the loosening of credit conditions induces a positive correlation.

Our results show that, even if all shocks are relevant to explain housing variables, productivity, savings glut, and tax policies are the key drivers. Productivity and land shocks affect housing quantities more than prices, while tax policies and savings glut shocks affect house prices more than quantities. When the sample is closer to 2014, housing preferences and credit shocks become increasingly important to explain house prices and volume, while population shocks explain a larger share of the dynamics of residential investment. Finally, we show some

[1] We discuss each of these shocks in greater length in Section 2.

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

differences if we use house price indices constructed by government (like the popular 70 Cities Index) or private sources. The official indices show smaller increases in house prices and assign a smaller role to credit and preferences shocks.

This paper contributes to two sets of literature. First, we contribute to the small but growing literature that analyzes housing markets using structural vector autoregressions. We believe this is the first paper that derives theory-consistent sign restrictions to jointly identify each of the seven shocks discussed above. Second, by the topic of our study, we add a complementary methodology to the study of the drivers of housing markets in China. So far the literature has analyzed the topic either using quantitative macro models, or with panel data regressions. Interestingly, several of our results confirm results obtained with the other methodologies. In the following paragraphs we first briefly explain why the sign-restriction SVAR methodology is useful. We then provide a survey of related papers.

SVARs are appealing for two main reasons. First, relative to a quantitative model, SVARs allow more flexible specifications, and the integration of a larger number of shocks. Second, relative to a panel regression, the SVARs explicitly assume that all variables are endogenous and interact between them. SVARs are immune to arguments of reverse causality, and to incorrectly assuming that a variable is exogenous when it is not. Moreover, contrary to panel regressions, SVARs identified with sign restrictions do not need a variable to proxy for each shock. There is no direct link between variables and identified shocks. The sign restrictions methodology (Faust 1998, Canova and De Nicoló 2002, and Uhlig 2005) identifies economic shocks by exploiting differences in the correlations among variables conditional to a given shock. That is, if there are correlations between economic variables that can only be generated by one type of shock, then that shock can be identified with sign restrictions in the impulse responses of a VAR. Sign-restrictions SVARs, although not yet popular in studying real estate markets, have been applied to study other shocks, such as fiscal, monetary, news or technology shocks. See for example, Charnavoki and Dolado (2014) or Fratzscher and Straub (2013), among others.

This paper contributes to the literature that has used SVARs to analyze housing markets. For example, Lastrapes (2002) and Musso et al. (2011) use short or long run restrictions to identify monetary shocks in housing markets. Our contribution is the derivation of robust sign-restrictions to jointly identify the seven shocks we study. Vargas-Silva (2008) used sign restrictions to identify monetary policy shocks in housing markets. Gete (2014) decomposes a housing demand shock into a house price expectation shock, a population shock and a credit expansion shock. Then, he estimates housing dynamics in the OECD. Sa and Wieladek (2015) compare savings glut shocks and monetary policy in the U.S. None of these papers jointly identify the seven shocks as we do.

Concerning the literature on housing dynamics in China, Chen and Wen (2014) and Garriga et al. (2014) are quantitative studies of Chinese housing dynamics. Chen and Wen (2014) provide a model of a self-fulfilling, growing housing bubble that can account for the growth dynamics of Chinese house prices. Garriga et al. (2014) analyze a model of structural transformation, and their quantitative results suggest that the development process accounts for two-thirds of house and land price movements.

Several papers using panel data methods find that the main drivers of Chinese house prices 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. Our complementary methodology allows us to study seven different factors simultaneously. In a panel regression, this could only be done if each factor was proxied by a variable. It is difficult to find such proxies for all shocks. Moreover there is the problem of endogeneity of the regressors.

This paper proceeds as follows. Section 2 describes housing dynamics in China and motivates the seven shocks that we study. Section 3 presents the model that we use to derive the restrictions. Section 4 discusses the restrictions we use to identify the shocks. Section 5 estimates vector autoregressions, imposes the sign restrictions and contains the results and robustness tests. Section 6 concludes. Appendix I contains the data sources. Appendix II discusses the house price indices.

2 What can explain China's housing dynamics?

House prices in China have increased quickly in recent years. Figure 1 compares real house prices in China with several OECD economies. Since the reliability of the official house price indices is often controversial, Figure 1 includes the "70 Cities Index" constructed by China's National Bureau of Statistics (NBS), and the Centaline Index produced by the private sector. Figure 2 compares more housing indices. It plots the 70 Cities Index, the Average Selling Price Index (also computed by the NBS), the Quality-Controlled Index reported by Tsinghua University and the Residential Land Price Index from Deng et al. (2012). We describe the indices carefully in Appendix II. 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. The official indices display the smaller price appreciations. This fact is consistent with the concerns that official statistics underestimate house price growth in China.[3] Next, we discuss the seven shocks that we study.

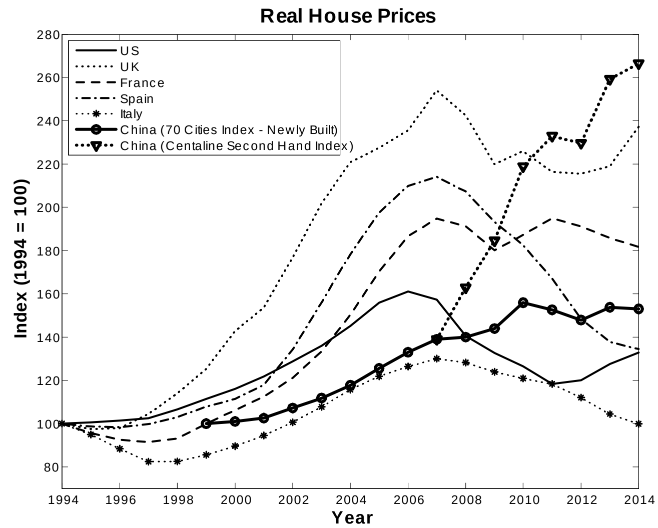

Figure 1: Real house prices in OECD countries and China.

Figure 2: Real house price indices in China.

[3]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).

Table 1: Growth Rates of Real House Price Indices

	70 Cities Index	Average Selling Price	Centaline Index	Residential Land Price	Quality-Controlled Index
Average (YoY)	2.94%	6.09%	10.37%	17.86%	11.95%
Standard Deviation	3.72%	6.46%	11.92%	24.84%	14.16%

Note: Sample size is from 1999Q1 to 2014Q3 for 70 Cities and Average Selling Price, from 2007Q1 to 2014Q3 for Centaline, from 2004Q1 to 2014Q3 for the Residential Land Index, and from 2006Q1 to 2014Q3 for the Quality Controlled Index .

Table 2: Correlation among Growth Rates of Real House Price Indices

	70 Cities Index	Average Selling Price	Centaline Index	Residential Land Price	Quality-Controlled Index
70 Cities Index	1	0.321	0.764	0.618	0.854
Average Selling Price		1	0.311	0.303	0.233
Centaline Index			1	0.777	0.849
Residential Land Price				1	0.846
Quality-Controlled					1

Note: Sample size is from 1999Q1 to 2014Q3 for 70 Cities and Average Selling Price, from 2007Q1 to 2014Q3 for Centaline, from 2004Q1 to 2014Q3 for the Residential Land Index, and from 2006Q1 to 2014Q3 for the Quality Controlled Index .

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. Additionally, the percentage of the population in cities with more than one 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.

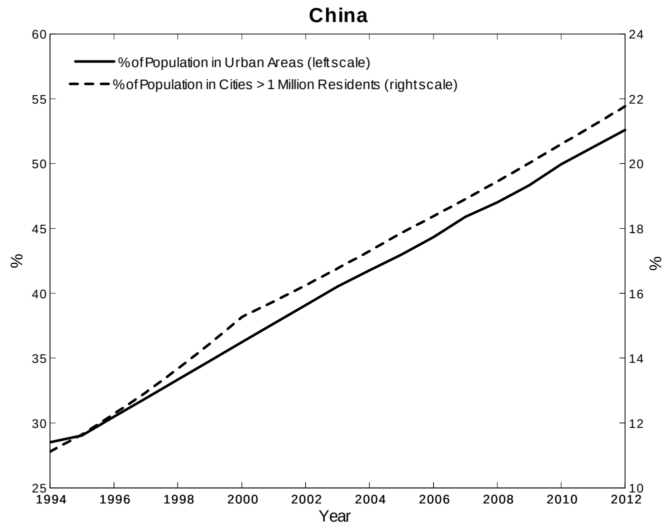

Figure 3: Population dynamics in China.

2.2 Relaxation of credit constraints

China's financial system is highly regulated and the Chinese government has used credit policies to either stimulate housing development or to prevent the housing market from overheating. For example, in late 2008, facing the global financial crisis the government lowered the minimum down payment ratio to 20%. Moreover, in recent years banks 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 China's 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 who 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 suggested 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 at an average annual growth rate of 2.2% from 1996 to 2007. Higher productivity translates into higher household 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, for example 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. 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) discussion of a "savings glut".

High savings rates create demand for assets that serve as a store of value.[4] Real estate is among the few assets available to Chinese households given the capital controls that limit their ability to invest overseas and the non-competitive caps on banks' deposit rates. Households invest in 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, 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 by 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 house 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. The restrictions we impose to identify an increase

[4] Chen and Wen (2014) propose a model to capture this mechanism.

in the preferences for housing are consistent with both a bubble, and with an increase in the value of housing as a status good.

2.6 Land supply

Land supply in China is controlled by the government, which is the ultimate owner of the land. The Ministry of Land and Resources decides how much land the local governments can allocate to non-agricultural construction, and distributes the quotas of construction land among the provinces. Then, the local governments sell the land through auctions or other mechanisms.[5] Thus, in China, land supply is a policy tool which affects housing markets. Moreover, a share of the supply of new land must go to the provision of public housing, whose price is below the market level. The share of this public housing decreased from more than 16% in 2001 to merely 3% in 2010. Since then the government has announced several policies to increase the share of land allocated to public housing. Increases in the supply of public housing imply that the land is not used for free-market housing units.

2.7 Tax policies

Tax policies have been used often to stimulate or cool the housing market. For example, in response to the global financial crisis, between January 2009 and December 2009 the government reduced the property deed tax rate for first-time home buyers from 1.5% to 1% for properties below 90 square meters, and it waived the stamp duty and the land value added taxes. Moreover, if a residential property was held for more than two years, the seller was exempted from the 5.5% transaction tax. Similarly, during 1998–2002, many house-related taxes such as the personal income tax, the sales tax, and the property tax were considerably reduced or exempted entirely to stimulate the housing market (Zhang et al. 2012). Since 2010 the government has used tax policies to slow-down house prices, like extending the holding period to 5 years to enjoy the transaction tax exemption, reducing mortgage rate discounts from 30% to 15%, or suspending mortgage loans to non-residents of a city unless they can prove that they have paid taxes in that city for at least one year.

[5] See World Bank (2005) for a description of the legal framework.

3 Model

In this section we present the model we use to derive the identifying restrictions for the seven shocks. We use sign restrictions that are robust across different parameterizations. The model integrates the multiple ways in which housing markets interact with the economy.

There are two countries. 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. The impatient households are credit-constrained. Figure 4 illustrates the structure of the model.

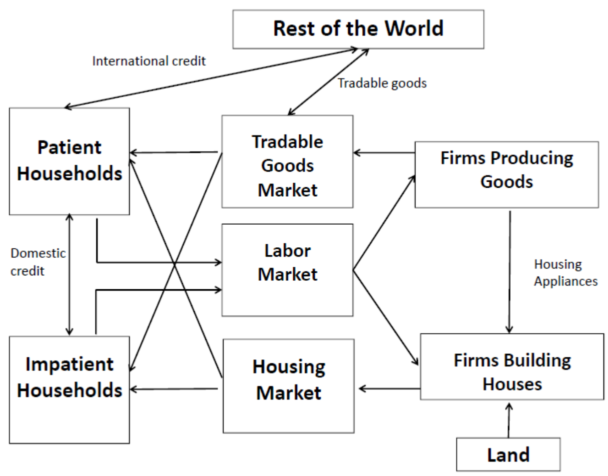

Figure 4: Structure of the DSGE model.

3.1 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. 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 households. 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 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 $N_{d,t}$ of the domestic country can change over time but the share of patient and impatient remains constant.

3.1.1 Domestic patient households

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

$$\mathbb{E}_0 \sum_{t=0}^{\infty} \left(\beta_{dt}^{p}\right)^t (1-\phi) N_{d,t} u\left(c_{d,t}^{p}, h_{d,t}^{p}\right), \tag{1}$$

where $c_{d,t}^{p}$ and $h_{d,t}^{p}$ are the per capita consumption of tradable goods and housing respectively. 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 variable that determines 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 increases in $\theta_{d,t}$. 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 $\hat{b}_{dt}^{p}$ are the patient households' per capita holdings of the international bond, and $b_{d,t}^{p}$ the per capita holdings of the domestic bond.

The budget constraint for the representative domestic patient household is:

$$C_{d,t}^{p} + B_{d,t}^{p} + \hat{B}_{d,t}^{p} + (1+\varphi_t)\, q_{d,t} \left(H_{d,t}^{p} - (1-\delta)\, H_{d,t-1}^{p}\right) + (1-\phi)\, N_{d,t} \frac{\psi_B}{2} \left(\hat{b}_{d,t}^{p} - \bar{b}_d\right)^2 =$$
$$= R_{t-1} B_{d,t-1}^{p} + \hat{R}_{t-1} \hat{B}_{d,t-1}^{p} + (1-\phi)\left(I_{d,t} + T_{dt}\right), \tag{7}$$

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, φ_t is a tax on housing transactions, T_{dt} is a lump-sum tax rebate 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 ensure that there is a unique steady state; this is a standard technique to close international models with incomplete markets (Schmitt-Grohe and Uribe 2003).

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

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

When the adjustment cost goes to zero both bonds offer the same return, that is, $R_t = \hat{R}_t$.

3.1.2 Domestic impatient households

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

$$\mathbb{E}_0 \sum_{t=0}^{\infty} \left(\beta_{dt}^i\right)^t \phi N_{d,t} u(c_{d,t}^i, h_{d,t}^i), \tag{9}$$

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

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

$$\beta_{dt}^i = \zeta \beta_{dt}^p, \tag{11}$$

with $\zeta \in (0,1)$. Thus, $\beta_{dt}^i < \beta_{dt}^p$. The aggregate variables are

$$C_{d,t}^i = \phi N_{d,t} c_{d,t}^i, \tag{12}$$

$$H_{d,t}^i = \phi N_{d,t} h_{d,t}^i, \tag{13}$$

$$B_{d,t}^i = \phi N_{d,t} b_{d,t}^i. \tag{14}$$

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

$$C_{dt}^i + B_{dt}^i + (1+\varphi_t)\, q_{dt}\left(H_{dt}^i - (1-\delta)\, H_{dt-1}^i\right) = R_{t-1} B_{d,t-1}^i + \phi\left(I_{d,t} + T_{dt}\right) \tag{15}$$

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

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

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.

3.2 Domestic firms

Firms use labor to produce tradable goods ($Y_{Td,t}$). They use labor and an exogenous flow of new land (L_{dt}) 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 or as housing appliances. That is, a share of $Y_{Td,t}$ can be used as $Y_{ad,t}$. The production functions are:

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

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

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

where α, γ, and τ are parameters. $N_{Td,t}$ and $N_{sd,t}$ are the domestic labor allocated to the tradable goods and housing sector respectively. Equation (18) captures that land plays a role in the production of housing. Equation (19) says 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. Equation (19) implies than in equilibrium:

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

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

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

3.3 Foreign country

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

$$\mathbb{E}_0 \sum_{t=0}^{\infty} \left(\beta_f^p\right)^t N_{f,t} u(c_{f,t}, h_{f,t}), \tag{22}$$

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

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 its 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:

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

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

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

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

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

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

3.4 Market clearing and taxes

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.

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

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

$$TB_{d,t} = Y_{Td,t} - Y_{ad,t} - C^p_{d,t} - C^i_{d,t} - (1-\phi) N_{d,t} \frac{\psi_B}{2} \left(\hat{b}^p_{d,t} - \bar{b}^p_d\right)^2 , \tag{39}$$

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

From the housing transactions, the government rebates the tax proceedings to the households:

$$T_{dt} = \varphi_t q_{d,t} Y_{hd,t}. \tag{41}$$

4 Deriving the sign restrictions

In this section we derive the sign restrictions that we use to identify the shocks. We use correlations between variables following shocks that increase house prices. Our identification strategy is based on the sign of those correlations.

4.1 Parametrization

Table 3 summarizes our benchmark parametrization. We checked that the restrictions that we use are robust across different calibrations. 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 we divide the parameters into 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. The value for intratemporal elasticity of substitution ε is under open debate, as discussed in Ferrero (2015). 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 the steady state; this parameter pins down the real interest rate in the 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, equation (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 (2015) 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 (2015) works with 100%. Iacoviello estimates that the wage income share of the patient households is 0.64. Justiniano et al. (2015) 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 2015 and Justiniano et al. 2015). We set as the steady state $m = 0.9$. For the housing transaction tax in the steady state we use 5.5%, which is the Chinese mean transaction tax.

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 house 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 steady state per capita supply of land is $\frac{L_d}{N_d} = \frac{L_f}{N_f} = 0.0001$, reflecting the scarcity of land resources. 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. Our choice of house depreciation rate is within the range of values the literature describes: in quarterly models, Iacoviello and Neri 2010 chooses 1%, while Punzi (2013) chooses 1.5%.

4.2 Identification

Figure 5 contains the impulse responses that we use to disentangle and identify the shocks as we discuss next. Without loss of generality, we focus on shocks which increase house prices. We use transitory shocks for all shocks except for population and TFP. For 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.

Table 3: **Benchmark Calibration**

Description	*Parameter*	*Value*
Steady state patient households' discount factor	β^p	0.97
Ratio of 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
Loan-to-value	m	0.9
Share of housing in utility function	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	0.66
Labor intensity in tradable goods sector	α_T	0.66
Land share in housing production	$1-\gamma$	0.2
Steady state populations	$N_d = N_f$	1
Steady state per capita land supply	$\frac{L_d}{N_d} = \frac{L_f}{N_f}$	0.0001
Steady state housing transaction tax	φ	.055
International bond adjustment cost	ψ_B	0.008

Table 4 summarizes the sign restrictions we use. Our identification strategy proceeds as follows. First, we can separate the seven shocks into two groups by examining the correlation between the change in consumption of tradable goods and house prices. This can be seen from Panels a) and b) in Figure 5. Group 1 shocks (housing preferences and savings glut shocks) imply a negative correlation between households' consumption of tradable goods and house prices. Facing a positive housing preferences shock, households prefer housing services more than non-housing goods. 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. The process is similar for savings glut shocks because, when Chinese households want to save more, a house is one of the few assets available to them. The other five shocks (population, credit, TFP, land and tax policy shocks) form group 2. For these shocks, the correlation between house prices and non-housing consumption is positive because these shocks increase aggregate demand for both housing and non-housing (they are all normal goods).

Then, we separate the two shocks in Group 1 by looking at the correlation between house prices and the current account to GDP ratio. This can be seen from Panels a) and c) in Figure 5. A savings glut shock leads to savings, and therefore an increase in the current account to GDP ratio. On the other hand, a housing preferences shock leads to a current account deficit for three reasons: 1) Increases in house prices soften collateral constraints and allow an increase in consumption and imports that generates a current account deficit; 2) Building houses generates imports of tradable goods for construction, appliances, furniture, utilities and related sectors; 3) Residential investment generates reallocation of labor and capital from industries producing tradable goods towards construction and related industries. Countries import tradable goods to replace the goods that used to be produced by the capital and labor reallocated to building houses. Gete (2014) is a quantitative study of the impact of housing demand shocks on the current account and confirms these sign restrictions.

Now we turn to separate 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 land shock from the other shocks in Group 2 we look at the correlation between house prices and residential investment. Only for land shocks this correlation is negative. Intuitively, reductions in the supply of land lead to higher house prices but also to less construction since less land is available. This can be seen from Panels a) and d) in Figure 5.

Then, using the ratio of aggregate consumption to GDP we can separate the credit shock from the other remaining shocks in Group 2. The correlation between that ratio and house prices is positive only for the credit shock. This can be seen from Panels a) and e) in Figure 5. When LTV increases, the credit constrained households borrow more and consume more of both housing and tradable goods. Since they are impatient they have, at the margin, a higher preference for tradable consumption. Thus, conditional on a positive credit shock, aggregate consumption over GDP increases at the same time as house prices. However, population and tax policy shocks imply a negative correlation between house prices and aggregate consumption over GDP. Higher population increases house prices. However, keeping everything else constant, higher population means lower marginal product of labor and thus a negative per capita wealth effect and more savings. This is a robust result from the neoclassical growth model. With population shocks the increase in house prices comes with a reduction in the ratio of aggregate consumption over GDP. The same negative correlation is generated by a tax policy shock. If housing transaction taxes decrease that implies lower house prices net of taxes. Households shift their consumption more towards housing since the tax change has lowered its relative price. Hence the negative correlation of Panels a) and e) in Figure 5. Panels a) and f) show how to separate population from the tax shocks. The reduction in taxes generates more consumable income for households, thus creating a positive correlation between house prices and per capita consumption. As discussed above, this correlation is negative for population since higher population means lower marginal product of labor and higher savings.

Table 4: Sign Restrictions

Variable/Shocks	Population	Credit Shock	Housing Preference	Savings Glut	Permanent TFP	Land Supply	Tax Policy
Consumption	> 0	> 0	< 0	< 0	> 0	> 0	> 0
CA/GDP			< 0	> 0			
House prices	> 0	> 0	> 0	> 0	> 0	> 0	> 0
Residential investment						< 0	
Consumption per capita	< 0	> 0			> 0		> 0
TFP					> 0		
Consumption/GDP							< 0

Note: Section 4 discusses the sign restrictions.

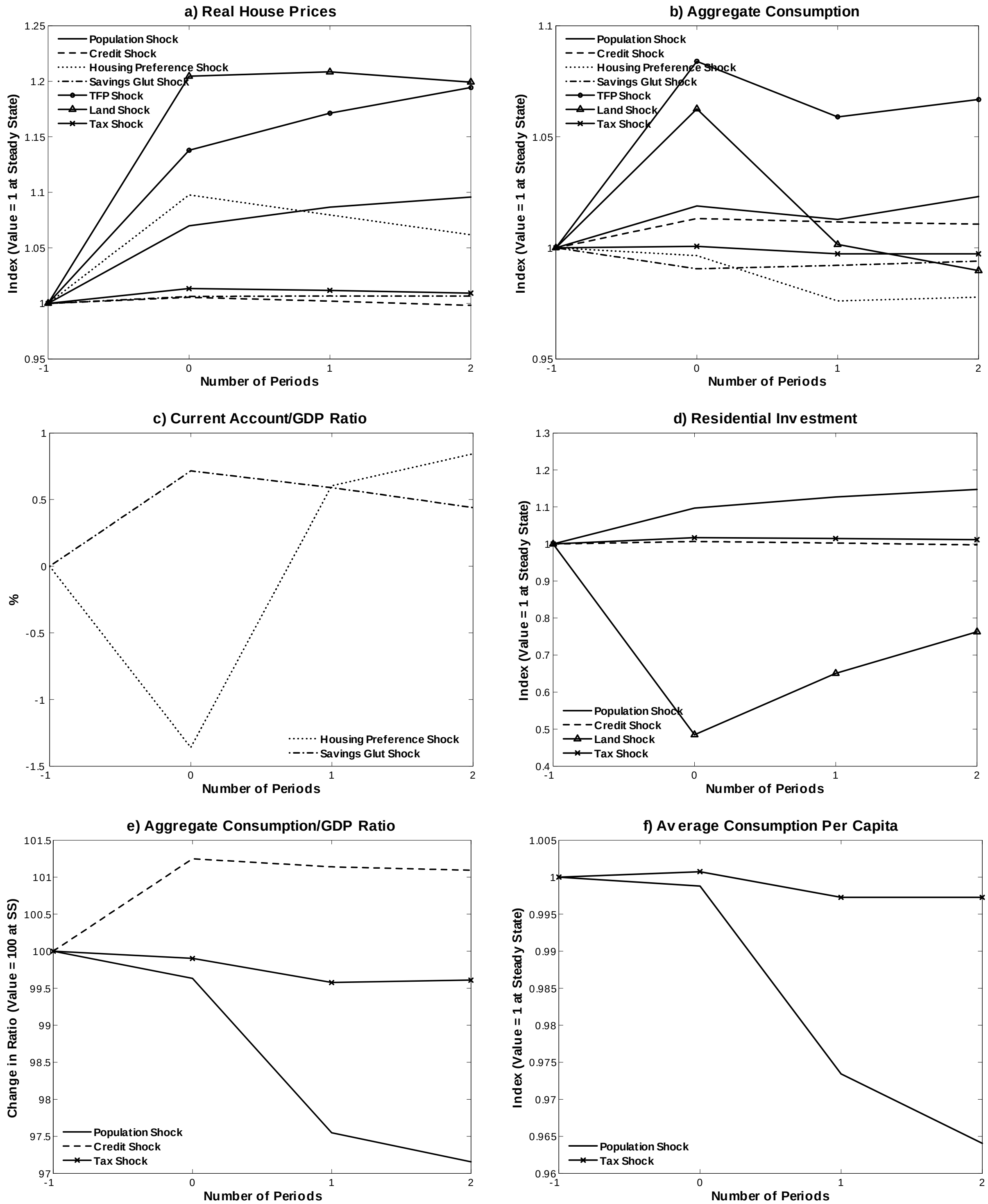

Figure 5: Impulse responses in the model to shocks that increase house prices.

5 Sign restriction SVARs

In this section we estimate the VARs, impose the sign restrictions and discuss the results.

5.1 Methodology

We follow an efficient algorithm proposed by Rubio-Ramirez et al. (2005) to implement the sign restriction methodology. First, we estimate a reduced-form VAR with log of aggregate consumption of nondurables, the current account to GDP ratio, log of house prices, log of residential investment, log of per capita consumption of nondurables, log of TFP, log of the volume of housing transactions (volume of housing space sold), and the ratio of aggregate consumption to GDP.[6] Appendix I lists our data sources. All variables are in real terms and seasonally adjusted. For the house prices we compare different house price indices. These indices start from different dates and are discussed in Appendix II. We use the 70 Cities and the Average Selling Price Indices (quarterly data from 1999Q1 to 2014Q3), as well as the Centaline Index (data available from 2007Q1 to 2014Q3), the Residential Land Index (for which we have data from 2004Q1 to 2014Q3), and the Quality Controlled Index (data available from 2006Q1 to 2014Q3). We checked different information criteria to choose lag length, and two lags were enough to adequately capture the dynamics of the data when using data since 1999, one lag when using the shorter samples. 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. We estimate the following VAR in companion form

$$Y_t = BY_{t-1} + u_t. \tag{42}$$

The goal of any Structural Vector Autoregression is to map the reduced-form forecast errors (u_t) into structural shocks (ε_t) with economic meaning, and orthogonality between them.[7] If the link between reduced-form and structural shocks is

$$u_t = A\varepsilon_t, \tag{43}$$

[6] TFP is computed as

$$\log(TFP) = \log(Real\ GDP) - \alpha \log(Employment),$$

where α is the labor share of output assumed to be 0.66.

[7] Their variance-covariance matrix is the identity matrix, $E(\varepsilon_t \varepsilon_t') = I$.

then the objective of a SVAR is to characterize the matrix A.[8] Once A is identified we can study the effect of the structural shocks on the economic variables of interest. Recursive (Cholesky) identification assumes that A is lower triangular, but it is hard to justify that assumption in a model of housing markets. The sign restrictions methodology identifies a set of A matrices consistent with the theoretical signs of the impulse responses to the structural economic shocks, which are contained in Table 4 of this paper. These impulse responses are

$$\frac{\partial Y_{t+j}}{\partial \varepsilon_t} = B^j A, \tag{44}$$

where j is the period of the impulse response in question. In the results that we present in Section 5.2, we imposed the restrictions for two periods.[9] We checked restrictions imposed for one, three and four periods and found similar results. In Section 5.2 we follow the common procedure in the literature and show the results for the median of our set of A matrices (see for example Charnavoki and Dolado 2014).

5.2 Results

Tables 5 to 11 report the percentage of the variance of the forecasting error that is attributable to the different shocks. The tables differ in the price indices and samples used. For the 70 Cities Index and the Average Selling Price Index we compute decompositions using the full sample (Tables 5 and 7), and then, in Tables 6 and 8, using the shorter sample (2007Q1 to 2014Q3) on which the Centaline Index (Table 9) is available. Finally, Tables 10 and 11 contain the results for Residential Land Index and the Quality Controlled Index, respectively.

All tables report the results for real house prices, residential investment and volume of housing transactions at forecast errors of 1 and 3 years. All tables suggest that, even if all shocks are relevant to explain housing variables, productivity (our proxy for income), savings glut (housing as a store of value), and tax policies (a proxy for government intervention in housing markets) are the key drivers. Productivity and land shocks affect housing quantities more than prices, while tax policies and savings glut shocks affect house prices more than quantities. When the sample is closer to 2014, housing preferences and credit shocks increase their importance to explain house prices and volume, while population shocks increase their

[8] The matrix A is unique up to an orthonormal transformation, that is, wherever $QQ' = I$ then $E(u_t u_t') = AQQ'A'$.

[9] We use the following algorithm of Rubio-Ramirez et al. (2010). 1) Compute $E(u_t u_t') = \Sigma$, and assume $A = chol(\Sigma)$. 2) Draw a matrix X, whose cells come from a standard normal distribution. 3) Compute the QR decomposition of X. 4) Normalize the diagonal of R to be positive and check if AQ satisfies the sign restrictions. If it does, keep AQ, if not discard and draw again. 5) Keep drawing until obtaining 100 successes.

importance to explain residential investment (Table 5 vs. Table 6, and Table 7 vs. Table 8). Finally, the 70 Cities Index assigns less importance to credit shocks and to preferences shocks than the non-official indices. This is consistent with the evidence from Tables 1 and 2 that the growth rates of the different house price indices are not perfectly correlated.

Figure 6 reports the historical decomposition for the different house price indices. That is, we allocate the changes in house prices among the different structural shocks. The figure graphically confirms the importance of government intervention policies as drivers of housing markets.

Table 5: Variance Decompositions Using 70 Cities Index (1999Q1 to 2014Q3)

	Real House Prices		Residential Investment		Volume	
Forecast Horizon :	*1 Year*	*3 Years*	*1 Year*	*3 Years*	*1 Year*	*3 Years*
Population	3.6%	7.3%	10.1%	7.1%	8.6%	9.2%
Credit shock	7.8%	7.1%	12.8%	12.4%	7.4%	8.4%
Housing preferences	4.6%	4.9%	11.7%	9%	7.7%	8.6%
Savings glut	16.2%	12.7%	5.4%	5.9%	9.2%	10.3%
TFP	7.2%	11.5%	12.8%	20.8%	10.8%	13.2%
Land Supply	5%	5.4%	7.9%	7.1%	8.4%	7.6%
Tax Policy	13.9%	14.8%	9.5%	15.8%	12.4%	12.4%

Note: Quarterly data from 1999Q1 to 2014Q3.

Table 6: Variance Decompositions Using 70 Cities Index (2007Q1 to 2014Q3)

	Real House Prices		Residential Investment		Volume	
Forecast Horizon :	*1 Year*	*3 Years*	*1 Year*	*3 Years*	*1 Year*	*3 Years*
Population	5.9%	7.8%	15.8%	6.1%	14.1%	15%
Credit shock	8.1%	9.4%	7.3%	9.1%	5.6%	8.8%
Housing preferences	7.5%	5.8%	3.4%	3.6%	8.1%	7.8%
Savings glut	11.3%	8.1%	8.3%	7.2%	8.5%	10.8%
TFP	12.5%	15.4%	14.1%	18%	12.5%	12.6%
Land Supply	6.1%	7.4%	14.2%	10.9%	10.5%	11.1%
Tax Policy	17.8%	16.4%	15.9%	14.8%	8.6%	9.8%

Note: Quarterly data from 2007Q1 to 2014Q3.

Table 7: Variance Decompositions Using Average Selling Price (1999Q1 to 2014Q3)

	Real House Prices		Residential Investment		Volume	
Forecast Horizon :	*1 Year*	*3 Years*	*1 Year*	*3 Years*	*1 Year*	*3 Years*
Population	6.6%	8.2%	6.3%	5.3%	8.4%	8.6%
Credit shock	10.7%	10.8%	9.2%	9.1%	8.7%	9.8%
Housing preferences	4.3%	5.2%	8.4%	6.3%	5.1%	5.4%
Savings glut	10.1%	11.3%	7%	7.7%	16.3%	17.2%
TFP	12.2%	11.7%	17.3%	24%	12.2%	14.1%
Land Supply	7.8%	8.4%	7.4%	6.5%	6.3%	7.9%
Tax Policy	19.3%	19.1%	9.2%	18.9%	11.6%	11.8%

Note: Quarterly data from 1999Q1 to 2014Q3.

Table 8: Variance Decompositions Using Average Selling Price (2007Q1 to 2014Q3)

	Real House Prices		Residential Investment		Volume	
Forecast Horizon :	*1 Year*	*3 Years*	*1 Year*	*3 Years*	*1 Year*	*3 Years*
Population	5.9%	8.8%	19.7%	7.4%	16.4%	16.1%
Credit shock	16.4%	12.7%	10.7%	12.4%	10.7%	9.5%
Housing preferences	10.4%	9.4%	2.9%	4.9%	11.1%	10.4%
Savings glut	4.1%	5.6%	8.9%	7.1%	3.6%	6.2%
TFP	21%	16.3%	12.9%	12.7%	15.4%	12%
Land Supply	5.5%	8.9%	8.9%	7.6%	20%	17.4%
Tax Policy	27%	25.1%	19.2%	25.8%	4.3%	8.7%

Note: Quarterly data from 2007Q1 to 2014Q3.

Table 9: Variance Decompositions Using Centaline Index (2007Q1 to 2014Q3)

	Real House Prices		Residential Investment		Volume	
Forecast Horizon :	*1 Year*	*3 Years*	*1 Year*	*3 Years*	*1 Year*	*3 Years*
Population	6.8%	5.3%	10%	4.9%	7.6%	8.9%
Credit shock	19.9%	15.2%	15.6%	11%	19.8%	18.4%
Housing preferences	9.6%	7.6%	2.3%	3.5%	5.3%	8.5%
Savings glut	11%	11.2%	6.5%	7.9%	6.7%	10%
TFP	11%	14%	15.6%	21%	8.2%	10.7%
Land Supply	4.7%	4.1%	9.2%	8.4%	15.6%	11.8%
Tax Policy	29%	26.3%	23.1%	23%	8.3%	12.4%

Note: Quarterly data from 2007Q1 to 2014Q3.

Table 10: Variance Decompositions Using Residential Land Index (2004Q1 to 2014Q3)

	Real House Prices		Residential Investment		Volume	
Forecast Horizon :	*1 Year*	*3 Years*	*1 Year*	*3 Years*	*1 Year*	*3 Years*
Population	8.2%	9.4%	16.4%	10.1%	7.4%	10%
Credit shock	9.1%	8.3%	14.8%	15.7%	20.5%	18.3%
Housing preferences	15.4%	14.7%	6%	9.3%	13.6%	14.1%
Savings glut	22.1%	20.2%	4.4%	3.9%	5.6%	5.8%
TFP	9.9%	12.4%	15%	17.9%	15.6%	14.3%
Land Supply	9.5%	9.3%	4.2%	6.2%	6.8%	7.5%
Tax Policy	16.8%	9.4%	16.3%	19.4%	5.8%	6.8%

Note: Quarterly data from 2004Q1 to 2014Q3.

Table 11: Variance Decompositions Using Quality Controlled Index (2006Q1 to 2014Q3)

	Real House Prices		Residential Investment		Volume	
Forecast Horizon :	*1 Year*	*3 Years*	*1 Year*	*3 Years*	*1 Year*	*3 Years*
Population	2.9%	5.1%	7.7%	4.6%	10.2%	7.9%
Credit shock	4.3%	6.2%	17.7%	17.3%	8.5%	9.6%
Housing preferences	7%	7.7%	3.2%	4%	8.8%	8.6%
Savings glut	10%	10%	8.6%	6.9%	5.3%	9.3%
TFP	10.6%	14.2%	21.8%	22.6%	13.9%	12.8%
Land Supply	6.8%	6.3%	6.1%	6.4%	6.5%	7.1%
Tax Policy	35.2%	31.8%	17.1%	20.9%	12.4%	13.6%

Note: Quarterly data from 2006Q1 to 2014Q3.

6 Conclusions

In this paper we used vector autoregressions to study seven shocks usually discussed as drivers of Chinese housing dynamics. We identified the shocks using sign restrictions consistent with a standard DSGE model of housing markets. Our results suggest that, even if all shocks are relevant to explain housing variables, productivity (our proxy for income), savings glut (housing as a store of value), and tax policies (a proxy for government intervention in housing markets) are the key drivers. Productivity and land shocks affect housing quantities more than prices, while tax policies and savings glut shocks affect house prices more than quantities. When the sample is closer to 2014, housing preferences and credit shocks increase their importance to explain house prices and volume, while population shocks explain a larger share of the dynamics of residential investment. The official indices show smaller increases in house prices and assign a smaller role to credit and preferences shocks than the non-official indices.

Acknowledgements

We thank Wayne Archer, Matt Canzoneri, Behzad Diba, Christian Fernando, Rahul Kaul, William Lastrapes, Yongping Liang, Clark DuMontier, Guangyu Nie, Michael Reher, Natalie Tiernan, Jun Tu, Rossen Valkanov, Fan Dora Xia, Tony Yezer, anonymous referees and seminar participants at the 2014 ARES Annual Meeting, 2014 AREUEA National Conference, 2014 China International Conference in Finance and 2014 Chinese Economist Society North America, University of International Business and Economics, Nanjing University, Hunan University and Wuhan University for comments. We thank Peijing Qin for providing data and Chuqiao Bi for excellent research assistance.

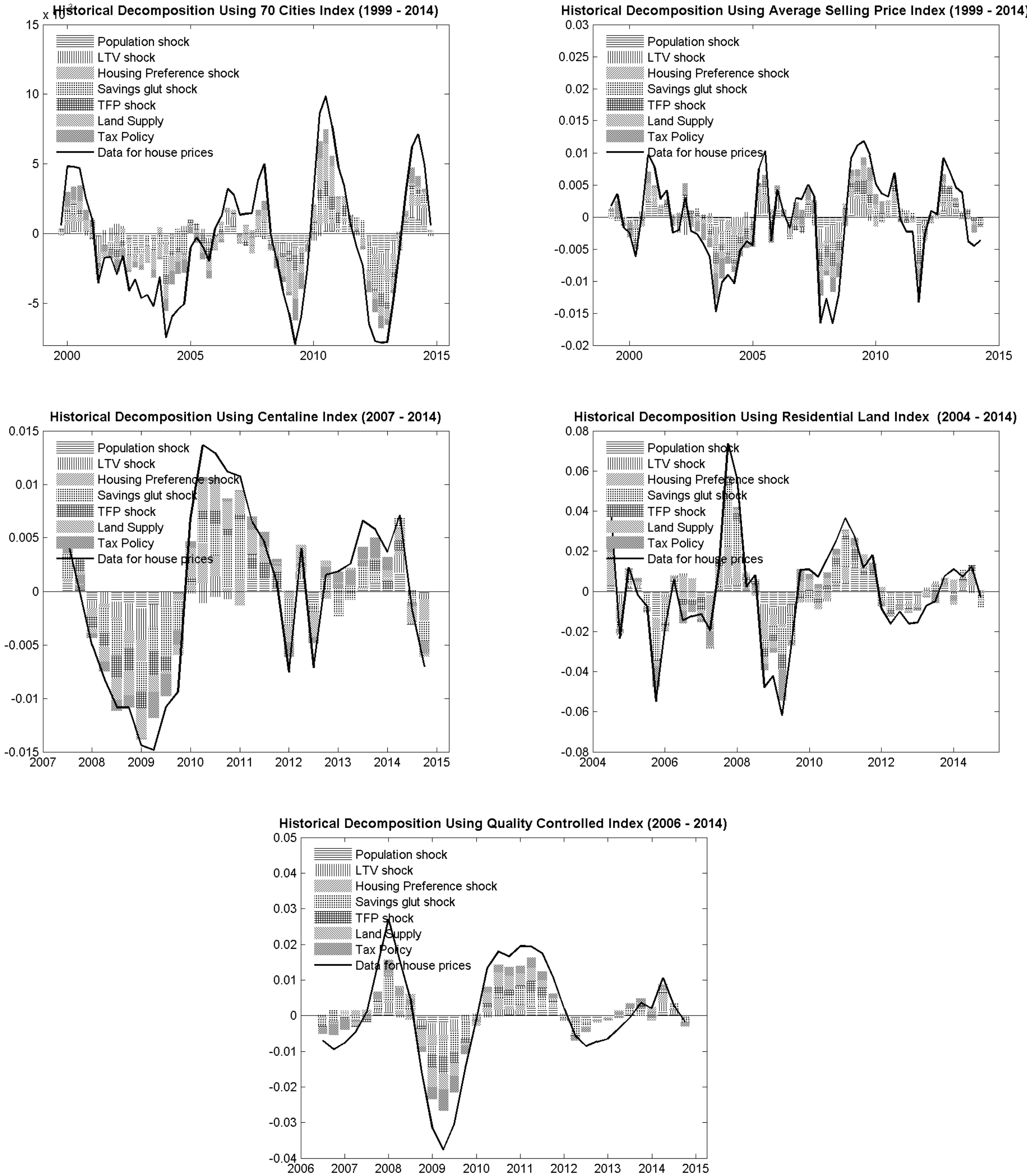

Figure 6: Historical decompositions using different price indices.

References

Ahuja, A., Cheung, L., Han, G., Porter, N. and Zhang, W.: 2010, "Are House Prices Rising too Fast in China?", *IMF Working Papers* pp. 1–31.

Bai, C., Li, Q. and Ouyang, M.: 2013, "Property Taxes and Home Prices: A Tale of Two Cities", *Journal of Econometrics* .

Barth, J., Lea, M. and Li, T.: 2012, "China's Housing Market: Is a Bubble about to Burst?".

Bernanke, B.: 2005, "The Global Saving Glut and the US Current Account Deficit", *Sandridge Lecture* .

Canova, F. and Nicoló, G. D.: 2002, "Monetary Disturbances Matter for Business Fluctuations in the G-7", *Journal of Monetary Economics* **49**(6), 1131–1159.

Charnavoki, V. and Dolado, J. J.: 2014, "The Effects of Global Shocks on Small Commodity-Exporting Economies: Lessons from Canada", *American Economic Journal: Macroeconomics* **6**(2), 207–237.

Chen, K. and Wen, Y.: 2014, "The Great Housing Boom in China".

Davis, M. and Heathcote, J.: 2005, "Housing and the Business Cycle", *International Economic Review* **46**(3), 751–784.

Deng, Y., Gyourko, J. and Wu, J.: 2012, "Land and Housing Price Measurement in China", Reserve Bank of Australia.

Faust, J. and Rogers, J. H.: 2003, "Monetary Policy's Role in Exchange Rate Behavior", *Journal of Monetary Economics* **50**(7), 1403–1424.

Favilukis, J., Ludvigson, S. C. and Van Nieuwerburgh, S.: 2010, "The Macroeconomic Effects of Housing Wealth, Housing Finance, and Limited Risk-Sharing in General Equilibrium", NBER.

Fawley, B. W. and Wen, Y.: 2013, "The Great Chinese Housing Boom", *Economic Synopses* .

Ferrero, A.: 2015, "House Price Booms, Current Account Deficits, and Low Interest Rates", *Journal of Money, Credit and Banking* **47**(S1), 261–293.

Financial Times: 3/11/2010, "Fears of China Property Bubble Grow".

Forbes: 6/17/2013, "China: Massive Credit Bubble Fueled by Shadow Banking and Securitization Could Collapse Banks".

Fratzscher, M. and Straub, R.: 2013, "Asset Prices, News Shocks, and the Trade Balance", *Journal of Money, Credit and Banking* **45**(7), 1211–1251.

Garriga, C., Tang, Y. and Wang, P.: 2014, "Rural-Urban Migration, Structural Transformation, and Housing Markets in China", *Federal Reserve Bank of St. Louis Working Paper Series* (2014-028).

Gete, P.: 2014, "Housing Markets and Current Account Dynamics".

Glindro, E. T., Subhanij, T., Szeto, J. and Zhu, H.: 2011, "Determinants of House Prices in Nine Asia-Pacific Economies", *International Journal of Central Banking* **7**(3), 163–204.

Heathcote, J., Storesletten, K. and Violante, G. L.: 2009, "Quantitative Macroeconomics with Heterogeneous Households", *Annual Review of Economics* **1**(1), 319–354.

Iacoviello, M.: 2005, "House Prices, Borrowing Constraints, and Monetary Policy in the Business Cycle", *American Economic Review* (95 (3)), 739–764.

Iacoviello, M. and Neri, S.: 2010, "Housing Market Spillovers: Evidence from an Estimated DSGE Model", *American Economic Journal: Macroeconomics* **2**(2), 125–164.

Justiniano, A., Primiceri, G. E. and Tambalotti, A.: 2015, "Household Leveraging and Deleveraging", *Review of Economic Dynamics* **18**(1), 3–20.

Kahn, J. A.: 2008, "What Drives Housing Prices?", Staff Report, Federal Reserve Bank of New York.

Lastrapes, W. D.: 2002, "The Real Price of Housing and Money Supply Shocks: Time Series Evidence and Theoretical Simulations", *Journal of Housing Economics* **11**(1), 40–74.

Moro, A. and Nuño, G.: 2012, "Does Total-Factor Productivity Drive Housing Prices? A Growth-Accounting Exercise for Four Countries", *Economics Letters* **115**(2), 221–224.

Musso, A., Neri, S. and Stracca, L.: 2011, "Housing, Consumption and Monetary Policy: How Different Are the US and the Euro Area?", *Journal of Banking & Finance* **35**(11), 3019–3041.

Punzi, M. T.: 2013, "Housing Market and Current Account Imbalances in the International Economy", *Review of International Economics* **21**(4), 601–613.

Ren, Y., Xiong, C. and Yuan, Y.: 2012, "House Price Bubbles in China", *China Economic Review* **23**(4), 786–800.

Rubio-Ramirez, J. F., Waggoner, D. F. and Zha, T.: 2010, "Structural Vector Autoregressions: Theory of Identification and Algorithms for Inference", *The Review of Economic Studies* **77**(2), 665–696.

Rubio-Ramirez, J., Waggoner, D. and Zha, T.: 2005, "Markov-Switching Structural Vector Autoregressions: Theory and Application".

Sá, F. and Wieladek, T.: 2015, "Capital Inflows and the U.S. Housing Boom", *Journal of Money, Credit and Banking* **47**(S1), 221–256.

Schmitt-Grohé, S. and Uribe, M.: 2003, "Closing Small Open Economy Models", *Journal of International Economics* **61**(1), 163–185.

Sharpe, A.: 2001, "Productivity Trends in the Construction Sector in Canada: A Case of Lagging Technical Progress", *International Productivity Monitor* **3**, 52–68.

Sims, C., Stock, J. and Watson, M.: 1990, "Inference in Linear Time Series Models with Some Unit Roots", *Econometrica* **58**(1), 113–144.

Siniavskaia, N.: 2008, "Spending Patterns of Home Buyers", National Association of Home Builders.

The Economist: 7/1/2013, "The Credit Kulaks".

The Wall Street Journal: 10/9/2013, "Chinese Think Tank Puts Shadow Banking at 40 percent of GDP".

Uhlig, H.: 2005, "What Are the Effects of Monetary Policy on Output? Results from an Agnostic Identification Procedure", *Journal of Monetary Economics* **52**(2), 381–419.

Vargas-Silva, C.: 2008, "Monetary Policy and the US Housing Market: A VAR Analysis Imposing Sign Restrictions", *Journal of Macroeconomics* **30**(3), 977–990.

Wang, S., Yang, Z. and Liu, H.: 2011, "Impact of Urban Economic Openness on Real Estate Prices: Evidence from Thirty-five Cities in China", *China Economic Review* **22**(1), 42–54.

Wang, Z. and Zhang, Q.: 2014, "Fundamental Factors in the Housing Markets of China", *Journal of Housing Economics* .

Wei, S.-J., Zhang, X. and Liu, Y.: 2012, "Status Competition and Housing Prices", National Bureau of Economic Research.

World Bank: 2005, "China: Land Policy Reform for Sustainable Economic and Social Development".

Wu, J., Deng, Y. and Liu, H.: 2013, "House Price Index Construction in the Nascent Housing Market: The Case of China", *The Journal of Real Estate Finance and Economics* pp. 1–24.

Wu, J., Gyourko, J. and Deng, Y.: 2012, "Evaluating Conditions in Major Chinese Housing Markets", *Regional Science and Urban Economics* **42**(3), 531–543.

Xu, Y. and Yu, S.: 2012, "Total Factor Productivity among Cities in China: Estimation and Explanation", The Conference Board, Economics Program.

Yang, D. T., Zhang, J. and Zhou, S.: 2011, "Why Are Saving Rates so High in China?", National Bureau of Economic Research.

Zhang, Y., Hua, X. and Zhao, L.: 2012, "Exploring Determinants of Housing Prices: A Case Study of Chinese Experience in 1999–2010", *Economic Modelling* **29**(6), 2349–2361.

Appendix I. Data sources

a) Series from Datastream: Gross Domestic Product (CHGDP...A); Consumer Price Index (CHQCP009F); Current Account Balance (CHBPQCURA); Urban Population (CHURBPOP); Urban Employed Persons (CHEMPALLP); Real Estate Development - Residential Building (CHINVHRCA).

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).

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) Residential Land Price Index from Wu et al. (2012).

e) Quality-Controlled Index from the Hang Lung Center for Real Estate at Tsinghua University.

Appendix II. House price indices

There are several house price indices available in China. Some are published by the government while others by private organizations. Here we discuss those indices that we use:

1) Price Index of Newly Constructed Residential Buildings in 70 Cities ("The 70 Cities Index") published by the National Bureau of Statistics (NBS). This index has been published since 1998. Until 2005 it covered 35 major cities. Since 2005 it has covered 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 has been published monthly. It uses a matching approach to control for quality changes (see Wu et al. 2013 for a discussion of the methodology).[10]

2) Average Selling Price of Newly Constructed Residential Buildings ("The Average Selling

[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 the city level is then calculated as the average (weighted by transaction volume) of all complexes' growth rates in the corresponding month.

Price Index"). This index has also been published by the NBS since 1998. 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 has collected data directly from local housing authorities (who have all housing transaction records). Since July 2005, the NBS has also published a price index for secondary transactions in residential buildings.

3) Since 2005 the real estate developer Centaline Group has published its own house price indices ("the Centaline Indices") for Shanghai, Beijing, Guangzhou, Shenzhen and Tianjin based on secondary transaction data. Since 2012 Chengdu is also included. We constructed a national index by averaging house price growth rates across these different cities.

4) Some Chinese scholars and institutes have built their own house price indices. For example, the PKU–Lincoln Institute Center for Urban Development and the Hang Lung Center for Real Estate at Tsinghua University jointly publish a urban house price index ("the Quality-Controlled Index"). It is a quarterly index which starts from 2006 and covers eight urban housing markets: Beijing, Shanghai, Tianjin, Shenzhen, Chengdu, Dalian, Wuhan, and Xi'an (Wu et al. 2013).

5) Wu et al. (2012) collected data on residential land sales in 35 cities since 2004. Since 2013, every quarter they publish the Wharton/NUS/Tsinghua Chinese Residential Land Price Indices ("Residential Land Price Index").