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Monetary policy, hot money and housing price growth across Chinese cities

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ABSTRACT

We use a dynamic hierarchical factor model to identify the national, regional and local factors of the city-level housing price growth in China. During the zero-lower-bound (ZLB) episode in the U.S., local factors account for 78% of variations in the month-on-month city-level housing price growth. However, as the time horizon extends, the national factor gets a larger variance share, reaching 51% in a half-year horizon. This indicates that the city-level housing price growth in China is more of a national phenomenon in the long run. We then use a VAR model to investigate the driving forces of the national factor and find that monetary policy and hot money shocks affect the national housing price growth significantly. A tightening monetary policy shock has a significant negative impact on the national factor, which lasts for more than 2 years. An increase in hot money inflows causes a significant but transitory rise in the national factor. Moreover, we find that the quantitative easing measure adopted by the U.S. Fed is behind the surge of capital inflows into China.

KEYWORDS

Housing price; monetary policy; hot money; dynamic factor model

JEL CLASSIFICATION

E43; E52; E58; F32; R31; C11; C32

I. Introduction

Since the new millennium, housing prices in China have increased dramatically. In China's top cities, real prices grew by 13.1% annually from 2003 to 2013 (Fang et al. (2016)). Real land prices in 35 large Chinese cities increased almost five-fold between 2004 and 2015 (Jing, Gyourko, and Deng (2016)). Real estate construction is also in full swing. Between 2003 and 2014, Chinese builders added 100 billion square feet of floor space or 74 square feet for every person in China (Glaeser et al. (2017)). As a contrast, the U.S. housing boom before the 2007–08 financial crisis, with a real price growth rate of 5% per year,[1] looks gentle and dull. Figure 1 illustrates the real housing prices from June 2005 to April 2015 in the four so-called 'first-tier' cities in China – Beijing, Shanghai, Guangzhou and Shenzhen. Take Beijing as an example, the average real housing price in Beijing increased by more than 5 times from June 2005 to March 2014. In certain areas, such as areas with good school districts, the prices have increased even more. This rapid rise in housing prices was not peculiar to big cities. Figure 2 reports the ratio of the highest to the lowest housing prices during the sample period (2005M6–2015M4) for 70 major cities in our data set. We can see that on average, housing prices across cities almost tripled in the decade. Even housing prices in third- and fourth-tier cities witness growth rates of 70% and more, almost the same growth rate as that during the U.S. housing boom.

The property prices in China soared against the backdrop of a flood of global liquidity. Since the outbreak of financial crisis in 2007, the global economy has witnessed a cascade of policy interventions by central banks around the world. After lowering policy rates to close to the zero lower bound (ZLB, henceforth), the United States Federal Reserve announced a hitherto unprecedented policy of unconventional monetary intervention, involving a 600 USD billion purchase of mortgage-backed securities. As a response to the crisis, the central banks of other major economics also followed suit. This unconventional monetary policy measure, also known as quantitative easing, has raised the concern about the global impact of excessive liquidity, especially on emerging market economies (EMEs). For example, Brazil's President

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[1]The data comes from Federal Housing Finance Agency.

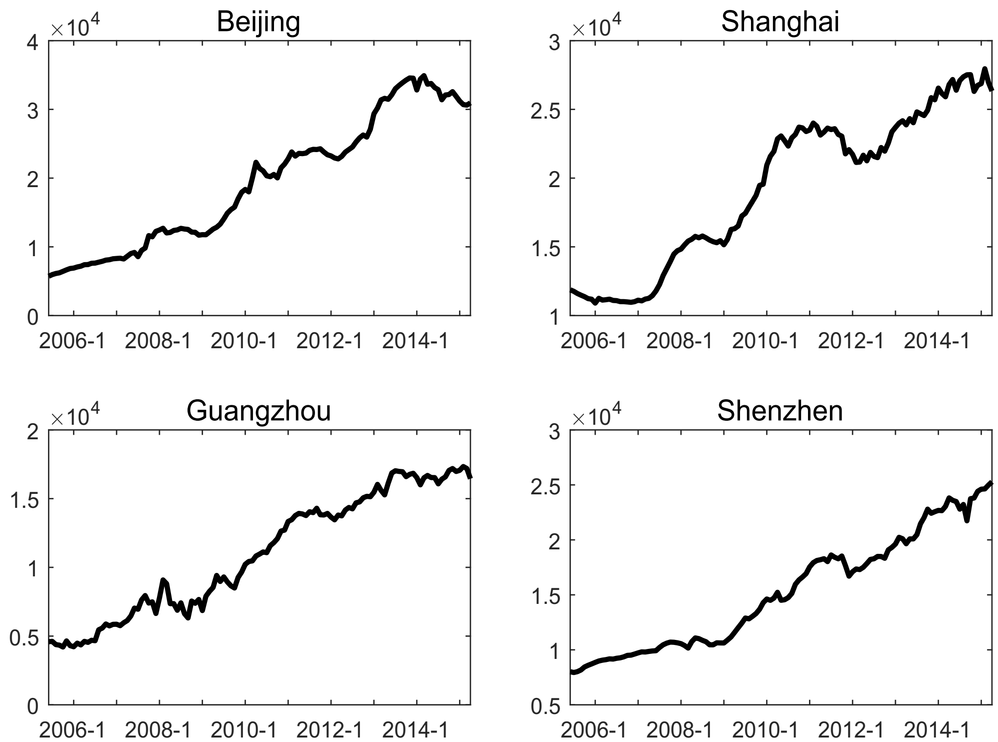

Figure 1. Housing prices in Beijing, Shanghai, Guangzhou and Shenzhen. Note: The sample period is from June 2005 to April 2015. Housing prices are converted to 2005 CNY and are seasonally adjusted.

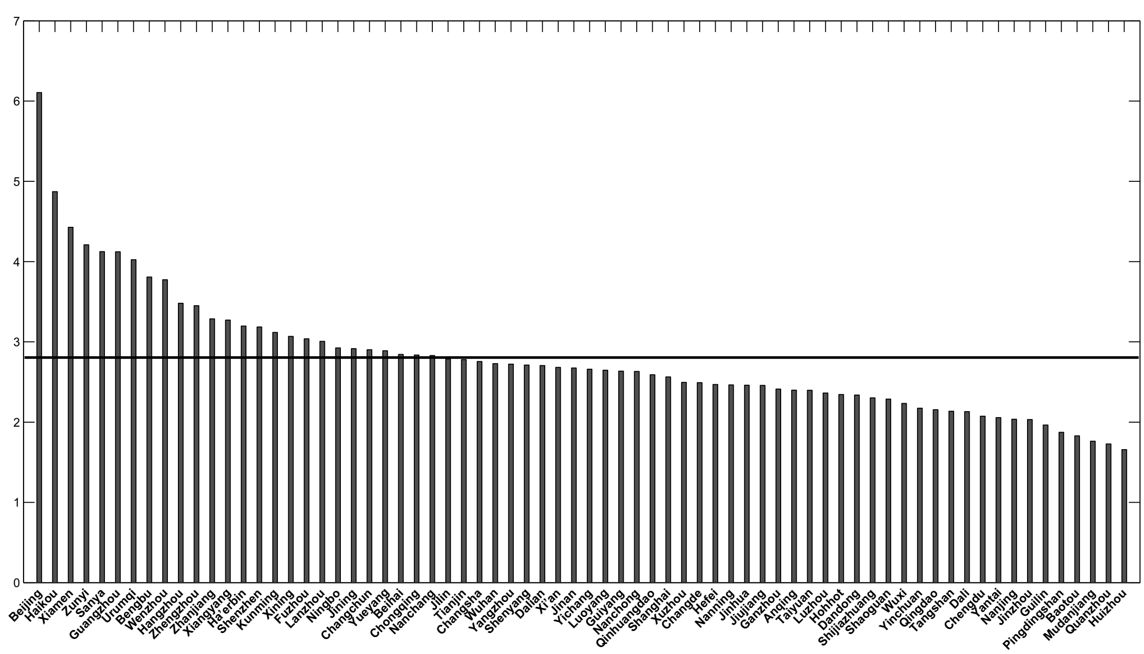

Figure 2. Housing price increase across cities. Note: For each city, the vertical grey bar indicates the ratio of its highest to lowest housing price during June 2005–April 2015. All housing prices are converted to 2005 CNY and are seasonally adjusted. The horizontal line corresponds to the average value.

Rousseff criticized the Fed's policies, arguing that these have caused the massive acceleration of capital flows to EMEs between 2009 and 2012. These capital inflow surges, or the so-called 'hot money', are usually in the form of short-term portfolio investment, which can be reversed quickly and easily. These cross-border capital flows are widely blamed for appreciation pressures on EME currencies, financial imbalances, credit expansion and a built-up of asset price bubbles in EMEs (Blanchard et al. (2010), Rose and Spiegel (2011), Lim, Mohapatra, and Stocker (2014), Fratzscher, Duca, and Straub (2018), Ho, Zhang, and Zhou (2018)). China, as one of the major emerging economies which had maintained years of high return on capital investment and strong economic growth, appeared to be an attractive investment destination for these overseas hot money. According to Zhang and Huang (2011), inflows of the hot money accelerated after the 2007–08 financial crisis. According to their calculation, hot money surged after the crisis, and the average size between 2008 and 2010 is 178 USD billion, more than twice before the crisis (the average size between 2003 and 2007 is 86 USD billion).

The outbreak of financial crisis triggered a shift in Chinese monetary policy. To reinvigorate its economy, China exited from its moderately tight monetary policy that has been adopted since 2003 and switched to an expansionary monetary policy in November 2008. These measures include cutting done the interest rates to a historical low level, lowering bank reserve requirement ratios, removing quota control on lending by commercial banks, etc. The loosening monetary policy fuels the flames of the real estate market in China.

The financial crisis brought about a loose credit condition internationally and domestically. On one hand, the unconventional monetary policy in the U.S. and other major economics created excessive hot money, which seek for investment alternatives in EMEs. On the other hand, the loosening monetary policy resulted in an easier access to credit in domestic market. Since the growth of housing prices across Chinese cities has been sizable in that period, we are curious about what is behind the rapid increase. Admittedly there are many reasons leading to housing boom, but here we focus on two factors: hot money and monetary policy, which are of especially importance in this ZLB episode. Therefore, in this article, we try to quantify the contributions of these two forces to the growth of housing prices across major Chinese cities and to understand their interplay in Chinese economy.

A handful of literature laid down the theoretical foundation about how hot money and monetary policy contribute to a rise in housing price. In terms of hot money, one of the most influential channel is the so-called *global savings glut* hypothesis, pioneered by Bernanke (2005). This hypothesis argues that the large increase in overseas capital, also referred as *global savings glut*, flows to the U.S. Treasury markets and thus drove down the long-term real rates. These large capital inflows and low-interest rates directly lead to investor's appetite for alternative investment, such as real estate projects, resulting in a housing price bubble. Lots of literature use this channel to explain the source of the U.S. housing boom since 2000 (Himmelberg, Mayer, and Sinai (2005), Bernanke (2007), Caballero, Farhi, and Gourinchas (2008), Mendoza, Quadrini, and Jose-Victor (2009), Caballero and Krishnamurthy (2009), Bernanke (2010)), Adam, Kuang, and Marcet (2012), Taylor (2013), etc.).

In terms of monetary policy, by raising or lowering short-term interest rates, monetary policy affects the housing market directly or indirectly through several channels. These channels, as summarized by Mishkin (2007), include the user cost of capital channel (Jorgenson (1963), Poterba (1984)), expectation channel (Case and Shiller (2003)), the supply channel (McCarthy and Peach (2004)) and the credit channel (Kearl (1979), Hendershott, Bosworth, and Jaffee (1980)). Among them, the user cost of capital channel is one of the most direct and important channel of monetary policy transmission. According to the standard neoclassical models of housing activity, the user cost of capital is increasing in mortgage rate and decreasing in the expected rate of appreciation of housing prices.[2] When monetary policy raises short-term interest

[2]The formulation of the user cost of capital can be written as: $uc = ph[(1-t)i - \pi_h^e + \delta]$, where ph is the relative purchase price of new housing capital, i is the mortgage rate, π_h^e is the expected rate of appreciation of housing prices, and δ is the depreciation rate for housing.

rates, long-term mortgage rates also tend to rise because they are linked to expected future short-term rates; consequently, the user cost of capital rises and the demand for housing falls, leading to a decline in housing prices.

The literature above supports theoretically the significant roles hot money and monetary policy play on real estate market. In this article, we quantitatively investigate their impacts on Chinese housing markets during the ZLB period. Our quantitative analysis consists of two steps. In the first step, we use a purely statistical factor model to distinguish the component of the fluctuations of the city-level housing prices that are common to all cities from those that are idiosyncratic to some regions or local cities. The common component is meant to capture the comovement of housing prices across cities. This decomposition helps us identify the drivers behind the increases in city-level housing prices. In other words, the housing boom is more of a national phenomenon or a collection of local bubbles? In this step, we avoid making too many a priori assumptions on the factors. Instead, all the factors, common and idiosyncratic factors, are latent variables, which are inferred from the data. After having obtained an estimate of the common factor from the statistical model, in the second part we explore what is behind this comovement of housing prices. We restrict attention to the ZLB episode (2009–2015) after the financial crisis, during which the U.S. Fed launched three rounds of quantitative easing. In particular, we focus on the role of hot money and monetary policy in this housing price comovement. Specifically, we adopt a vector autoregression (VAR) model to quantify the extent to which the shocks of hot money and monetary policy account for the increases in house prices.

We summarize our findings as follows. First, the national factor accounts for 18% of the fluctuations of the monthly city-level housing prices, while the local factor reaches 78%. Most of the movements in housing prices are still driven by the local factors. It is not surprising since the housing price in each city most relates to the local economic development and characteristics. However, when we extend the time horizon of housing price growth rate from 1 month to half a year, the variance share of national factor soars to 51%, indicating a prominent comovement of city-level housing prices in longer horizon. Moreover, we also examined the heterogeneity of housing price dynamics for each city. For the majority of cities, the national factor has become increasingly important in accounting for the fluctuations of housing prices during the ZLB episode compared with the period before the crisis. These results indicate that the city-level housing price growth in China has become more of a national phenomenon in recent years. Second, monetary policy and hot money flows have significant impacts on this comovement of housing price growth, which is represented by the national factor estimated using the dynamic factor model. More specifically, a tightening monetary policy shock has a significant negative impact on the national factor, which lasts for more than 2 years. An increase in hot money inflows does cause a significant increase in the national factor, but this effect is transitory and reverses in half a year. The inflation shock also induces an immediate increase in national factor, nevertheless followed by a significant drop 2 months later. The reversed effects of hot money and inflation shocks on the national factor can be explained by the monetary tightening induced by these shocks. Moreover, using Wu-Xia shadow rate as an extension of the effective federal fund rate during the ZLB period, we find that the quantitative easing measure indeed induces a surge of capital inflows into China, which then leads to a significant increase in housing prices. This finding is consistent with that of Ho, Zhang, and Zhou (2018), who focus on the spillover effect of the U.S. monetary policy on Chinese economy and suggest that hot money can be potential channel of this spillover effect.

Our work contributes to several strands of literature. The first is a growing literature on cross-country capital flows and their impacts on housing markets. Zhimin, Shen, and Zhang (2020) find real estate capital inflows from China have a positive and significant effect on local housing and labour markets in three California cities between 2007 and 2013. Other papers, such as Gorback and Keys (2020) and Cvijanović and Spaenjers (2020), also support the judgment. Extensive literature has also emphasized the role of international capital flows during the U.S. housing boom. A common hypothesis is that the rapid increase in house price is closely related to a rise in the net foreign inflows into the U.S. during that period. One possible channel is that the capital inflows directly contribute to the house price increase, summarized in the *global savings glut* hypothesis as we previously mentioned (Bernanke (2005), Himmelberg, Mayer, and Sinai (2005), Bernanke (2007), Caballero, Farhi, and Gourinchas (2008), Mendoza, Quadrini, and Jose-Victor (2009), Caballero and Krishnamurthy (2009), Bernanke (2010), Adam, Kuang, and Marcet (2012), Taylor (2013)). The other channels rely on some other factors, such as higher domestic demand, to simultaneously drive both house prices and capital flows in the same direction (Gete (2010), Laibson and Mollerstrom (2010), Ferrero et al. (2011)).

This article is also related to literature on the impact of monetary policy on housing market. Many studies are increasingly suggesting loose monetary policy does leads to house booms (Ahrend, Cournède, and Price (2008), Bordo and Landon-Lane. (2013)). Mishkin (2007) reviews several channels through which monetary policy affects the housing market. Taylor (2007, 2009) shows that the loose monetary policy during the period between 2002 and 2005 may have been the cause of the U.S. housing boom. Other literature, on the contrary, ascribes only a small role to monetary policy (Del Negro and Otrok (2007), Jarocinski and Smets (2008), Dokko et al. (2011), Glaeser, Gottlieb, and Gyourko (2012), etc.). They point out that monetary policy is not the primary contributing factor to the extraordinary strength in housing markets, as the link between interest rates and housing markets is not that strong.

Finally, our article contributes to the growing literature on housing market in China. For instance, Fang et al. (2016) and Glaeser et al. (2017) focus on the housing boom in China. A limited number of papers have explored the impact of monetary policy or international capital flows on house prices in China. Tan and Chen (2013) study whether China's central bank, the People's Bank of China (PBoC), responds to house price shocks, and their findings roughly match our results. Koivu (2012) finds that a loosening of China's monetary policy does lead to higher asset prices. Some studies find that 'hot money' inflows indeed have driven house prices in China (Feng, Lin, and Wang (2017), Liya (2008)). Most of these studies focus on the pre-crisis period.

Our study differs from previous ones in several ways. First, we focus on the ZLB episode, during which quantitative easing measures launched by the major economics trigger a surge of hot money inflows to China. At the same time, Chinese monetary policy loosened as a response to the crisis. Therefore, we are curious about the effects of hot money and monetary policy and their interplay on the soaring housing prices during that period. Second, since the fluctuations of house prices in different cities display various patterns and magnitude, we employ the dynamic hierarchical factor model proposed by Moench, Serena, and Potter (2013) to disentangle the comovement of house prices. This new approach effectively filters out the noise contained in the data and extracts easy-to-interpret common factors. Third, instead of going to details of each city's housing prices, we take a macro perspective and investigate the driving forces of the common factor. We especially focus on the impact of two shocks, hot money and monetary policy, as well as their interplay in Chinese housing markets.

The rest of the article is organized as follows. Section 2 introduces the dynamic hierarchical factor model. Section 3 describes the data that we use. Section 4 presents the results from the factor model and VAR analysis. Section 5 is the robustness check. Section 6 concludes.

II. The dynamic hierarchical factor model

Our quantitative analysis consists of two steps. In the first step, we adopt a dynamic hierarchical factor model, which is a purely statistical model to distinguish the component of the fluctuations of city-level housing prices that are common to all cities from those that are idiosyncratic to some regions or local cities. Considering the heterogeneity of housing markets in different cities, the factor model is utilized to extract the common component of the housing price dynamics of each city. In that sense, the common component captures the comovement of housing prices across cities. After having obtained an estimate of the common factor from the statistical model, in the second step we explore what is behind this comovement of housing prices. We focus on the ZLB episode and investigate the roles hot money and monetary policy play in the comovement. In this section, we first introduce the statistical model to decompose the housing prices.

We adopt a dynamic hierarchical factor model proposed by Moench, Serena, and Potter (2013) to estimate the factors of different levels that contribute to city-level housing price growth fluctuations. Based on the geographic locations and administrative divisions, we build a four-level dynamic factor model to capture the comovement of housing price growth of major Chinese cities at different levels. It should be noted that the factor model is a purely statistical model. All the factors are latent variables, which instead of presumed, will be completely inferred from the data. Therefore, we avoid making too many a priori assumptions on the factors.

Suppose we have N series of city-level monthly housing price growth rates, each with T time-series observations. These series are assumed to be stationary and are standardized to have zero mean and unit variance. The N cities are grouped into B different blocks; each block corresponds to a geographic region of China which usually consists of several provinces. Let N_b denote the number of cities in the bth block. We further divide each block into S_b sub-blocks, each of which corresponds to a provincial level administrative division of China (i.e. a province, autonomous region or direct-controlled municipality). At time t, the house price growth of city n in a given sub-block s of block b is affected by variations of four different levels: national (common), regional (block-specific), provincial (sub-block-specific) and municipal (idiosyncratic). The four-level dynamic factor model is then specified as follows:

$$Z_t^{bsn} = \Lambda_H^{bsn}(L)H_t^{bs} + e_{Z_t^{bsn}}, \tag{1}$$

$$H_t^{bs} = \Lambda_G^{bs}(L)G_t^b + e_{H_t^{bs}}, \tag{2}$$

$$G_t^b = \Lambda_F^b(L)F_t + e_{G_t^b}, \tag{3}$$

$$\phi_{F_k}(L)F_{kt} = \in_{F_{kt}} \tag{4}$$

In the above equations, Z_t^{bsn} is the monthly housing price growth of the nth city in province s of region b at time t; H_t^{bs}, a $K_H^{bs} \times 1$ vector, is the provincial factor for province s in region b; G_t^b is the $K_G^b \times 1$ regional factor vector for region b; F is the $K_F \times 1$ vector of the national factor; Λ_H^{bsn}, Λ_G^{bs}, and Λ_F^b are the distributed lag of loadings on the provincial, regional and national factors, respectively. Equation (4) is replicated as Equation (7), and more explanation about it can be found there.

From Equations (1)–(4), we see that series in a given province are correlated through the national factor F_t, regional variations $e_{G_t^b}$ and provincial variations $e_{H_t^{bs}}$. Provinces in a given region are correlated through the national factor F_t and regional variations $e_{G_t^b}$. Regions are correlated only through the national factor F_t. The four-level model captures variations between and within regions or provinces. We call Equations (1), (2) and (3) the equation of the first, second and third level, respectively. The auto-regressive process for F_t (Equation [4]) is the fourth level. Based on the aforementioned definition of levels, some provincial level administrative divisions contain only one city, and the four-level structure actually collapses to a three-level one. In these situations, the three-level dynamics are specified as follows:

$$X_t^{bn} = \Lambda_G^{bn}(L)G_t^b + e_{X_t^{bn}}, \tag{5}$$

$$G_t^b = \Lambda_F^b(L)F_t + e_{G_t^b}, \tag{6}$$

where X_t^{bn} represents the monthly housing price growth of city n in region b (without the provincial level) at time t, Λ_G^{bn} is the distributed lag of loadings on the regional factors. Equations (5) and (6) (which is a replicate of Equation [3]), along with Equation (4), constitute a three-level model.

The national factor, and the error terms in the regional, provincial and municipal level equations are assumed to follow auto-regressive process of lag q_{F_k}, $q_{G_j^b}$, $q_{H_i^{bs}}$, $q_{X^{bn}}$ and $q_{Z^{bsn}}$, respectively. Namely, for $b = 1, \ldots, B$,

$$\begin{aligned}\phi_{F_k}(L)F_{kt} = \in_{F_{kt}}, \qquad \in_{F_{kt}} \sim N(0, \sigma^2_{F_k}), \\ k = 1, \ldots, K_F\end{aligned} \tag{7}$$

$$\begin{aligned}\phi_{G_j^b}(L)e_{G_{jt}^b} = \in_{G_{jt}^b}, \qquad \in_{G_{jt}^b} \sim N(0, \sigma^2_{G_j^b}), \\ j = 1, \ldots, K_G^b\end{aligned} \tag{8}$$

$$\phi_{H_i^{bs}}(L)e_{H_{it}^{bs}} = \in_{H_{it}^{bs}}, \qquad \in_{H_{it}^{bs}} \sim N(0, \sigma^2_{H_i^{bs}}), \quad i = 1, \ldots, K_H^{bs} \tag{9}$$

$$\phi_{X^{bn}}(L)e_{X_t^{bn}} = \in_{X_t^{bn}}, \qquad \in_{X_t^{bn}} \sim N(0, \sigma^2_{X^{bn}}), \quad n = 1, \ldots, N_X^b \tag{10}$$

$$\phi_{Z^{bsn}}(L)e_{Z_t^{bsn}} = \in_{Z_t^{bsn}}, \qquad \in_{Z_t^{bsn}} \sim N(0, \sigma^2_{Z^{bsn}}), \quad n = 1, \ldots, N_Z^{bs} \tag{11}$$

where all the ε-terms are assumed to be mutually independent, $\phi_\bullet(L)$ are polynomials in the lag operator L, and the lag orders may vary across regions, provinces and cities.

The estimation method follows Moench, Serena, and Potter (2013). Namely, an improved Markov Chain Monte Carlo (MCMC) algorithm is employed to sample a Markov chain whose stationary distribution gives the posterior distribution of the parameters and unknown quantities. Following Moench, Serena, and Potter (2013), we assume that the factor loading matrix is constant and estimates one national factor, one regional factor per region and one provincial factor per province. For the priors, we assume the prior distribution of factor loadings Λ and autoregressive coefficients Φ to be Gaussian with mean zero and unit variance. The prior distribution of the variance parameters is an inverse χ^2 distribution with 4 degrees of freedom and a scale of 0.1.

III. The data

Housing prices

In this study, we employ the resale house price data for 70 major cities in China during a 119-month period from June 2005 to April 2015[3] These data are obtained from the CNFS Real Estate Database, which is a comprehensive data set for the housing market in China.[4] As the new-built houses are usually located in the suburban area of cities, we think the resale house price is a better index for studying the housing market in China. The house prices are deflated by the CPI for All Items Less Food. In the VAR analysis in this article, we will also use other macroeconomic variables. All the series used in this study, except for the loan rates and stock market index, are seasonally adjusted using a modified version of the U.S. Census Bureau's X-13ARIMA-SEATS Seasonal Adjustment Program, which accounts for the Chinese New Year effect. In the house price data set, there are dozens of missing observations, and we estimate them using the EM algorithm introduced by Stock and Watson (2002). The growth rates are calculated by taking the log difference.

The cities constitute the bottom level of the dynamic hierarchical factor model, and each city belongs to a province. Provinces constitute regions. According to the division by the State Council Development Research Center, all the provinces are divided into eight economic regions based on their geographical locations and economic development status. The eight economic regions – i.e. the Northern Coastal, Eastern Coastal, Southern Coastal, Middle-Reach of Yellow River, Middle-Reach of Yangtze River, Northeastern, Southwestern and Northwestern Area – constitute the regional level. For direct-controlled municipalities (Beijing, Shanghai, Tianjin and Chongqing) and other provincial level administrative divisions with only one city in our data set, there are only three levels. That is, the provincial and city levels collapse into one. The details of the regional division are presented in Table 1.

Hot money

'Hot money' is commonly used to refer to the flow of speculative capital from one country to another in order to mainly earn a short-term profit on interest rate differences and/or anticipated exchange rate shifts (Martin and Morrison (2008)). Although Chinese authority adopts stringent capital control measures, a large amount of short-term capital flows into China illegally. Prasad and Wei (2009) report that there have been huge capital inflows into China since 2003 that cannot be

[3]The asset purchase program was halted in October 2014. So we extend our sample period to April 2015, half a year after the QE3 quitted..

[4]There have been traditional concerns over the accuracy and integrity of the official housing price data published by the National Bureau of Statistics of China. Deng, Girardin, and Joyeux (2018) criticize the data to be overly smooth with little housing price growth in the recent decade (See also Ahuja et al. (2010), Wu et al. (2014)). To avoid this problem, we turn to CNFS Real Estate Data instead of the NBS data.

Table 1. Structure of the four-level model.

Blocks	Sub-blocks	Series
(Regions)	(Provinces)	(Cities)
The Northern Coastal Area	Beijing	Beijing
	Tianjin	Tianjin
	Hebei	Shijiazhuang, Qinhuangdao, Tangshan
	Shandong	Jinan, Qingdao, Yantai, Jining
The Eastern Coastal Area	Shanghai	Shanghai
	Jiangsu	Nanjing, Wuxi, Xuzhou, Yangzhou
	Zhejiang	Hangzhou, Ningbo, Wenzhou, Jinhua
The Southern Coastal Area	Fujian	Fuzhou, Xiamen, Quanzhou
	Guangdong	Guangzhou, Shenzhen, Huizhou, Zhanjiang, Shaoguan
	Hainan	Haikou, Sanya
The Middle-Reach of Yellow River	Shaanxi	Xi'an
	Shanxi	Taiyuan
	Henan	Zhengzhou, Luoyang, Pingdingshan
	Inner Mongolia	Hohhot, Baotou
The Middle-Reach of Yangtze River	Hubei	Wuhan, Yichang, Xiangyang
	Hunan	Changsha, Yueyang, Changde
	Jiangxi	Nanchang, Jiujiang, Ganzhou
	Anhui	Hefei, Bengbu, Anqing
The Northeastern Area	Jilin	Changchun
	Liaoning	Shenyang, Dalian, Dandong, Jinzhou
	Heilongjiang	Ha'erbin, Mudanjiang
The Southwestern Area	Guangxi	Nanning, Guilin, Beihai
	Guizhou	Guiyang, Zunyi
	Chongqing	Chongqing
	Sichuan	Chengdu, Luzhou, Nanchong
	Yunnan	Kunming, Dali
The Northwestern Area	Qinghai	Xining
	Ningxia	Yinchuan
	Xinjiang	Xinjiang
	Gansu	Lanzhou

Note: The table summarizes the hierarchical structure of the four-level model for city-level housing price growth. The four levels are: national level, regional level, provincial level and city-specific level. The bottom level consists of the cities, and each city belongs to a province according to the administrative division of China. Provinces constitute the sub-block level, and they are divided into 8 economic regions based on their geographical locations and economic development, according to the State Council Development Research Center. For municipalities and provinces with only one city in the data set, there are only three levels, since the provincial level and city-specific level collapse into one level.

explained by trade surplus or foreign direct investments.

Because hot money flows quickly and poorly monitored, there has been no consensus among researchers on a precise method for estimating its amount. The common ways in the literature include a direct and an indirect measurement (see Kant (1996)). The direct way calculates hot money by adding up variables that constitute the hot money flows. For example, Prasad and Wei (2009) and Cheung and XingWang (2011) take the approach of adding up the errors and omissions and portfolio flows. Cuddington (1986) and Loungani and Mauro (2001) add up the errors and omissions and non-bank private short-term capital accounts. The indirect way of approximating the flow of 'hot money' is to subtract a nation's trade surplus (or deficit) and its net flow of foreign direct investment (FDI) from the change in the nation's foreign reserves. It is the most commonly used method in literature (Martin and Morrison (2008), Guo and Huang (2010), Chen-Yuan and Baker (2004)) and also adopted by the National Bureau of Statistics of China. In a similar way, the residual method of Bank (1985) defines capital inflows as increases of international reserves minus current account surpluses, net inflows of foreign direct investment and increases of external debts.

Both of these two methods have their own pros and cons. On one hand, the direct method is subject to an unduly narrow statistical scope and fails to take the various channels of hot money inflows into account. Therefore, the direct method tends to underestimate the scale of hot money. On the other hand, the indirect method implicitly assumes that except for the trade and service account and FDI account, the net inflows through all the other accounts in Balance of Payment are altogether considered as 'hot money', thus leading to an overestimate of the scale of hot money. In sum, neither of these two methods precisely measures the hot money flows.

In this article, we adopt the indirect way of calculating hot money, mainly because it is the only way we can obtain monthly estimates of hot money. To be specific, we follow Martin and Morrison (2008) to approximate the flows of hot money by subtracting a nation's trade surplus (or deficit if negative) and its net flow of foreign direct investment (FDI) from the change in the nation's foreign reserves. To verify the robustness of the effects of hot money, we also adopt the direct method to calculate hot money as an alternative. We follow Prasad and Wei (2009) to measure hot money by adding up the errors and omissions and net portfolio flows. Since both of these two constituents are measured at a quarterly frequency, we can only obtain a quarterly series of hot money flows. In section 5, we use this alternative hot money series as a robustness test. The related data are obtained from the Wind Database. The estimated series of hot money is seasonally adjusted and converted to 2005 CNY.

Other macroeconomic data

Other data used in VAR analysis include a proxy variable for monetary policy, growth rates of hot money and stock market index, industrial production growth and inflation rates. Specifically, monetary policy is proxied by 1-year benchmark lending rate, which is the major monetary policy tool of China's central bank PBoC. All the variables used in constructing the hot money are converted into 2005 CNY. Stock price index is proxied by the Shanghai Stock Exchange (SSE) Composite Index. Industrial production measures the total value added of large-scale industrial firms and is converted to 2005 CNY. The data used in VAR are obtained from the Wind Database. All these data are at monthly frequencies, and the sample period is from June 2005 to April 2015.

IV. Empirical results

To estimate the dynamic hierarchical factor model, we run the MCMC algorithm for 1,000,000 iterations and discard the first 500,000 draws as the burn-in. For the remaining 500,000 draws, we store every 50th draw. The results for the posterior distributions are based on these 10,000 draws.

The comovement of housing price growth

First, we assess the relative importance of the national, regional, provincial and idiosyncratic factors in the month-on-month housing price growth. There are five charts in Figure 3. The top chart shows the monthly growth rates of housing prices for the 70 major cities from July 2005 to April 2015. The second chart shows the estimated national factor components of these cities' housing price growth rates which correspond to $\Lambda_H^{bsn}(L)\Lambda_G^{bs}(L)\Lambda_F^{b}(L)F_t$ in Equations (1)–(4). The third chart illustrates the estimated regional components (with the national components removed) which correspond to $\Lambda_H^{bsn}(L)\Lambda_G^{bs}(L)e_{G_t^b}$ in Equations (1)–(3). The fourth chart illustrates the estimated provincial components (with the idiosyncratic components removed) which correspond to $\Lambda_H^{bsn}(L)e_{H_t^{bs}}$ in Equations (1) and (2). The last chart depicts the estimated idiosyncratic components which correspond to $e_{Z_t^{bsn}}$ in Equation (1). All the curves in the second chart are proportional to each other and positively correlated, with different amplitudes that reflect different exposures of housing price growth to the national factor. The relatively-highly-volatile period of the housing price growth rates coincides with that of the national factor, which is, roughly speaking, from 2007 to 2011.

Figure 4 shows that the estimated national factor and the 'month-on-month growth of resale house prices in the 70 major cities' released by the NBS of China[5] are highly correlated, with a correlation coefficient of 66.8%. The national factor soared in four major periods, namely, 2006M11–2007M10, 2008M9–2010M4, 2010M7–2010M11 and 2011M11–2013M1. Since housing system reform in 2003, we have seen a rapid development of the Chinese housing market. Real estate soon became the pillar industry of the Chinese economy, contributed to the two-digit growth rates of GDP between 2003 and 2007. In order to cool down the overheated economy, PBoC consecutively raised the benchmark loan rate six times in 2007. The year of 2008 witnessed a dramatic change in the macroeconomic policy. After a short tightening period in early 2008, PBoC announced an easing monetary policy to save the economy from a worldwide recession. Since then, the Chinese housing market revived at an unprecedented pace, and the authorities had to take a series of stringent administrative measures to moderate the rapid housing price growth in 2010. The housing prices kept rising until the mid-2011. In 2011, many cities in China started to impose house purchase restrictions, and the housing price in

[5]The 'month-on-month growth of resale house prices in the 70 major cities' reports the nominal growth rates. The black curve in Figure 4 depicts the seasonally adjusted real month-on-month growth calculated from the NBS data.

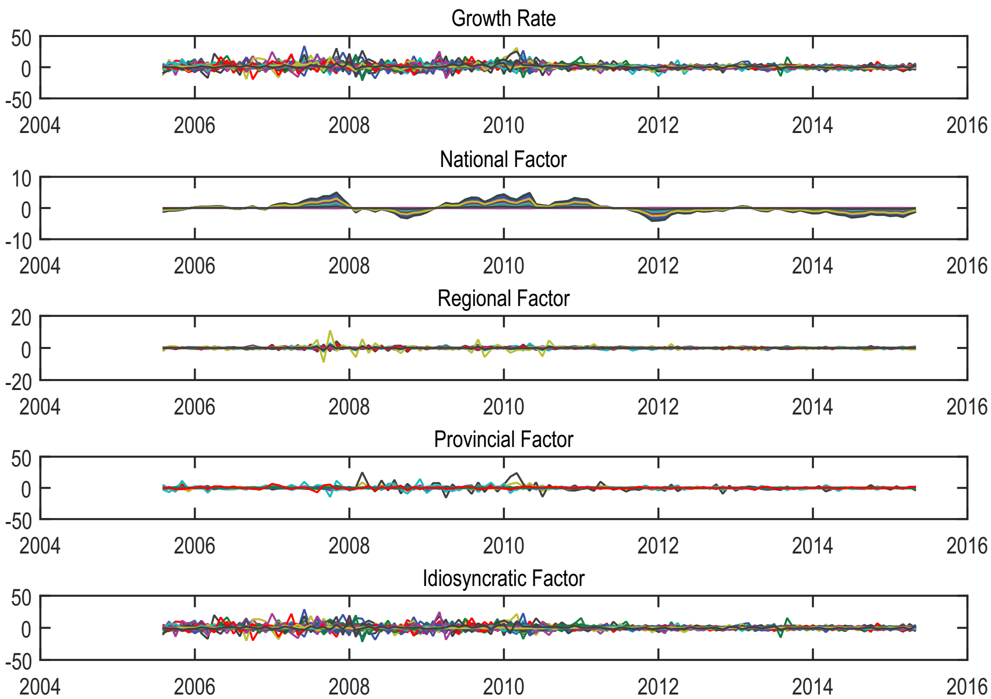

Figure 3. Factors at different levels. Note: The top chart shows the monthly growth rates of housing prices for the 70 major cities from July 2005 to April 2015. The other four charts from top to bottom are the national, regional, provincial and idiosyncratic factors for each city's housing price growth, corresponding to $\Lambda_H^{bsn}(L)\Lambda_G^{bs}(L)\Lambda_F^{b}(L)F_t$, $\Lambda_H^{bsn}(L)\Lambda_G^{bs}(L)e_{G_t^b}$, $\Lambda_H^{bsn}(L)e_{H_t^{bs}}$ and $e_{Z_t^{bsn}}$ in Equations (1)–(4), respectively. The numbers on the vertical axes are in log points.

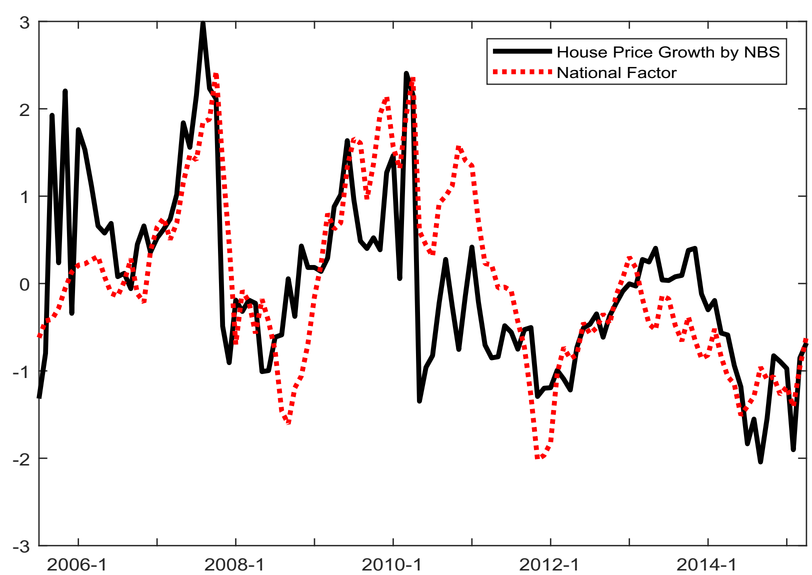

Figure 4. Estimated national factor and the 'month-on-month growth of resale house prices in the 70 major cities'.. Note: The red dashed curve is the national factor estimated from the dynamic hierarchical factor model. The black curve is the 'month-on-month growth of resale house prices in the 70 major cities' released by the NBS of China. We convert the original series into seasonally adjusted real month-on-month growth. Both series are normalized to have zero mean and unit variance.

China fell slightly since then. In summary, the national factor estimated in this study synchronizes with the changes in the monetary policy and administrative measures in China.

We will explore the relationship between the monetary policy and national factor further in Section 4.2.

Variance decomposition We also compare the relative importance of the national, regional, provincial and idiosyncratic components in generating the variation of the city-level housing price growth. In Equations (1)–(4), the total unconditional variance of Z^{bsn} is decomposed into fluctuations caused by F, e_{G^b}, $e_{H^{bs}}$ and $e_{Z^{bsn}}$. Specifically,

$$\begin{aligned} Var(Z^{bsn}) = \gamma_F^{bsn} vec(Var(F)) + \gamma_G^{bsn} vec(Var(e_{G^b})) \\ + \gamma_H^{bsn} vec(Var(e_{H^{bs}})) \\ + vec(Var(e_{Z^{bsn}})) \end{aligned} \tag{12}$$

where γ_F^{bsn}, γ_G^{bsn}, γ_H^{bsn} are functions of parameters in $\Lambda_H^{bsn}(L)$, $\Lambda_G^{bs}(L)$ and $\Lambda_F^{b}(L)$. The variance shares of the national, regional and local factors are denoted by $Share_N$, $Share_R$ and $Share_L$, respectively, and are measured as

$$Share_N = \frac{\gamma_F^{bsn} vec(Var(F))}{Var(Z^{bsn})}, \tag{13}$$

$$Share_R = \frac{\gamma_G^{bsn} vec(Var(e_{G^b}))}{Var(Z^{bsn})}, \tag{14}$$

and

$$\begin{aligned} Share_L &= Share_{H^{bs}} + Share_{Z^{bsn}} \\ &= \frac{\gamma_H^{bsn} vec(Var(e_{H^{bs}}))}{Var(Z^{bsn})} + \frac{vec(Var(e_{Z^{bsn}}))}{Var(Z^{bsn})}. \end{aligned} \tag{15}$$

Table 2 shows the mean and standard deviation of the estimated variance shares for all regions, provinces and municipalities. The national factor accounts for 12% of the city-level housing price growth fluctuations for the 70 major cities during 2005M7–2015M4 on average. For Beijing, Shanghai, Chongqing and nine other big cities, the national factor accounts for more than 20% of total variations. For the Northern Coastal, Eastern Coastal, Yangtze River, Northeastern and Southwestern areas, the shares of the national factor are relatively high, all above 10% on average. On the other hand, provinces in the Southern coastal, Yellow River and Northwestern areas, such as Shanxi, Hainan, Ningxia and Gansu, the national factor plays a much less important role, while other components (regional, provincial or idiosyncratic) are much more influential.

Besides the full sample results reported in Table 2, we also investigated subsample variance shares for the city-level housing price growth. Table 3 shows the corresponding results for the subsample period from January 2009 to April 2015. We particularly focus on this subsample period for two reasons. First, this period corresponds to the ZLB episode in the U.S. when the international capital flows were much more active than before. We expect that the international capital, and particularly, hot money, that flows into and out of China is one of the key factors that contributes to the comovement of city-level housing price growth. If it were the case, we should expect a larger proportion of national factors in accounting for the variance of city-level housing prices. Second, the global economy, including China, has experienced dramatic changes since the end of 2008, and some of these changes were structural.[6] As a consequence, during 2009M1 through 2015M4, the national factor played a more important role and accounted for 18% of the fluctuations in the monthly city-level housing price growth on average, which echoes with our conjecture.

Figure 5 displays for each province the magnitude of $Share_N$ (in Equation(13)) for the ZLB period (2009M1-2015M4) on the vertical axis, and the period before ZLB (2005M7-2008M12) on the horizontal axis. $Share_N$ represents the variance of house prices fluctuations due to the national factor as a fraction of the variance of all components. For all the provinces that are above the 45° line, the common component of fluctuations becomes more important in the ZLB period than the period before ZLB. We can see that the relative importance of national factors has increased for the majority of provinces, except for Guangdong, Henan, Inner Mongolia, Jiangxi and Shanghai. Some of the provinces or cities witness prominent increases in the share of national factor. For example, the relative

[6]Other studies also find this phenomenon. For instance, Ho, Zhang, and Zhou (2018) find that the responses of the Chinese economy to U.S. monetary policy shocks and policy uncertainty shocks exhibit different dynamics in periods before and after the federal funds target rate hit the ZLB in the United States, which suggests the existence of structural changes both in the Chinese economy and in the transmission mechanism of U.S. monetary policy.

Table 2. Variance decomposition for city-level housing price growth: full sample (2005M7–2015M4).

Regions (Blocks)	Provinces (Sub-blocks)	Share of National Factor		Share of Regional Factor		Share of Local Factors	
The Northern Coastal Area	Beijing	0.43	(0.00)	0.03	(0.00)	0.54	(0.00)
	Tianjin	0.09	(0.00)	0.01	(0.00)	0.91	(0.00)
	Hebei	0.17	(0.06)	0.01	(0.00)	0.82	(0.06)
	Shandong	0.08	(0.05)	0.01	(0.00)	0.92	(0.06)
	Average	0.19	(0.14)	0.01	(0.01)	0.80	(0.15)
The Eastern Coastal Area	Shanghai	0.28	(0.00)	0.04	(0.00)	0.68	(0.00)
	Jiangsu	0.12	(0.02)	0.02	(0.00)	0.86	(0.02)
	Zhejiang	0.13	(0.14)	0.02	(0.02)	0.86	(0.16)
	Average	0.18	(0.08)	0.02	(0.01)	0.80	(0.08)
The Southern Coastal Area	Fujian	0.09	(0.07)	0.01	(0.01)	0.89	(0.08)
	Guangdong	0.05	(0.04)	0.01	(0.01)	0.95	(0.04)
	Hainan	0.01	(0.01)	0.00	(0.00)	0.99	(0.01)
	Average	0.05	(0.03)	0.01	(0.00)	0.94	(0.04)
The Middle-Reach of Yellow River	Shaanxi	0.09	(0.00)	0.04	(0.00)	0.86	(0.00)
	Shanxi	0.01	(0.00)	0.01	(0.00)	0.98	(0.00)
	Henan	0.07	(0.07)	0.04	(0.05)	0.88	(0.13)
	Inner Mongolia	0.12	(0.11)	0.07	(0.07)	0.81	(0.19)
	Average	0.07	(0.04)	0.04	(0.02)	0.88	(0.06)
The Middle-Reach of Yangtze River	Hubei	0.12	(0.13)	0.01	(0.01)	0.87	(0.14)
	Hunan	0.15	(0.07)	0.02	(0.01)	0.84	(0.08)
	Jiangxi	0.13	(0.13)	0.01	(0.01)	0.86	(0.14)
	Anhui	0.03	(0.04)	0.00	(0.00)	0.97	(0.04)
	Average	0.11	(0.05)	0.01	(0.00)	0.88	(0.05)
The Northeastern Area	Jilin	0.20	(0.10)	0.02	(0.01)	0.78	(0.11)
	Liaoning	0.09	(0.06)	0.01	(0.01)	0.90	(0.07)
	Heilongjiang	0.09	(0.10)	0.01	(0.01)	0.90	(0.11)
	Average	0.13	(0.05)	0.01	(0.00)	0.86	(0.06)
The Southwestern Area	Guangxi	0.11	(0.05)	0.03	(0.01)	0.87	(0.07)
	Guizhou	0.04	(0.04)	0.01	(0.01)	0.96	(0.05)
	Chongqing	0.27	(0.00)	0.06	(0.00)	0.66	(0.00)
	Sichuan	0.09	(0.10)	0.02	(0.02)	0.89	(0.13)
	Yunnan	0.14	(0.16)	0.03	(0.04)	0.82	(0.20)
	Average	0.13	(0.08)	0.03	(0.02)	0.84	(0.10)
The Northwestern Area	Qinghai	0.04	(0.00)	0.12	(0.00)	0.84	(0.00)
	Ningxia	0.00	(0.00)	0.00	(0.00)	1.00	(0.00)
	Xinjiang	0.25	(0.00)	0.73	(0.00)	0.02	(0.00)
	Gansu	0.01	(0.00)	0.04	(0.00)	0.95	(0.00)
	Average	0.08	(0.10)	0.22	(0.29)	0.70	(0.40)
National Average		0.12	(0.09)	0.05	(0.13)	0.84	(0.18)

Note: This table reports the variance decomposition for the four-level model of the city-level housing price growth in the full sample period (July 2005–April 2015). For each (sub-)block, 'Share of National Factor', 'Share of Regional Factor', and 'Share of local Factors' stand for the average variance shares of shocks in the total variations of city-level housing price growth in the corresponding levels. Numbers in brackets are the standard deviations of variance shares.

Table 3. Variance decomposition for city-level housing price growth: since the ZLB period in the U.S. (2009M1–2015M4).

Regions (Blocks)	Provinces (Sub-blocks)	Share of National Factor		Share of Regional Factor		Share of Local Factors	
The Northern Coastal Area	Beijing	0.52	(0.00)	0.03	(0.00)	0.45	(0.00)
	Tianjin	0.10	(0.00)	0.01	(0.00)	0.89	(0.00)
	Hebei	0.29	(0.03)	0.02	(0.00)	0.69	(0.03)
	Shandong	0.11	(0.11)	0.01	(0.01)	0.88	(0.11)
	Average	0.25	(0.17)	0.02	(0.01)	0.73	(0.18)
The Eastern Coastal Area	Shanghai	0.26	(0.00)	0.03	(0.00)	0.71	(0.00)
	Jiangsu	0.14	(0.03)	0.02	(0.00)	0.84	(0.04)
	Zhejiang	0.20	(0.17)	0.03	(0.02)	0.77	(0.19)
	Average	0.20	(0.05)	0.03	(0.01)	0.77	(0.05)
The Southern Coastal Area	Fujian	0.27	(0.28)	0.02	(0.02)	0.71	(0.30)
	Guangdong	0.05	(0.03)	0.00	(0.00)	0.95	(0.03)
	Hainan	0.01	(0.01)	0.00	(0.00)	0.99	(0.01)
	Average	0.11	(0.11)	0.01	(0.01)	0.88	(0.12)
The Middle-Reach of Yellow River	Shaanxi	0.13	(0.00)	0.06	(0.00)	0.81	(0.00)
	Shanxi	0.09	(0.00)	0.03	(0.00)	0.87	(0.00)
	Henan	0.08	(0.05)	0.04	(0.04)	0.88	(0.09)
	Inner Mongolia	0.11	(0.10)	0.06	(0.07)	0.83	(0.17)
	Average	0.10	(0.02)	0.05	(0.01)	0.85	(0.03)
The Middle-Reach of Yangtze River	Hubei	0.21	(0.26)	0.02	(0.02)	0.78	(0.28)
	Hunan	0.18	(0.13)	0.01	(0.01)	0.81	(0.14)
	Jiangxi	0.13	(0.10)	0.01	(0.01)	0.85	(0.11)
	Anhui	0.12	(0.14)	0.01	(0.01)	0.87	(0.15)
	Average	0.16	(0.03)	0.01	(0.00)	0.83	(0.04)
The Northeastern Area	Jilin	0.44	(0.20)	0.03	(0.01)	0.53	(0.21)
	Liaoning	0.15	(0.14)	0.01	(0.01)	0.84	(0.14)
	Heilongjiang	0.11	(0.10)	0.01	(0.01)	0.88	(0.10)
	Average	0.24	(0.15)	0.01	(0.01)	0.75	(0.16)
The Southwestern Area	Guangxi	0.20	(0.14)	0.02	(0.01)	0.78	(0.15)
	Guizhou	0.05	(0.04)	0.00	(0.00)	0.94	(0.04)
	Chongqing	0.48	(0.00)	0.04	(0.00)	0.47	(0.00)
	Sichuan	0.14	(0.19)	0.01	(0.02)	0.85	(0.20)
	Yunnan	0.27	(0.34)	0.02	(0.03)	0.71	(0.37)
	Average	0.23	(0.15)	0.02	(0.01)	0.75	(0.16)
The Northwestern Area	Qinghai	0.05	(0.00)	0.07	(0.00)	0.88	(0.00)
	Ningxia	0.00	(0.00)	0.00	(0.00)	1.00	(0.00)
	Xinjiang	0.41	(0.00)	0.56	(0.00)	0.03	(0.00)
	Gansu	0.01	(0.00)	0.02	(0.00)	0.97	(0.00)
	Average	0.12	(0.17)	0.16	(0.23)	0.72	(0.40)
National Average		0.18	(0.14)	0.04	(0.10)	0.78	(0.19)

Note: This table reports the variance decomposition for the four-level model of the city-level housing price growth in the subsample period (January 2009–April 2015). See also the note to Table 2.

importance of national factor for Beijing increases from 25% before the financial crisis to 52% during the ZLB period. Chongqing also finds a significant rise in the share of national factor, from 11% to 48%. For provinces, such as Jilin and Fujian, the explanatory power of the national factor in terms of the variance of house price movements has increased by around 7 times. However, some provinces in northwestern and southwestern area, the importance of the national factor remains negligible even during the ZLB period. Although heterogeneity across provinces is still large, the national factor has become increasingly important in

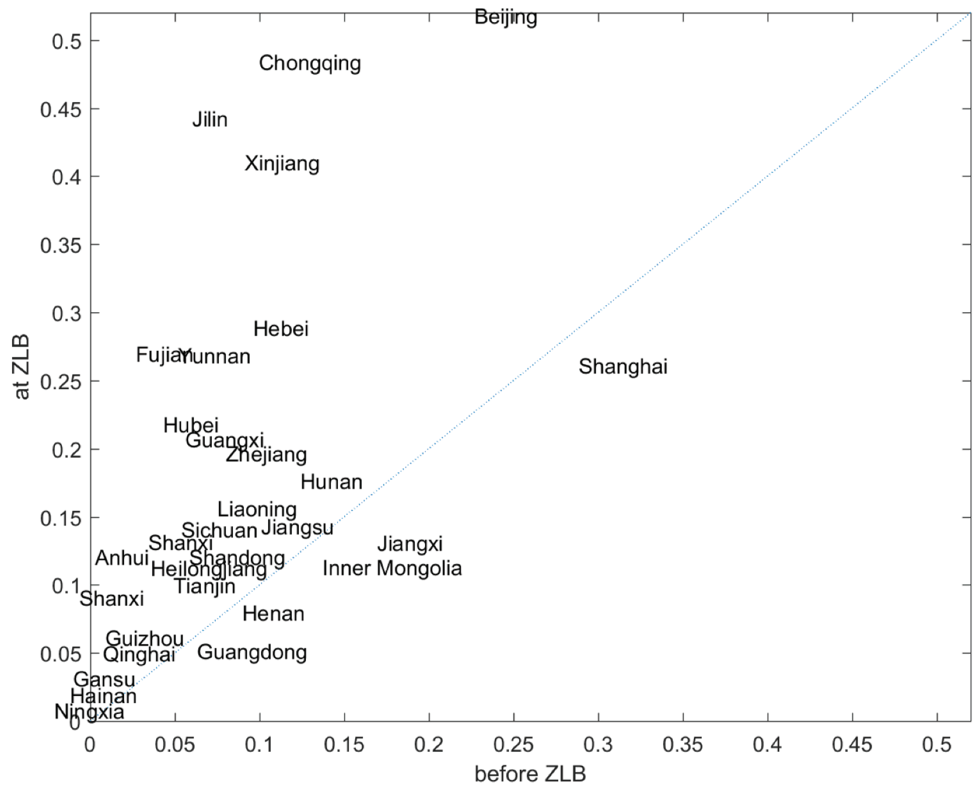

Figure 5. Province-level variance share of national factor. Note: This figure displays for each province the magnitude of $Share_N$ (in Equation 13) for the ZLB period (2009M1-2015M4) on the vertical axis, and the period before ZLB (2005M7šC2008M12) on the horizontal axis.

accounting for the fluctuations of housing prices since the crisis.

Variance shares of extending horizons Now lets us check the relative importance of the national, regional and local factors in city-level housing price growth in multiple month periods. Instead of looking into the monthly housing price growth, we can also explore the housing price growth in longer periods. To be specific, let Z_h^{bsn} represents the $h-$month housing price growth of the nth city in province s of region b. Instead of the monthly growth rate Z^{bsn} in Equation (12), Z_h^{bsn} is the growth rate in h months, where h ranges from 1 to 60. In a similar pattern to Equation (12), the variance of Z_h^{bsn} can be decomposed into four components, i.e. fluctuations caused by national factor F_h, region factor $e_{G_h^b}$, provincial factor $e_{H_h^{bs}}$ and idiosyncratic part $e_{Z_h^{bsn}}$. Specifically,

$$\begin{aligned} Var(Z_h^{bsn}) = {} & \gamma_{F_h}^{bsn} vec(Var(F_h)) + \gamma_{G_h}^{bsn} vec(Var(e_{G_h^b})) \\ & + \gamma_{H_h}^{bsn} vec(Var(e_{H_h^{bs}})) \\ & + vec(Var(e_{Z_h^{bsn}})) \end{aligned} \tag{16}$$

where all these factors F_h, $e_{G_h^b}$, $e_{H_h^{bs}}$ and idiosyncratic part $e_{Z_h^{bsn}}$ are the $h-$month counterparts of the monthly factors F, e_{G^b}, $e_{H^{bs}}$ and $e_{Z^{bsn}}$ in Equation (12). Given a multiple month period, the variance shares of the national, regional factors and local factors can be defined in a way similar to Equation (13)–(15):

$$Share_N^h = \frac{\gamma_{F_h}^{bsn} vec(Var(F_h))}{Var(Z_h^{bsn})}, \tag{17}$$

$$Share_R^h = \frac{\gamma_{G_h}^{bsn} vec(Var(e_{G_h^b}))}{Var(Z_h^{bsn})}, \tag{18}$$

and

$$Share_L^h = Share_{H_h^{bs}} + Share_{Z_h^{bsn}} = \frac{\gamma_{H_h}^{bsn} vec(Var(e_{H_h^{bs}}))}{Var(Z_h^{bsn})} + \frac{vec(Var(e_{Z_h^{bsn}}))}{Var(Z_h^{bsn})}. \tag{19}$$

where $Share_N^h$ ($Share_R^h$, $Share_L^h$) represents the share of $h-$month national (regional, local) factor.

The upper part of Figure 6 shows the variance shares of the national, regional and local factors in city-level housing price growth as the time horizon h changes from 1 month to 5 years for the full sample period (2005M7–2015M4). We see that the share of the national factor increases drastically from 12% for the 1-month horizon to 47% for the 1-year horizon. Meanwhile, the shares of the regional and local factors decrease sharply. The share of the national factor roughly stays unchanged at around the 48% level when the horizon increases from 13 months to 2 years and a half. Then, it keeps rising as horizon increases. When the horizon comes to 5 years, the share of the national factor reaches 56%. Note that from Figure 3, we see that the national factor looks much 'smoother' than the regional and local factors. In other words, the national factor is much more persistent or of 'lower frequency' than the regional and local factors. As the horizon gets longer and longer, the housing price growth of a city will follow the trend set by the national factor more closely. Thus, it is natural to see that the share of the national factor increases. Similarly, the regional and local factors gradually cancel each other out as time horizon extends. It is thus intuitive that the shares of regional and local factors decrease. The results indicate that, in the medium and long term, the national factor plays the most important role in the city-level housing price growth fluctuations, and the city-level housing price growth in China is more of a national phenomenon in longer horizons.

When we focus on the ZLB period from January 2009 to April 2015, the results follow a similar pattern. The detailed variance shares for various horizons for this subsample period are depicted in lower part of Figure 6. For example, the national factor accounts for nearly 60% of the fluctuations in yearly housing price growth. We can see that during the ZLB period, the share of the national factor is even larger for all the time horizons compared with the share in full sample period. It suggests that the housing price dynamics

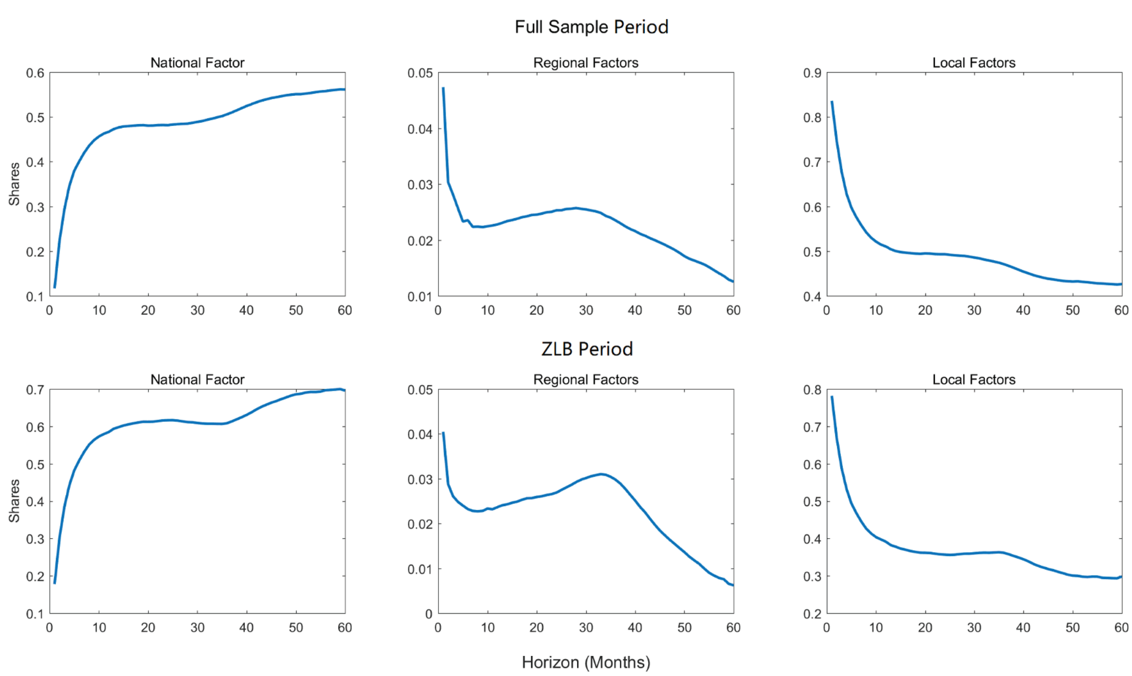

Figure 6. Variance decomposition for city-level housing price growth of various horizons. Note: This figure displays the average shares of different factors in the total variations in the city-level housing price growth of various horizons (1–60 months). The upper part corresponds to full sample period from July 2005 to April 2015, while the lower part corresponds to the ZLB period from January 2009 to April 2015.

across cities became more synchronized after the 2007–08 financial crisis.

What is behind the comovement of housing prices?

So far, we have demonstrated a nationwide comovement of housing price growth. In this section, we further explore what is behind this comovement (represented by national factor). The 2008 financial crisis swept the global economy, and central banks around the world provided abundant liquidity to save the financial system from collapsing. The excess liquidity flowed into emerging markets in the following several years, especially into China before the year of 2014, resulting in an overheated financial market and an expansion of capital market bubble. As it is widely conceived that the real estate fluctuation in China is related to the overseas capital flows, we now try to quantify its impact on housing prices. Moreover, the outbreak of financial crisis triggered a shift in Chinese monetary policy from a tightening stance to a loosening one. We are especially curious about the potential interactions between the national factor and these two shocks, namely the shocks of hot money inflows and of monetary policy shift, during the ZLB episode. Therefore, we employ a VAR model to quantify their interactions. The reduced form VAR is as follows

$$Y_t = C + A(L)Y_{t-1} + u_t,\ u_t \sim N(0, \Sigma), \tag{20}$$

where Y_t is a 6×1 vector, C is a constant vector, u_t is the error term that follows a multinomial normal distribution with mean 0 and variance matrix Σ, $A(L)$ is the matrix polynomial in the lag operator L, and the lag order of the VAR system is chosen to be 1 according to the Bayesian and Hannan–Quinn information criteria. The six variables in Y_t are ordered as follows: the seasonally adjusted monthly growth of the industrial production, seasonally adjusted CPI, national factor for city-level housing price growth estimated in the aforementioned dynamic hierarchical factor model, the benchmark loan rate (as a proxy for monetary policy), seasonally adjusted hot money growth and month-on-month growth of the SSE Composite Index. Stock market index is included since it is one of the major investment alternatives besides housing market for Chinese household. Glaeser et al. (2017) argue that Chinese savers have been pushed towards housing as a crucial form of investment because of the limited investment opportunities. Also researchers support an intense correlation, or wealth effect, between housing and stock markets (Tsai, Lee, and Chiang (2012), Green (2002)). Moreover, the industrial production and CPI are included to control the economic environment. We use the monthly series of industrial production instead of GDP because the latter variable is measured at a quarterly frequency. One of the main goals of this study is to investigate these variables' dynamic responses to shocks of monetary policy and hot money flows. For this end, we order these variables from the most exogenous one to the most endogenous one and from the most slow-moving one to the most fast-moving one, and the identification is achieved by assuming that variables do not respond contemporaneously to shocks to variables ordered after it. Specifically, the national factor is assumed not to respond to monetary policy shocks and hot money shocks contemporaneously.

Impulse response Figure 7 illustrates the impulse responses of the national factor to each of the six one-standard-deviation shocks in the VAR model. The dashed lines present the 68% bootstrap confidence bands, and the black solid lines present the median. The national factor gives a significantly positive response to an exogenous increase in hot money inflows in the short run (i.e. 1–6 months). Real estate was widely deemed as a prospective sector in China due to the so-called 'rigid demand' for housing and the rapid economic growth of the Chinese economy. The booming housing market in China attracted domestic as well as foreign investors, as the developed economies, especially the United States, implemented 'quantitative easing' policy and the capital returns were low. The result from the VAR model confirms that the international capital flows are one of the factors that influence the comovement of housing price fluctuations.

However, the influence of a positive shock to hot money inflows on the national factor reverses in the medium term, and the national factor goes negative for the following 2 years. This reversal pattern can be explained by the effect of the tightening of monetary policy. That is, the PBoC will

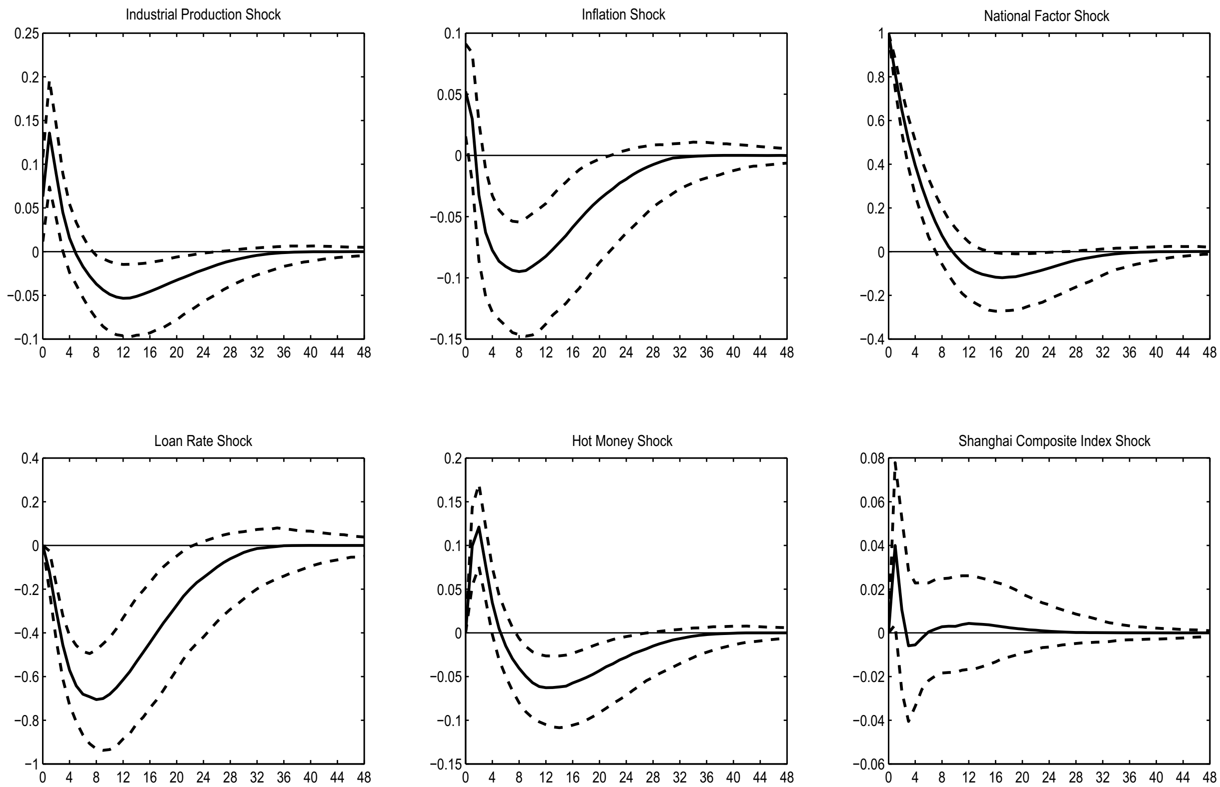

Figure 7. Impulse responses of the national factor to various shocks: 2009M1–2015M4. Note: The above six panels depict the impulse responses of the national factor to positive industrial production, CPI, national factor, loan rate, hot money and SSE Composite Index shocks from 0 to 48 months, respectively. The dashed lines indicate the 68% bootstrap confidence bands, and the solid lines are the bootstrap median. The shock sizes equal to one standard deviation of the corresponding variable. The numbers on the vertical axes are in standard deviation units.

implement a contractionary monetary policy in response to a positive hot money shock to offset the extra money supply. Figure 8 depicts the impulse responses of all the variables in the VAR model to a one-standard-deviation positive hot money shock. We see that the loan rate does rise significantly in response to a positive hot money shock. This confirms our previous argument that the PBoC tightens monetary policy when extra international capital flows in.

From the top middle panel of Figure 7, we see that a positive inflation shock induces a significant increase in the national factor for 1 month, followed by sizable significant decreases for 1 year and a half. This result may look surprising at the first glance, as in China, real estate has been traditionally viewed as a good asset to hedge against inflation and to serve as a store of value. However, if we take central bank's reaction into account, this result is natural. When inflation gets high, the central bank tightens its monetary policy to stabilize prices. As a consequence, house buyers face rising mortgage payments, which suppress housing demand. Moreover, the bottom right panel of Figure 7 shows that a positive shock to stock prices has moderate positive impacts on the national factor in the short term, suggesting a wealth effect on the stock market. People get rich when stock market runs well and their demand for houses will also increase.

Historical decomposition In addition to the shape and significance of impulse responses, the historical decomposition provides further evidence on the quantitative importance of monetary and hot money shocks. Historical decomposition estimates the individual contribution of each structural shock to the movement of housing factor over the sample period. Figure 9 illustrates the historical decomposition of the national factor. From the large green area for the loan rate and light blue area for the inflation, we see that monetary policy plays a crucial role in generating the

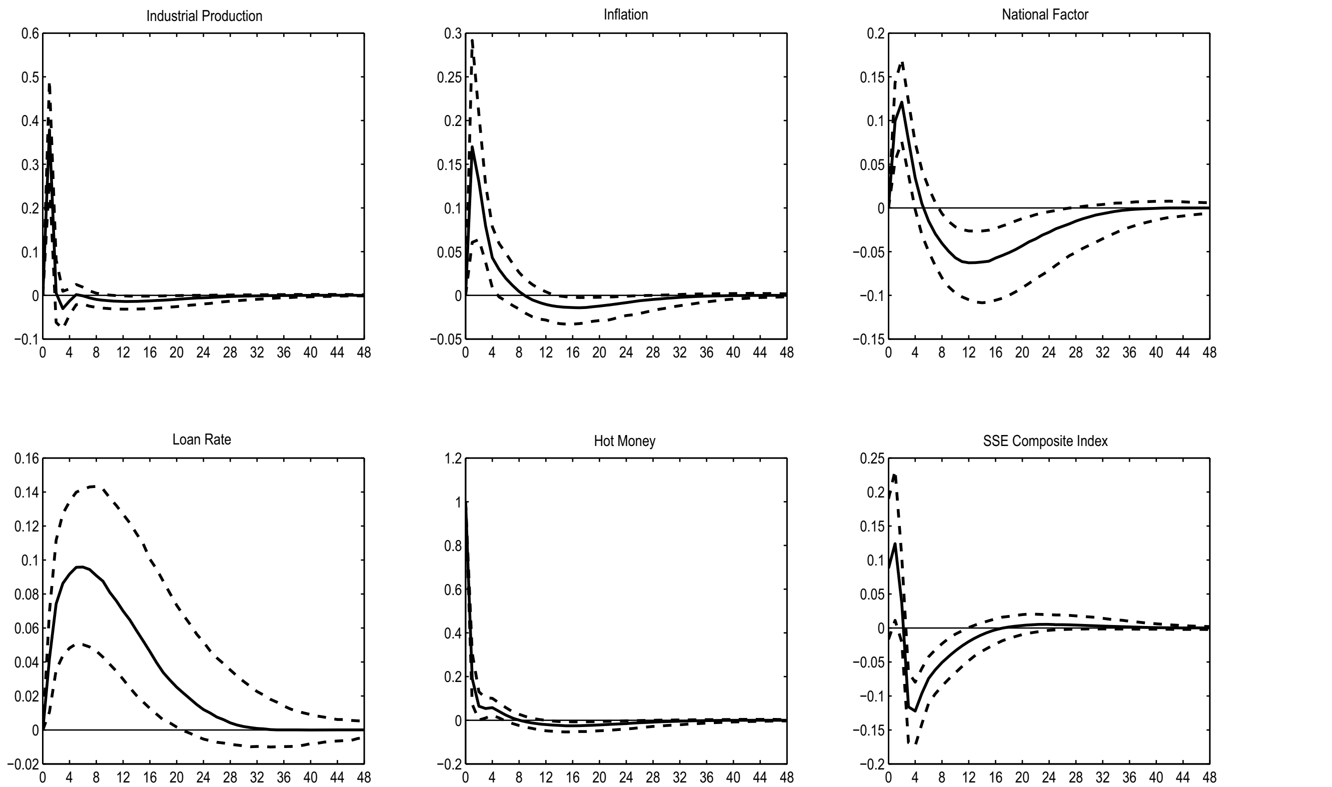

Figure 8. Impulse responses of various variables to a positive hot money shock: 2009M1–2015M4. Note: The above six panels depict the impulse responses of industrial production, CPI, national factor, loan rate, hot money and SSE Composite Index to a positive hot money shock from 0 to 48 months. The dashed lines indicate the 68% bootstrap confidence bands, and the solid lines are the bootstrap median. The shock size equals to one standard deviation of the seasonally adjusted hot money growth. The numbers on the vertical axes are in standard deviation units of the corresponding variables.

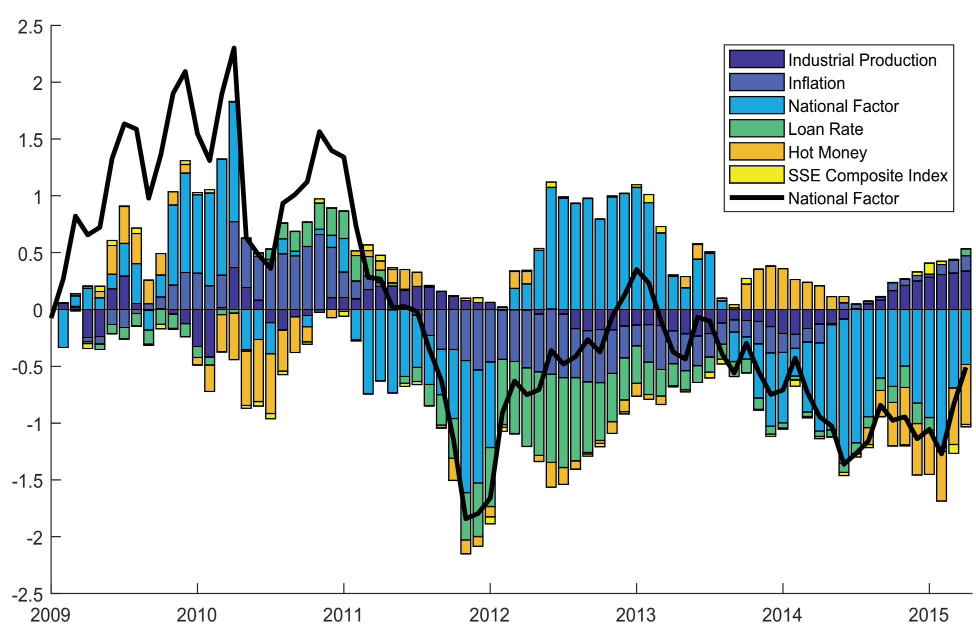

Figure 9. Historical decomposition of the national factor: 2009M1–2015M4. Note: The black curve is the national factor of housing price growth, which is normalized to have zero mean and unit variance. The bars of various colours represent the contributions of various types of shocks to the movement of the national factor. The numbers on the vertical axes are in standard deviation units.

national factor fluctuations. In general, hot money shocks contribute relatively less to the national factor fluctuations than the monetary policy, but they significantly affected the national factor in some periods. Figure 9 shows that hot money shocks increased the national factor by 0.3 and 0.4 standard deviation units in the third quarter of 2009 and around the beginning of 2014, respectively. Hot money shocks lowered the national factor by nearly 0.6 standard deviation units in the middle of 2010; in 2014Q4 and 2015Q1, hot money shocks also lowered the national factor by about a half standard deviation unit.

Forecast error variance decomposition Forecast error variance decomposition is also carried out to provide additional evidence for the importance of the impacts that monetary policy and hot money shocks have on the national factor. Table 4 presents the result of decomposing the variance of the national factor forecast error into six parts at selected horizons, and each part corresponds to one type of shocks. The shocks to the national factor itself explain a large portion of the forecast error, and at the 24- to 48-month horizons, they can explain about 30% of the forecast error. At the same horizons, monetary policy shocks and hot money shocks explain around 37% and 10% of the error, respectively. Inflation shocks account for around 14% of the error, and the logic here is similar to the one mentioned in the analysis of impulse responses. That is, price shocks will result in monetary policy adjustments and hence lead to responses of the housing prices. According to the forecast error variance decomposition, monetary policy shocks, hot money shocks and inflation shocks are the three major sources of the fluctuations in the comovement of city-level housing price growth.

Table 4. Forecast error variance decomposition for the national factor: 2009M1–2015M4.

Horizon	Industrial Production	Inflation	National Factor	Loan Rate	Hot Money	Stock Price Index
1	7.36	1.52	87.01	0.15	3.52	0.43
6	5.68	5.58	69.92	12.26	6.29	0.27
12	5.15	11.93	46.72	29.90	6.13	0.18
18	5.98	14.04	35.72	36.16	7.96	0.14
24	6.58	14.43	32.13	37.52	9.21	0.12
30	6.87	14.42	31.16	37.61	9.82	0.12
36	6.99	14.36	30.97	37.51	10.06	0.12
42	7.02	14.33	30.96	37.43	10.13	0.12
48	7.03	14.32	30.98	37.40	10.15	0.12

Notes: This table presents the result of decomposing the variance of the national factor forecast error into six parts at selected horizons, and each part corresponds to one type of shocks. All numbers are in percentage points. The six types of shocks are the industrial production shocks, price shocks, shocks to the national factor, monetary policy shocks, hot money shocks and shocks to SSE Composite Index.

The impact of quantitative easing measures of the U.S. Fed

We have so far established that the hot money inflows significantly contribute to the housing price increase during the ZLB period. In that period, the global economy witnessed an unprecedented launch of unconventional monetary policy around the world. We are curious about whether the quantitative easing measure launched by the U.S. Fed is behind the hot money surge in that period. To this end, we include one more variable, the U.S. federal fund rate, into the VAR model in Equation (20) to investigate its impact on hot money inflows and house price increases in China.

One question remains that, during the ZLB period, the effective Fed fund rate stays round zero and does not reflect the scale of quantitative easing measures. We instead use the shadow rate measure as constructed by Wu and Xia (2016) as an extension of the effective federal fund rate during the times when the ZLB is binding, and this measure is designed to capture the U.S. monetary policy stance when unconventional monetary policy is implemented. Unlike the observed short-term interest rate, the Wu-Xia shadow rate allows the policy to drop below zero. Whenever the Wu-Xia shadow rate is above one-fourth per cent, it is exactly equal to the observed effective federal fund rate by construction.

The Wu-Xia shadow rate is displayed in Figure 10. In this figure, we can see that before 2009 when the ZLB was not binding, the shadow rate was equal to the observed effective Fed fund rate. These two rates have diverged since the end of 2008, when the Fed began its asset purchase program. From then on, the effective federal fund rate has been stuck at the ZLB, while the shadow rate has become negative and still displays meaningful variation. The shadow rate declines all the way down with the growing amount of the asset purchase. It was not until the Fed began to taper its purchase in January 2014, when the shadow rate eventually rebounds. Therefore, the Wu-Xia

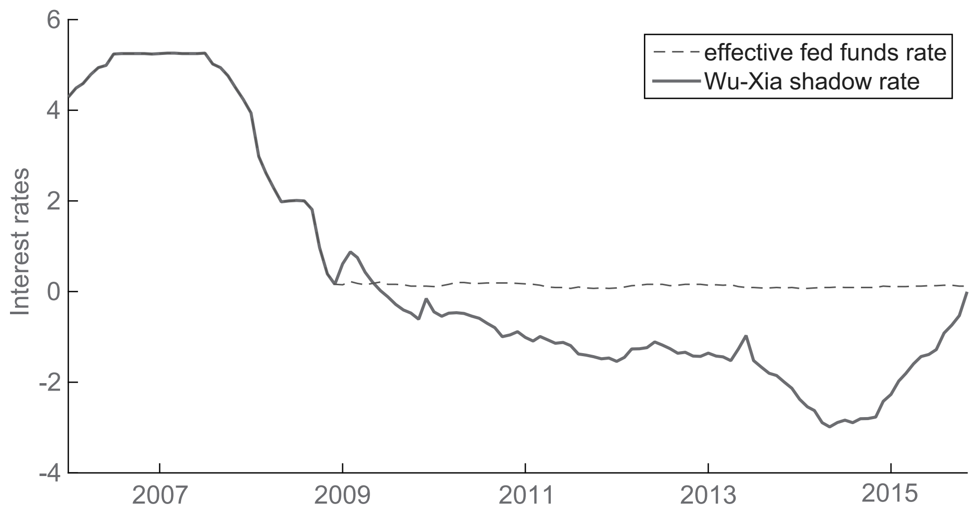

Figure 10. The Wu-Xia shadow rate compared with the effective federal funds rate. Note: The solid line indicates the shadow rate constructed by and Wu and Xia (2016), and the dashed line is the effective Fed fund rate, which is obtained from the Board of Governors of the Federal Reserve System.

shadow rate can be a useful measure of the Fed's monetary stance. So we use the shadow rate to replace the observed Fed fund rate series.

The specification of the VAR model is on the whole the same with Equation (20), except that Y_t here contains seven variables. Specifically, the variables in Y_t are ordered as follows: industrial production, CPI, national factor of house prices, the benchmark loan rate (as a proxy for monetary policy), the Fed fund rate (proxied by the Wu-Xia

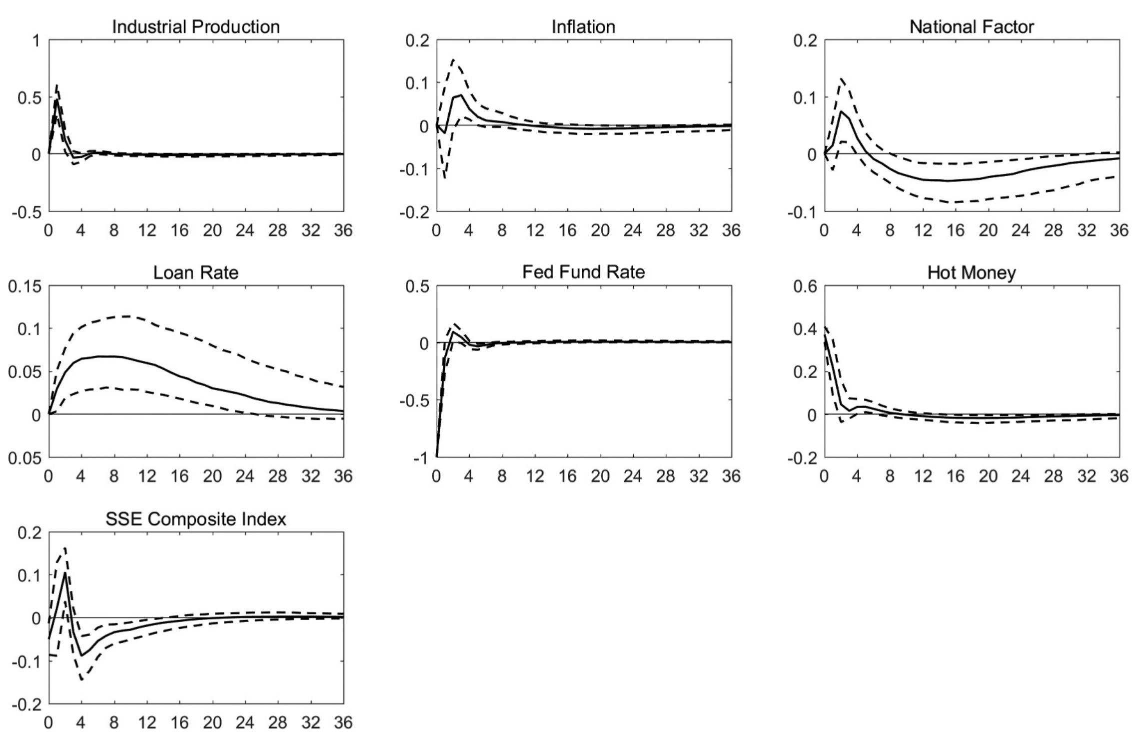

Figure 11. Impulse responses of various variables to a negative shadow rate shock: 2009M1–2015M4. Note: The above six panels depict the impulse responses of industrial production, CPI, national factor, loan rate, hot money and SSE Composite Index to a negative shadow rate shock from 0 to 36 months. The dashed lines indicate the 68% bootstrap confidence bands, and the solid lines are the bootstrap median. The shock size equals to one standard deviation of the first difference of the shadow rate. The numbers on the vertical axes are in standard deviation units of the corresponding variables.

shadow rate), hot money and the SSE Composite Index. Following the same rule, these variables are ordered from the most exogenous one to the most endogenous one and from the most slow-moving one to the most fast-moving one. In that sense, the identification is achieved by assuming that the stock market and hot money respond contemporaneously to Fed fund rate shocks, while industrial production, CPI, housing price and the benchmark loan rate do not. We are especially curious about the dynamic responses of hot money flows and the national factor of house prices to shocks of the Fed fund rate.

Figure 11 displays the impulse responses of all the variables in the VAR model to the Fed fund rate (proxied by shadow rate) shock, along with the 68% posterior coverage intervals. The hot money shows an immediate and significant rise following an exogenous drop in Fed fund rate, which is later followed by a prominent increase in the national factor of house prices. The results confirm that the quantitative easing measure indeed induces a surge of capital inflows into China. And these speculative capital flows into the thriving Chinese real estate market, further driving up the house prices. Therefore, hot money can be a valid channel through which the U.S. monetary policy spills over into the Chinese economy during the ZLB episode, which is consistent with the findings of Ho, Zhang, and Zhou (2018). Other variables respond in a similar pattern to those in Figure 7. The industrial production and inflation rate rise in the presence of excessive money supply induced by the inflows of hot money. The stock market goes up following a decrease in Fed fund rate and the induced hot money influx. The benchmark loan rate, which is the policy rate of PBoC, shows a significant and persistent increase as a response to the rising inflation and overheating real estate market. This tightening monetary policy of PBoC then triggers a reversed effect both on housing prices and on the stock market.

V. Robustness

In this section, we take an alternative approach to calculate hot money and then verify the robustness of its effect on housing prices. Following Prasad and Wei (2009), we calculate hot money as the sum of the errors and omissions and net portfolio flows. Since both of these two constituents are measured at a quarterly frequency, the hot money obtained from the addition is also a quarterly series. Therefore, we estimate the VAR model in Equation (20) at a quarterly frequency. The specification of the VAR model is exactly the same with those in Equation (20), where Y_t is a 6×1 vector with the six variables following the same order of industrial production, CPI, national factor, loan rate, hot money and the SSE Composite Index.

Figure 12 represents the national factor's responses to each of the six one-standard-deviation shocks in the VAR model. All the responses to various shocks follow a similar pattern to those in Figure 7. The national factor gives a significantly positive response to an exogenous increase in hot money inflows in the short run of 1–2 quarters, which exactly match the positive response of national factor in the first 6 months after the hot money shock in Figure 7. A contractionary monetary policy represented by a rise in the benchmark loan rate leads to a significant decline in the national factor of house prices. And a positive shock to stock prices has a prominent impact on the national factor. Moreover, we see that both a positive inflation shock and a positive production shock induce an immediate and significant increase in the national factor for about one-quarter and the effects reversed later on because of the tightening monetary policy the PBoC adopts to cool down the inflation, as we explained before. All these results support the robust effects of hot money under alternative measurements.

VI. Conclusions

Using a hierarchical dynamic factor model, we identify the national, regional and local factors that influence the city-level housing price growth across major cities in China, and evaluate their relative importance. Although local factors account for most of the fluctuations of the city-level housing price growth, national factor has played a more important role since the 2007–08 financial crisis. Moreover, when we extend the time horizon of housing price growth rate from 1 month to half a year, the variance share of the national factor leapt from 18% to 51%, indicating that the city-

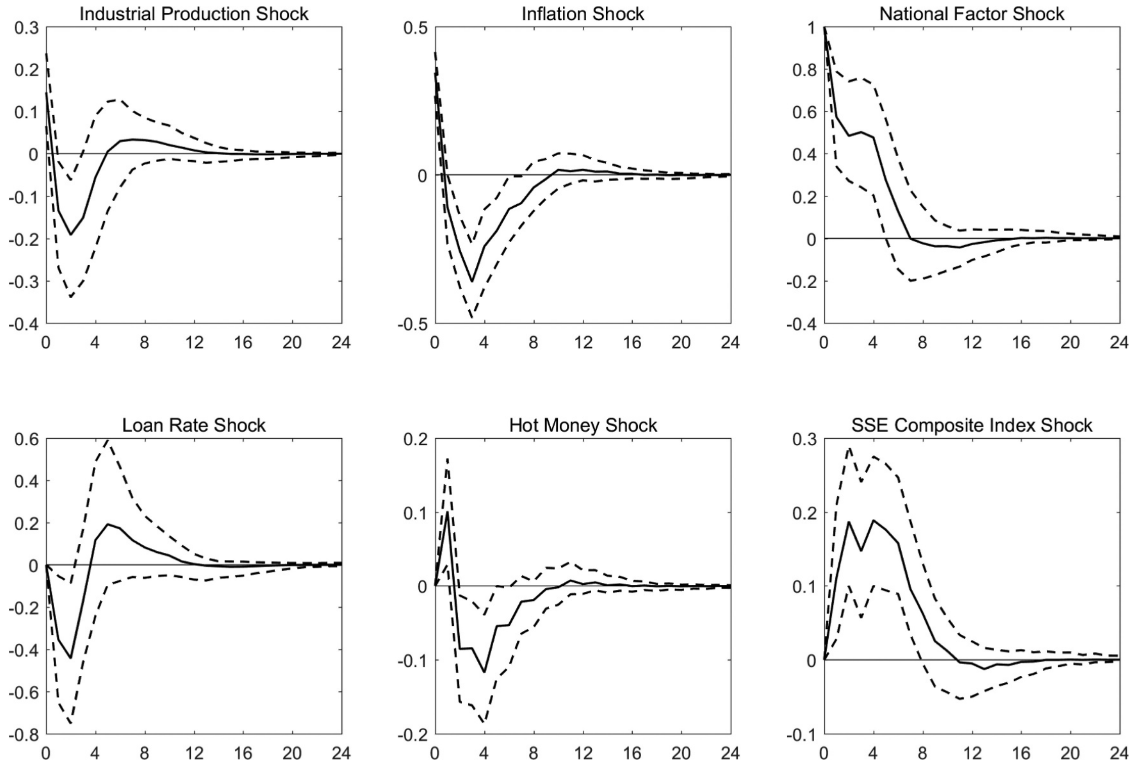

Figure 12. Impulse responses of national factor to various shocks: 2009Q1–2015Q2. Note: The above six panels depict the impulse responses of the national factor to positive industrial production, CPI, national factor, loan rate, hot money and SSE Composite Index shocks from 0 to 24 quarters, respectively. The dashed lines indicate the 68% bootstrap confidence bands, and the solid lines are the bootstrap median. The shock sizes equal to one standard deviation of the corresponding variable. The numbers on the vertical axes are in standard deviation units.

level housing price growth in China is more of a national phenomenon in longer horizons. After having obtained an estimate of the national factor from the dynamic factor model, we investigate the driving forces behind the comovement of housing prices. We find that: 1) contractionary monetary policy has a large negative impact on the national factor; 2) positive hot money shocks and inflation shocks have significant positive impacts on the national factor in the short run, which will be reversed later. The reversed effect can be explained by the PBoC's tightening policy induced by these two shocks. In addition, using Wu-Xia shadow rate as an extension of the effective federal fund rate, we find that the quantitative easing measure of the U.S. Fed is behind the hot money inflows into China during the ZLB period, suggesting a spillover effect of the U.S. unconventional monetary policy.

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