HOUSING PRICE, DISTRICTS, AND TRANSPORTATION INFRASTRUCTURE:

A STUDY OF PRICE SPILLOVER IN SHANGHAI BY GVAR METHOD

by

Changqing Mu

A dissertation submitted to the Faculty of the University of Delaware in partial fulfillment of the requirements for the degree of Doctor of Philosophy in Economics

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ABSTRACT

This dissertation provides an empirical study of housing price spillover in metropolitans Shanghai. In this study, Shanghai is divided into nineteen districts based on geographic locations and official administrative districts. Given the close connection among the districts, the spillovers in housing prices across districts are expected to be particularly strong. This study focuses on the spillover of housing prices at the district level, in particular, how a housing price shock in one district spreads over to other districts. A global vector autoregressive (GVAR) model is estimated with district-specific variables, weighted foreign variables, and common variables. The novelty of this study lies in the construction of a time-varying weight matrix used in the GVAR model. Previous GVAR studies on housing prices have used physical distance or neighbor indicators to construct the weight matrix, which is guaranteed to be a constant. This study instead uses commute time to construct the weight matrix, which is time-varying since several new lines of public transportation have been constructed during the sample period. In addition, using simulation study and counter-factual analysis, this study also estimates to what extent the newly-constructed public transportation affects the spillover effects in the Shanghai housing markets as well as the effect of money supply on housing prices. The conclusions from this dissertation could have significant policy implications for urban planning and public finance.

Chapter 1

INTRODUCTION

Since the reform and opening-up in the late 1970s, China has gained astounding achievements in economic development. It has been the world's fastest-growing major economy over the past 30 years with an annual growth rate averaging 10%. With an estimated $10.4 trillion nominal GDP in 2014, China is now the world’s second-largest economy.

At the same time, China has undergone an impressive urbanization process since the economic take-off. It has seen the world’s largest migration of rural residents into cities. The urban population has risen by more than 500 million, “the equivalent of America plus three Britains”[1]. China’s cities are now home to close to 740 million people, or about 54% of the population, compared to 20% in 1982. The World Bank forecasts that the number of city-dwellers is likely to grow by an annual average of about 13 million between now and 2030. This is roughly the population of Pennsylvania. By the year 2030, around a billion people, which is about 70% of China’s population, will live in cities.

In this unprecedented urbanization, over half of the immigrants have rushed into cities in the coastal regions of China, such as Shanghai, Shenzhen, and Guangzhou. People prefer these metropolises because they are more industrialized and provide greater opportunities. In addition, the Chinese government has also encouraged the development

[1] “Where China’s future will happen” *Economist* April, 2014

of these super cities because the postulated urban agglomeration benefits are high. For example, Au and Henderson (2006) found that per capita income rises sharply with increases in city size.

Among these metropolises in the coastal regions, Shanghai is the most attractive one to the immigrants. The population of Shanghai was less than 16.5 million in 2000. With a population growth rate of around 3.25% in the past 16 years, it is now home to 24.2 million people. It is projected that Shanghai will have a population of more than 50 million by 2050. It is now China's most populous city and probably will be the largest city in the whole world in the future.

While the massive immigration brings Shanghai an abundant workforce and economic growth, it brings urban diseases as well. This heavily populated metropolis is now facing worsening congestion, pollution, and especially surging housing prices. The highly volatile and sharply increased housing prices could be one of the most remarkable and interesting economic phenomenon in Shanghai.

Over the last decade, the housing prices in Shanghai have risen by over 400%. However, this growth is not evenly distributed geographically. In this dissertation, Shanghai is divided into nineteen districts based on geographic locations and official administrative districts (figure 1). These districts have had very different housing price growth patterns over the past decade (figure 2). However, given the close connection among those districts, the spillovers of housing prices across districts are expected to be particularly strong. A global vector autoregressive (GVAR) model is employed to study the price interaction/spillover among these districts, in particular, how a house price shock in one district spreads over to other districts. I focus on the short-term dynamics of housing prices at the district level because the short span of available data (from 2006m1 to 2014m8) does not allow me to study the long-run determination of housing prices in Shanghai.

Figure 1 Shanghai Is Divided into Nineteen Districts

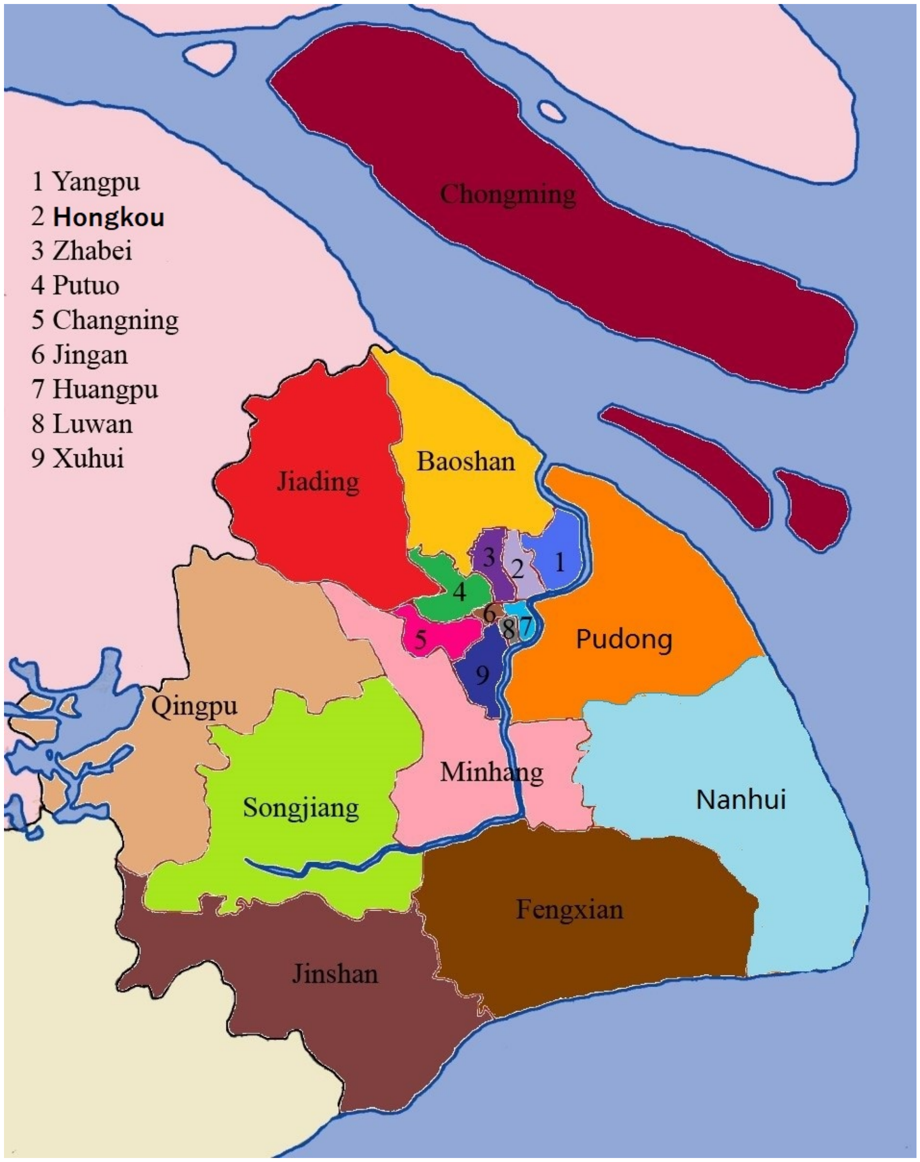
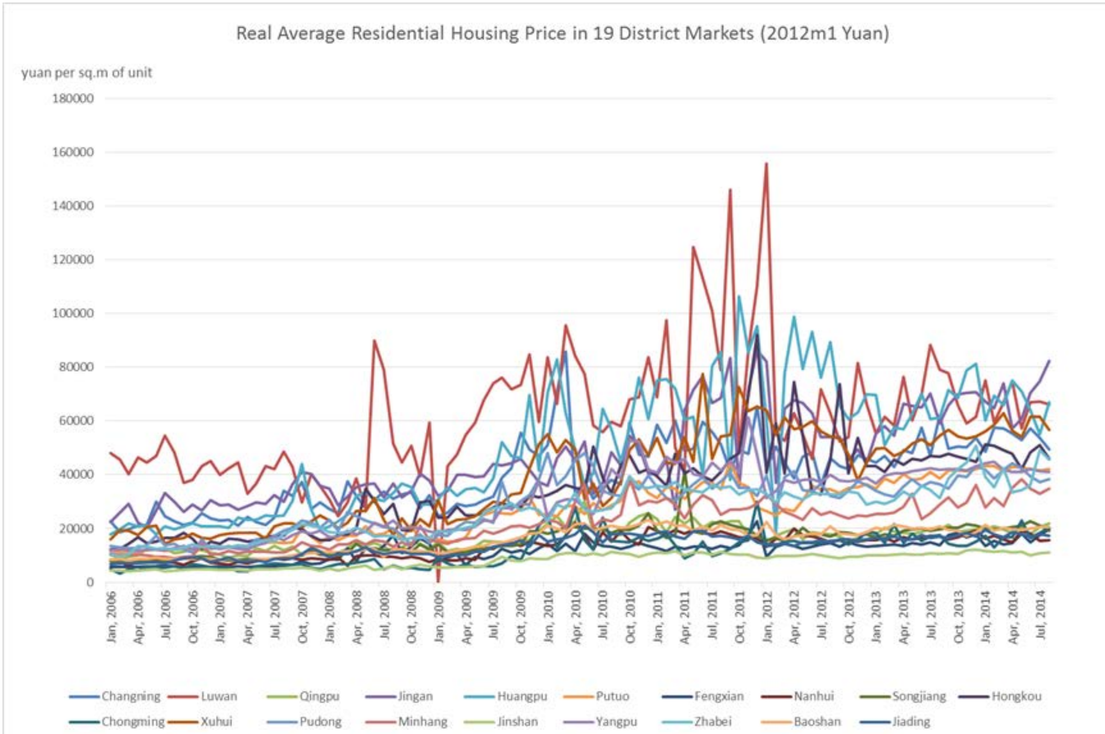


Figure 2 Price Trend in Nineteen Districts (the Separate Graphs are in Figure 4)



Besides the spillover effect, this dissertation also investigates the impact of transportation infrastructures on the housing price co-movements. Shanghai has constructed several large transportation infrastructures in last 12 years, such as new subway lines and the Yangtze River Bridge. These transportation infrastructures greatly shorten the commute time from some districts to others. For example, the newly-built Shanghai Yangtze River Bridge reduces the commute time between the district *Chongming* and city center from over 2 hours to 45 minutes. It is reasonable to speculate that the newly-built transportation infrastructures play an important role in changing the housing prices co-movement relationship. To capture the effects of new transportation infrastructures, I build a GVAR model with a time-varying weight matrix. This time-varying weight is based on the commute time. In addition, through simulation studies and counter-factual analysis, this dissertation also estimates to what extent the newly-constructed public transportation could affect the spillover impact among Shanghai housing submarkets. Additionally, this paper also studies the relationship between housing price and land price in Shanghai, and the impact of M2 (money policy) on housing price.

Findings from this dissertation have at least two policy implications. The first implication is for public finance. A new line of transportation would sharply increase the housing prices in some districts. At the same time, it could also harm other housing markets. It is unfair to distribute the construction cost evenly to residents in different districts. Homeowners whose property values are positively affected by these newly-built transportation infrastructures should pay more for these constructions in the form of increased property tax or a special assessment tax. People whose property value is negatively affected could get a reduction in their property tax. Although China does not collect property tax for now, the Chinese government has been debating the introduction of property tax over the last few years. It may be written into law by the end of 2017 and implemented soon after that. This paper could provide some empirical guidance for this discussion.

The second implication is for urban planning. Knowing to what extent public transportation affects households' preference for housing location could assist the government in making decisions on future infrastructure construction. If commute time plays a significant role in the choice of housing location, the government could encourage residents to live in a suburban area, such as satellite towns, by constructing more high-speed transportation infrastructure. Satellite towns are widely accepted as the future of the metropolis and the solution to urban diseases; By relieving congestion and decreasing pollution in cities, these towns will support China's sustainable urbanization in the future.

On the technical side, studying the spillover effect of housing prices requires adequate modeling of the close interconnection across housing markets at the district level. Although a few large global models exist, such models tend to be too large and complex, and cannot be applied to forecast and simulation analysis. The GVAR model fits this study perfectly. It provides a general yet practical modeling framework for the quantitative analysis. This model can quantify the relative importance of different channels of transmission mechanisms. It has been shown to be particularly suited to the analysis of shock transmission from one district to many others. By constructing a time-varying weight variable, the GVAR model is capable of capturing the price spillovers in Shanghai's housing market. To the best of my knowledge, this is the first empirical study using GVAR with a time varying weight matrix to explain the housing price movement.

Chapter 2

LITERATURE REVIEW

In this chapter, I give a review of the literature on three topics: long-run determinants of housing price, short-run dynamics of housing price, and the GVAR method and its applications to the housing market.

2.1 Housing Price and Its Long-Run Determinants

Many reviews of housing economics have noted that housing price could be explained by the fundamentals. These fundamentals can be sorted into two categories: demand side and supply side. The demand side fundamentals are factors that affect house buying decisions and user costs of home ownership, such as real interest rates, disposable income, and demographic development. The supply side factors are derived from factors influencing the available housing stock. The relationships between housing price and the fundamentals are expected to hold in the long-run however they have no close relationship in the short-run. Thus, this approach can only provide an explanation of the equilibrium or long-term housing price. The current price cannot be predicted by the fundamentals and often deviates significantly from the fundamental value.

Poterba, Weil, and Shiller (1991) test the role of tax policy and demography on house price dynamics using disaggregated data (both at the city level and at the household level). The authors coined the term “real user cost of home ownership.” It takes into account the financial returns associated with the owner-occupied housing. The returns contain potential rental cost, differences in risk, tax benefits, and any anticipated capital gains from owning the house. It also considers the cost of property tax, depreciation, and maintenance. The study finds that the movement of housing price and the phenomenon of different housing price growth patterns across cities is partly explained by the different user costs of home ownership combined with construction costs.

Terrones and Otrok (2004) estimate a dynamic panel regression on the housing markets of eighteen countries. Their data covers thirty-four years, from 1970 to 2003. The result shows that the growth rate of real house prices is stable in many countries around the world. The housing prices also show a long-run reversion to fundamental values. The differences in the economic fundamentals in those countries decide the relative price levels.

Black, Fraser, and Hoesli (2006) develop a time-varying present value approach computing fundamental values. The paper studies the UK housing market from 1974Q1 through 2004Q2. They find that the UK real housing prices deviate from fundamental values in many time periods. The authors explain these deviations with so-called "intrinsic bubbles," which are built on bounded rationality and self-fulfilling expectations. The intrinsic bubbles lead to real housing prices periodically reverting toward their fundamental values. Correction toward 'true' value is likely to be a prolonged process. This study precludes the existence of an explosive rational bubble due to non-fundamental factors. The authors also point out that arbitrage in the housing market is limited due to the characteristics of the market, which contributes to the long process of reverting toward the fundamental values.

Glaeser, Gyourko, and Saiz (2008b) emphasize the important role of supply on housing price movement. They examine the U.S. housing market during the period from 1982 to 2007 with a focus on the two booms, one in the 1980s and the other post-1996.

They find that supply elasticity is a crucial determinant of the depth and duration of a bubble. While cities with an inelastic supply experienced severe housing booms in the two periods, highly elastic locations experienced lower possibility and shorter spans of the housing bubble with the smaller price increase. However, the authors also admit that it is hard to predict what will happen exactly to elastic areas that experience price booms.

Several OECD surveys also examine the role of housing supply. The OECD (2004a) concludes that the high growth in Netherland real housing prices is mainly attributed by weak supply response. In Ireland, the sharp increase in the existing houses' prices relative to new houses', since the mid-1990s, may be due to the supply constraints (OECD 2006). However, another survey (OECD 2004) finds no evidence that weak supply response plays a role in the high growth in housing price in Spain.

Meen (2002) examines the U.S. (1981Q3-1998Q2) and the U.K. (1969Q3-1996Q1) housing markets. The author estimates error correction models for both countries. Meen argues that although U.S. and U.K. housing markets operate in very different ways, in terms of tenure and mortgage markets, the similarities are more striking than the differences. In terms of the effects of fundamentals, the demand side factors exert similar contributions to the high growth in real housing prices in both countries. The differences lie in the supply side. While weak supply response does not contribute to the high growth in real housing price in America, it partly contributes to the high growth in the U.K. real housing price.

Similar to Meen (2002), Aneett (2005) fits an error correction model to euro-area housing markets from 1976 to 2001. The author finds that real credit and money supply are important determinants of long run housing prices. Furthermore, this paper divides countries into sub-groups based on their institutional characteristics and runs a panel regression on those groups. The results show that institutional factors help explain the relationship between credit and house prices.

Himmelberg, Mayer, and Sinai (2005) propose a new fundamental calculation method that measures housing value by evaluating the cost of homeownership. This cost contains the imputed annual rental cost of owning a home and a variant of the user cost. Based on their method, housing price is critically impacted by long-term interest rates and property tax. An unexpected rise in real interest rates will raise the expected cost of homeownership which lowers housing demand. The shrinking demand could slow the growth of house prices, and possibly even lead to a house price decline. The authors conclude that house price is theoretically more responsive to interest rates when interest rates are already low. This relationship is much closer when the long-run growth rate of house prices is high.

Schnure (2005) emphasizes the important role of interest rates in housing prices. He examines U.S. housing markets from 1978 through 2004 using panel estimation. This paper compares housing price movement between different regions, especially in the short term. The study finds an increased sensitivity of housing prices to interest rates since 1990. The increased sensitivity is due to the liberalization of mortgage lending access and higher securitization.

The effects of other financial variables on housing markets are also heavily researched by economists. Nagahata et al. (2004) take panel co-integration analysis of the housing markets of forty-seven Japanese prefectures. They find that non-performing loan ratios have a significant explanatory power in housing price movement in the short run. Tsatsaronis and Zhu (2004) examine housing markets in seventeen countries. The authors group countries based on their mortgage finance structures. They find that countries with different mortgage finance structures have different inflation sensitivity to interest rates, and inflation accounts for nearly half of the total variation in housing price after five years from the homeownership transaction.

Restrictions on the availability of land for residential housing development also play an important role in housing price movement. These restrictions include tough zoning rules, cumbersome building regulations, and slow administrative procedures. All of the restrictions would limit the amount of developable land (Girouard et al. 2006). Mayer and Somerville (2000), Glaeser, Gyourko, and Saks (2003; 2005; 2006), Krainer and Wei (2004), Gyourko, Mayer, and Sinai (2006), Glaeser, Gyourko, and Saiz (2008a), Glaeser, Kahn, and Rappaport (2008) find that building regulations and low supply elasticity of housing play an important role in the post-1996 large price increases in U.S. urban markets. Baker (2004) points out that rigidity of housing supply should be responsible for the upward trend of the U.K. housing price and its high variability. This rigidity is due to complex and inefficient local zoning regulations and a slow authorization process. This review concludes that the land-use planning system is the main cause of supply shortages. Meen (2005) supports Baker's (2004) findings. Meen concludes that more house construction would be required in order to reduce the long-run real house price trend. Besides these papers, Gallent and Kim (2001) show that government restrictions on urban land supply and development zones have contributed to the rapid rise in Korean housing prices.

Knoll et al. (2017) find that land price has played a central role in housing price movement. By studying 14 advanced economies in the long sample period 1870 – 2012, Knoll et al. (2017) point out that land price itself can explain about 80 percent of global house price booms since 1945. In this study, the authors assume that long-run housing price trends are only driven by the replacement value and the value of the underlying land. Then they apply a stylized Cobb-Douglas technology model to study the different roles of these two factors. They find about 80 percent of the increase in house prices can be explained by higher land value.

Deng, Gyourko and Wu (2012) study the housing markets in 35 major cities in China from 2003 to 2010. They find that the escalating land value partly explains the housing price increase in nearly all cities examined. The land value movement has three notable characteristics: high volatility, mean reversion and strong impacts from common national factors, such as the monetary base. The authors also conclude that construction costs and wages in the construction sector have a negligible impact on the housing market.

This finding is corroborated by Wu, Gyourko, and Deng (2012), who examine Beijing's housing market. They conclude that much of the increase in housing prices is due to land value appreciation. Housing stock is adequate to meet the increase in urban demography and demand. No evidence suggests that housing demand growth has been outstripping new constructions over the last decade.

Yu (2010) examines the relationship between housing price and government real estate policy in China. The government sets new policies nearly every year. Real estate policies, especially land policies, have important effects on housing prices. This explains why no stable relationship has been found between economic fundamentals and housing price in China. Real estate policies distort their relationship.

Glaeser et al. (2017) compare house markets between China and the United States. This comparison has four aspects: housing price growth rate in the last 20 years, the size of construction floor space, a number of housing inventories and vacancies, and the role of government. In all aspects, the Chinese housing market's condition is even worse than the one of the U.S. housing market in 2007's financial crisis. The authors raise two questions: does China have a real estate bubble, and will the boom end in a bust? The authors conclude that China looks like a classic housing bubble. However, it is far from certain that this boom will end in a bust. The authors argue that a house is a kind of investment product in China. Homebuyers would like to invest for the long run rather than selling voluntarily when the home price drops.

The following table 1 is a summary of the literature on the fundamental factors.

Table 1 Summary of the Literature of Fundamental Factors

Determinants	Paper	Comments
Demography	Porterba, Weil and Shiller (1991)	Demography explains part of pricing movement.
Construction Costs	Porterba, Weil and Shiller (1991)	The phenomena of different housing price growth rates across cities are partly explained by construction costs.
	Deng, Gyourko and Wu (2012)	Housing prices are not driven by the construction costs or construction sector wages in China.
Land Price	Deng, Gyourko and Wu (2012)	House prices are driven by the land market in China.
	Wu, Gyourko and Deng (2012)	The increase in housing prices is partly due to land value appreciation.
	Knoll et al. (2017)	In the long-term, 80 percent of the increase in house prices can be explained by higher land value in 14 advanced economies.
Restricted Land supply	Baker (2004)	The rigidity of housing supply is responsible for the trend rise of UK housing price and its high variability.
	Gallent and Kim (2001)	Government limitations on urban land supply are an important factor in the rapid rise of Korean housing prices.
Housing Supply	Glaeser, Gyourko and Saiz (2008b)	Supply elasticity is a crucial determinant of the extension of a bubble.
	OECD (2004a)	High growth in real house prices is mainly attributable to weak supply response in the Netherlands.
	OECD(2006)	Supply constraints play an important role in the sharp price increase in Ireland.
	OECD (2004b)	High growth housing prices are not due to weak supply response in Spain.
	Meen (2002)	High growth in the real housing price is not attributable to a weak supply response in America, but is partly attributable to a weak supply response in the UK.
	Girouard et al. (2006)	The price elasticity of supply may

		vary over time and is difficult to estimate.
	Wu, Gyourko and Deng (2012)	No evidence shows that actual population growth has been outstripping new construction over the past decade in Shanghai.
Real credit	Aneett (2005)	Real credit is an important determinant of long-run housing price trends.
Money supply	Aneett (2005)	Money supply is an important determinant of long-run housing price trends.
	Hirata et al. (2012)	Global monetary policy shocks do not have sizeable impact.
Interest rate	Himmelberg, Mayer, and Sinai (2005)	Housing price is critically impacted by the long-run interest rate.
	Schnure (2005)	Interest rates play an important role in determining housing prices.
	Hirata et al. (2012)	Global interest rate shocks tend to have a significant effect on global housing prices.
Non-performing loan ratios	Nagahata et al. (2004)	Non-performing loan ratios have a significant explanatory power in housing price movements in the short run in Japan.
Inflation	Tsatsaronis and Zhu (2004)	Inflation accounts for nearly half of the total variation in housing prices after 5 years.

Like any other empirical study, the fundamental value approach is subject to a number of criticisms. The price elasticity of supply and demand may vary over time due to changes in regulatory conditions, demographic developments and taxes that cannot be adequately taken into account. This would cause the estimated relationship to be unstable (Girouard et al. 2006). Gürkaynak (2008) raises the concern that the fundamentals themselves could be misspecified, which could lead to wrong conclusions about asset value. As well, the econometric test is not effective, given the fact that it combines the null hypothesis of no bubble within the model of fundamentals. Mikhed and Zemčík

(2009) find that even after taking into account every fundamental that has been examined in the literature (these fundamental variables include population, personal income, stock market wealth, mortgage rate, building cost and real house rent), they still fail to explain housing prices in the market. Other criticisms point out that this approach ignores the interdependence between regional house markets. Due to these drawbacks, the fundamental value approach has very poor performance in forecasting housing price.

2.2 Short-Run Dynamics of Housing Price

Another thread of research has focused on the short-run relationship between housing price and its determinants as well as housing market synchronization and spillover. The estimated model can then be used to simulate and forecast.

Manski (1993, 2000) discusses the important role of interactions in the empirical economic analysis. The author introduces the notion “endogenous interactions.” It happens when agent behavior is permitted to vary with the mean behavior of the entire group. The endogenous interactions could be present in the synchronous house price movement.

More specifically for housing, Terrones (2004) takes a dynamic factor framework to study house price co-movement in eighteen advanced economies. The result shows that global shocks to housing markets alone explain nearly thirty percent of house price movements for the set of countries analyzed.

Otrok and Terrones (2005) support Terrones (2004). They use an augmented VAR model with latent factors to examine housing markets of eighteen industrialized countries. This study finds that the degree of co-movement in the growth rate of real house prices in industrialized countries is quite high. They also find that U.S. monetary shocks have a strong but delayed impact on housing price growth not only in the U.S. but also internationally.

Consistent with those findings, Hirata et al. (2012) explain house price fluctuations using various factor-augmented VAR models. This research covers eighteen advanced economies over forty years. House prices are found to be synchronized across countries. The degree of synchronization has increased over time. The effect of a variety of global shocks has also been estimated. Global interest rate shocks and uncertainty shocks (measured by the volatility of stock returns) tend to have a significant effect on global house prices, whereas productivity, credit shocks and global monetary policy shocks *per se* have an insignificant effect.

Gros (2006) finds a remarkably high correlation of housing prices between the US and the euro area over the long run. The US housing price plays an important role in the euro area housing market. Euro housing prices follow the U.S. with a lag of around one year. Although this study does not provide evidence of causality, it suggests that the linkage of housing markets across the two areas, either direct or indirect, is likely to exist.

Other papers study housing price spillover are confined to one country or region. For example, Klyuev (2008) examines regional house price movement across the United States at the state level. He finds strong evidence that regional housing price spillovers are present. Furthermore, this price synchronization has increased in degree since the 1990s.

Costello, Fraser, and Groenewold (2011) examine housing price interactions among Australian capital cities from 1984Q3 to 2008Q2. This paper utilizes a dynamic present value model within a VAR framework. It finds that price spillover exists across Australian capital cities. The mechanism of this price spillover is through “non-fundamental” components’ spillover from one capital city to another.

2.3 The GVAR Model and Its Applications in Housing Market

The global vector autoregressive (GVAR) model was first introduced by Pesaran, Schuermann, and Weiner (2004). It was originally developed as a tool to deal with credit risk analysis. The GVAR approach is relatively novel. It presents a complicated, yet simple to follow, spatial-temporal structure for the analysis of the global economy. This model combines time series, panel data, and factor analysis techniques. The methodological contributions of the GVAR approach lie in dealing with the curse of dimensionality (In an unrestricted vector autoregressive model, the number of unknown parameters rises sharply as the dimension of the model grows). The GVAR approach is one of the three common solutions to the curse of dimensionality, alongside factor based modeling approaches and Bayesian VAR approaches.

Pesaran, Schuermann, and Weiner (2004) originally proposed the GVAR approach as a pragmatic approach to building a coherent global model of the world economy. They estimate a global model over the period 1979Q1-1999Q1. The data comprises eleven countries/regions that account for 82% of world GDP in 1999. In estimating the GVAR model, they first estimate individual country specific VAR or vector error correcting models (VECMs). These models contain domestic macroeconomic (country-specific) variables such as gross domestic product (GDP), the general price level, the level of short-term interest rate, exchange rate, equity prices and money supply. They also contain cross-section averages of foreign variables (weighted by trade volume). The estimated individual country models are then stacked and combined to solve simultaneously as one large global VAR model. The GVAR is then used to generate forecasts and impulse response functions for all of the variables in the world economy. The individual VECMs in the Global VAR model are linked by the weight matrix, which is determined by pair-wise trade volumes.

Dees et al. (2007) advance GVAR research by providing a theoretical framework. It shows that the GVAR model can be taken as an approximation to a global unobserved common factor model. This model is shown to be quite effective in dealing with the common factor interdependencies and international co-movements of business cycles. The authors also develop a sieve bootstrap procedure for simulation of the GVAR as a whole. This procedure can be used in testing the structural stability of the parameters and in establishing confidence bounds for the impulse responses. Compared to the earlier work of Pesaran, Schuermann and Weiner (2004), the empirical example in this paper increases the geographical coverage and also extends the estimation period. The GVAR model is estimated for 26 countries over the period 1979-2003. It also addresses the issue of structural stability in Pesaran, Schuermann and Weiner (2004) and shows how the GVAR model can be used for structural impulse response analysis.

Cesa-Bianchi et al. (2012) examine the impact of China's economic emergence on the Latin America economy. It is the first paper estimating a GVAR model with a time-varying weight matrix. Following the GVAR literature, the authors use trade flows to build the weight matrix of foreign variables. However, due to the dramatic increase of China's share of global trade, a fixed weight matrix is unlikely to capture the spillover effect over the sample period from 1979 to 2009. A time-varying weight provides a solution to this problem. It is proven to be effective in analyzing interactions among economies in a dynamic environment.

Vansteenkiste (2007) is the first to apply GVAR analysis to the housing market. The author examines the 31 largest states in the United States over the period 1986 - 2005. In this study, individual state-specific VECMs contain two state-specific variables: housing price and real income per capita. The VECMs also contain corresponding state-specific weighted averages of the other states' variables. The state-specific weights are based on the distance between states. In addition, it includes a time trend and real interest rate as the exogenous/common variables. These two variables are nationwide and same for all states. Noticing that the housing price growth rates display considerable heterogeneity across cities, states, and regions, the author tries to answer two questions: first, how important are the common factors/country-level variables in driving US housing price development given the increase in state-level heterogeneity; second, to what extent a housing price shock in one state spills over across other states. To the first question, the author finds that while the role of long-term interest rates is non-negligible, it has not been the main driver behind recent US housing price development. To the second question, although housing price spillovers are present at the US state level, their magnitude only becomes important when house price shocks occur in certain states (CA, NY, etc.).

Following the method in Vansteenkiste (2007), Vansteenkiste and Hiebert (2011) estimate the housing price spillover in the euro area. The result shows that although country-specific housing price shocks spill over to other countries existing in the euro area, they do so at a relatively small magnitude. In terms of the general magnitude of housing price spillovers, a country's economic weight in the euro area plays an important role in determining the long-run impact. Price shocks in countries like France and Germany have a more significant impact. Geographic proximity also plays some role in housing price spillover.

Holly, Hashem Pesaran, and Yamagata (2011) apply the GVAR method to analyze the spatial and temporal diffusion of shocks in house markets in the UK. They focus on real house price changes at the regional level. In this study, a dominant region (London) exists. The region-specific weight is determined by whether two regions are contiguous. It equals 1 if the two regions share a border. Otherwise, it equals 0. Shocks to a dominant region propagate contemporaneously and spatially to other regions of the country. This dominant region is in turn influenced by the amplified shock echoing back. The shocks are amplified both by the internal dynamics of each region and by interactions with contiguous regions. The dominant region, London, is also influenced by international developments through its link to New York and other financial centers. The results show that effects of a shock decay more quickly along the time dimension as compared to the geographical dimension.

Chapter 3

DATA

3.1 Background of the Chinese Housing Market

According to the Chinese Constitution, the Chinese government retains ownership of all urban land. In the year 1988, the National People's Congress ratified a Constitutional Amendment that allows businesses and individuals to purchase land-use rights from the government. The purchased right lapses after 70 years for residential use, or 40 years for business use. Since the land-use right is paid in full upfront and the Chinese government retains ownership of land, there is no property tax for those who hold land-use rights.

Another important housing legislation was passed in 1998 when the government ended the national welfare housing distribution system. Urban residents need to purchase houses from the market by themselves. At the end of 2002, a new regulation by the Ministry of Land and Resource (MLR) required that all commercial and residential land-use rights are purchased through a public auction process. The bidders' names and winning prices are publicly reported after the auction. Before this, land transactions were made through closed-door negotiations, so the land transaction price did not necessarily reflect its true market value. These two laws transformed the Chinese housing market from being government-oriented to market-oriented. The MLR's new regulation took full effect by the end of 2003.

3.2 Housing Prices

3.2.1 Features of the Shanghai Housing Market

Shanghai's urban area has developed rapidly in the past 20 years. Most of the housing stock is relatively new in Shanghai, as is the case in most cities in China. Shanghai has plentiful new apartments and houses but only a few cases of multiple sales of existing houses. This provides a unique challenge to the use of a weighted repeat sales (WRS) index, which is the gold standard for the measurement of housing prices in the United States, see Case and Shiller (1987, 1989).

Two additional important considerations exclude the use of the repeat sales index. Shanghai in particular, but also China as a whole have experienced large volatility in the resale price of existing housing units. Without the ownership of land, the resale price is assessed only by characteristics of a housing unit itself. Although according to the provisions of the general principles of civil building design, in general, building life should be above 50 years, a recent report by the Ministry of Land and Resources shows that actual building life averages around only 30 years. The building structural safety and appearance decay more rapidly in China than in the United States. So the resale value of existing housing units depends heavily on a building's age, along with size, location, and luxury level. When two existing housing units are sold in the same location at the same time, their prices could be dramatically different due to their different building age. Consequently, the housing price of older buildings could decrease even when the housing market booms at nearby locations. The repeat sales index will always show a housing price decrease at the end of housing life in China. Due to these considerations, the use of weighted repeat sales (WRS) index is not a feasible choice for this dissertation.

3.2.2 Housing Price Data

This dissertation uses the average sale price of newly-built residential units. According to the Bureau of Statistics of Shanghai, over 60% of all the floor space in residential unit transactions is from newly-built units each year from 2004 to 2014, which covers the time period of this research. So, the price movement of the newly-built units can be used as a proxy for the overall price movement in Shanghai's housing market. This is in contrast to the U.S., where existing home sales are larger than new home sales. Per the United States Census Bureau data, existing home sales are ten times greater than new home sales in the U.S.

The housing price I use in this dissertation is the nominal price. The reasons to use the nominal price are, first, that while the consumer price index (CPI) measures changes in the price level of a market basket of consumer goods, housing price is not included in the basket. So, CPI is not a natural deflator for housing prices. Second, I have concerns about the quality of Chinese CPI. This CPI data is published by China's National Bureau of Statistics and is heavily impacted by political issues. Holz (2013), Guilford (2015) and Koch-Weser (2013) all point out that China's economic data are not reliable. Last, calculating the real housing price of each district requires the CPI of each district. Shanghai has a large geographic area with many districts. These districts differ widely in economic performance. It is unreasonable to use one city-level CPI for all districts. However, district level CPI is not publicly available. Hence, I use nominal prices in this dissertation instead of using real prices. The city-level CPI is included as a common variable to capture inflation.

In this dissertation, housing price is the average nominal price per square meter of new commodity housing units sold in a district for each month. The variable is calculated as the total value of new commodity housing sold in each month (in CNY) divided by the total square meters sold in the same month.

$$hp_{i,t} = \frac{total\ value\ of\ new\ commodity\ housing\ sold\ (in\ CNY)_{i,t}}{total\ square\ meters\ sold_{i,t}}$$

The housing price time series data are at the district level. They are at a monthly frequency, from 2006m01 to 2014m08. The data source is the China Index Academy.

To study the price spillover effects in the Shanghai housing market, I divide Shanghai into 19 districts based on geographic locations and official administrative districts. These 19 districts can be classified into five groups as described below.

Districts in center city: *Jing'an*, *Huangpu* and *Luwan*. These three districts are in the city core. They are small in size and have high population density (around 40,000 people per km^2). Their population has decreased by about 25% in the last decade.

Districts near center city: *Yangpu*, *Xuhui*, *Changning*, *Zhabei*, *Putuo* and *Hongkou*. These six districts are adjacent to the city center. They are slightly larger than the districts in the city's core. Except for *Putuo*, the population in these districts remains almost unchanged in the last decades. *Putuo's* population has increased by about 20%.

Districts in the outskirts: *Baoshan*, *Nanhui*, *Fengxian*, *Jinshan*, *Songjiang*, *Minhang*, *Qingpu*, and *Jiading*. These eight districts are large in size. Without rail transportation, the commute time between them and city's core is at least one hour. Their population has increased a lot in the last decades (*Baoshan*: 55%, *Nanhui:* 60%, *Fengxian:*74%, *Jinshan*: 26%, *Songjiang:*147%, *Minhang:* 100%, *Qingpu:*81% and *Jiading:*95%).

Pudong: *Pudong* is an emerging district adjacent to the city's core in Shanghai. *Pudong* is large in size and has the largest population among all districts in Shanghai. Its population has increased by about 56% in the last decade.

Chongming: *Chongming* is an island. Until November 2009, it had no bridge to other districts. Its population has remained almost unchanged in the last decade.

The recent population changes in Shanghai are due to two main reasons: first, urban renewal and new development have driven companies and residents away from the city's core. This population redistribution is driven by government policy (the White Paper of Shanghai Municipal Statistics Bureau, 2011). Second, about 94.1% of new immigrants have chosen to live in districts near the city center and in the outskirts. Table 2 shows the distribution of new immigrants from 2000 to the end of 2010 (The data comes from the White Paper of Shanghai Municipal Statistics Bureau, 2011).

Table 2 The Distribution of New Immigrants in Shanghai from 2000 to 2010

Districts	Population (in thousands)	Percentage (%)
	8,977	**100**
Districts in center city	**243.7**	**2.7**
Huangpu	132.5	1.5
Luwan	54	0.6
Jing'an	57.2	0.6
Districts near center city	**3,513.6**	**39.1**
Xuhui	279.5	3.1
Changning	175.4	2.0
Putuo	363	4.0
Zhabei	200	2.2
Hongkou	196.1	2.2
Yangpu	275.3	3.1
Pudong (include Nanhui)	2,024.3	22.6
Districts in the outskirts	**5219.7**	**58.2**

Minhang	1,203.7	13.4
Baoshan	766.1	8.5
Jiading	828.2	9.2
Jinshan	201.1	2.2
Songjiang	937.4	10.5
Qingpu	605	6.7
Fengxian	527.2	5.9
Chongming	151	1.5

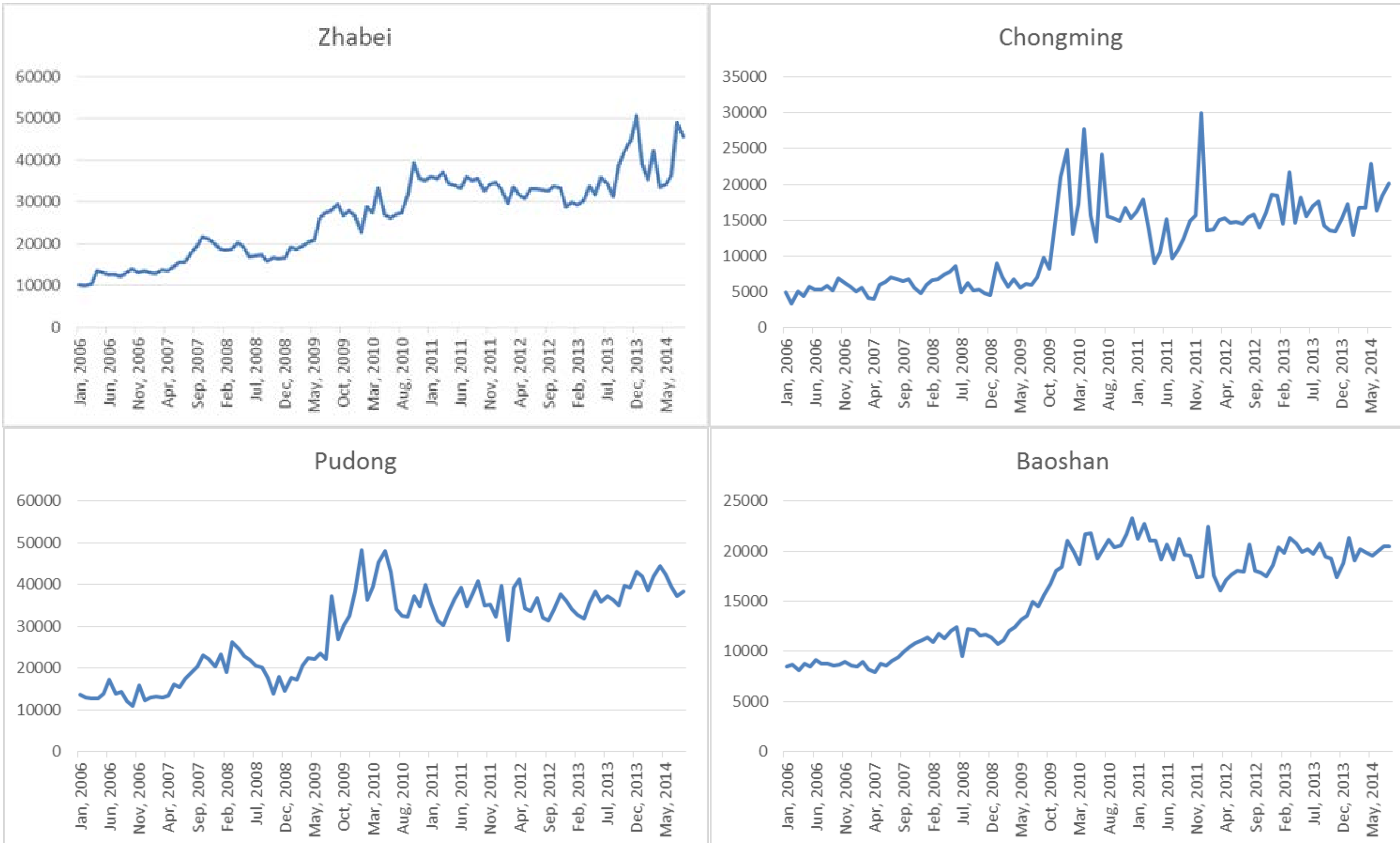
Data Source: Shanghai Municipal Statistics Bureau, 2011

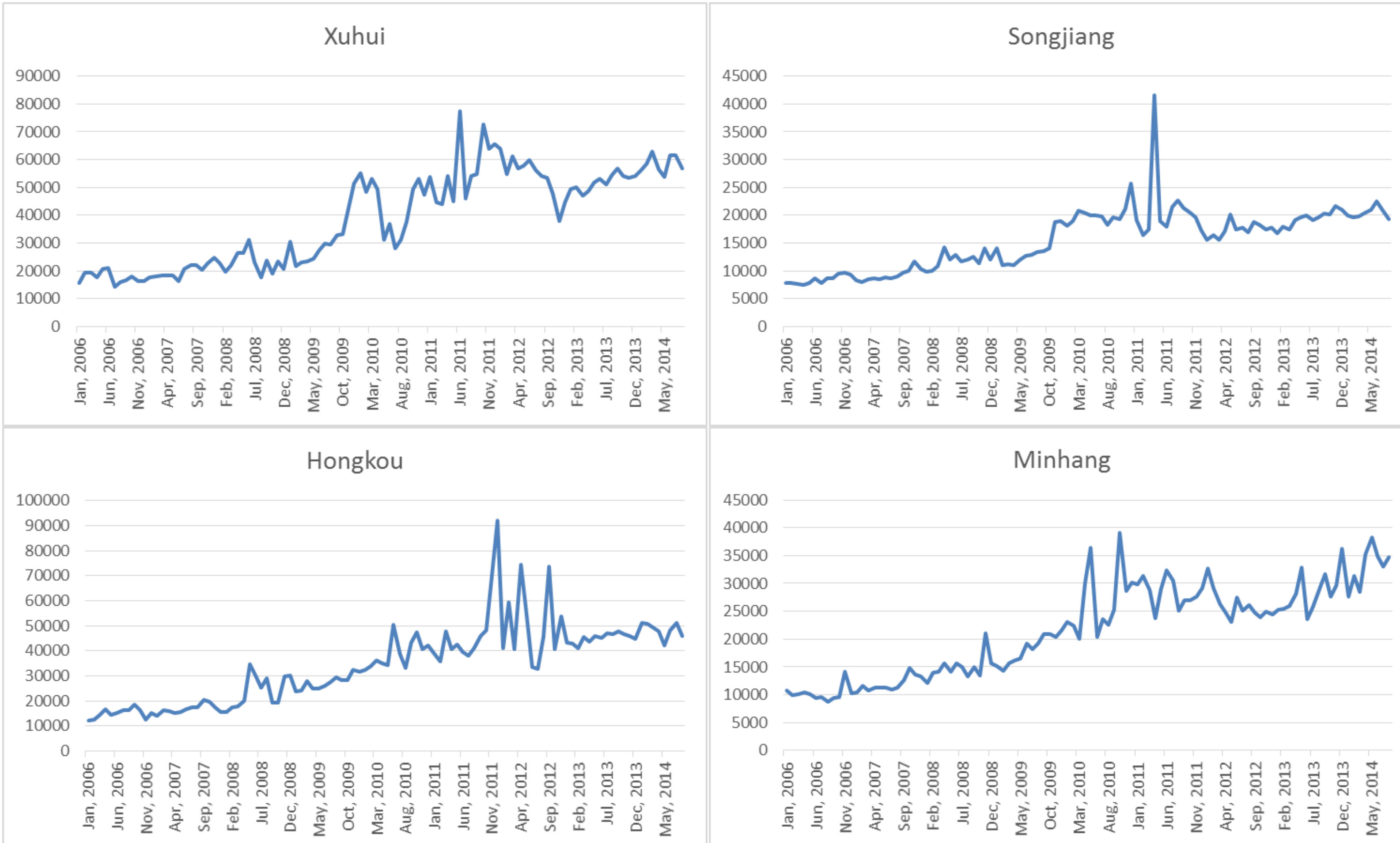
Housing price in these districts had very different growth patterns over the past years. Monthly data for these 19 districts over 9 years (2006m1-2014m9) is available. Figure 3 plots the average nominal housing price (yuan per square meter) for each district. It is worth pointing out that, in 2010-2012, many districts exhibited high volatility in housing prices. This volatility is mainly due to the frequently changed monetary policy and housing market regulations. In this study, I have the monetary variable and administered mortgage rate as common variables to capture this volatility. My sample starts from 2006 because the housing price was not determined by the market before the end of the year 2003, and the market prices for the next two years (2004, 2005) are not recorded at the district level. This short period of data presents extra challenges for doing quantitative research in China's housing market.

To reduce the heterogeneity of housing quality, I take two methods. First, Shanghai is divided into 19 small districts. Houses in the same district tend to have similar distance (commute time) to the urban core. As reported by Wu, Deng, and Liu (2014) and Deng, Gyourko, Wu (2012), the average distance to the city center plays an important role in housing price. In the housing markets of rapidly developing metropolises, distance from the urban core often has a determinant effect on housing location quality. It plays a more important role compared to factors like school district and local average income, which are two of the most important factors in the U.S.

housing market. Secondly, the data in this dissertation excludes public housing units because their transactions are not based on the market price. Public housing programs include low rental units *(lian zu fang*), public rental units (*gong gong zu lin fang*), affordable housing units (*jing ji shi yong fang*), and price-fixed units (*xian jia fang*).

Figure 3 Nominal Housing Prices (Yuan per Square Meter) in 19 Districts

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Songjiang
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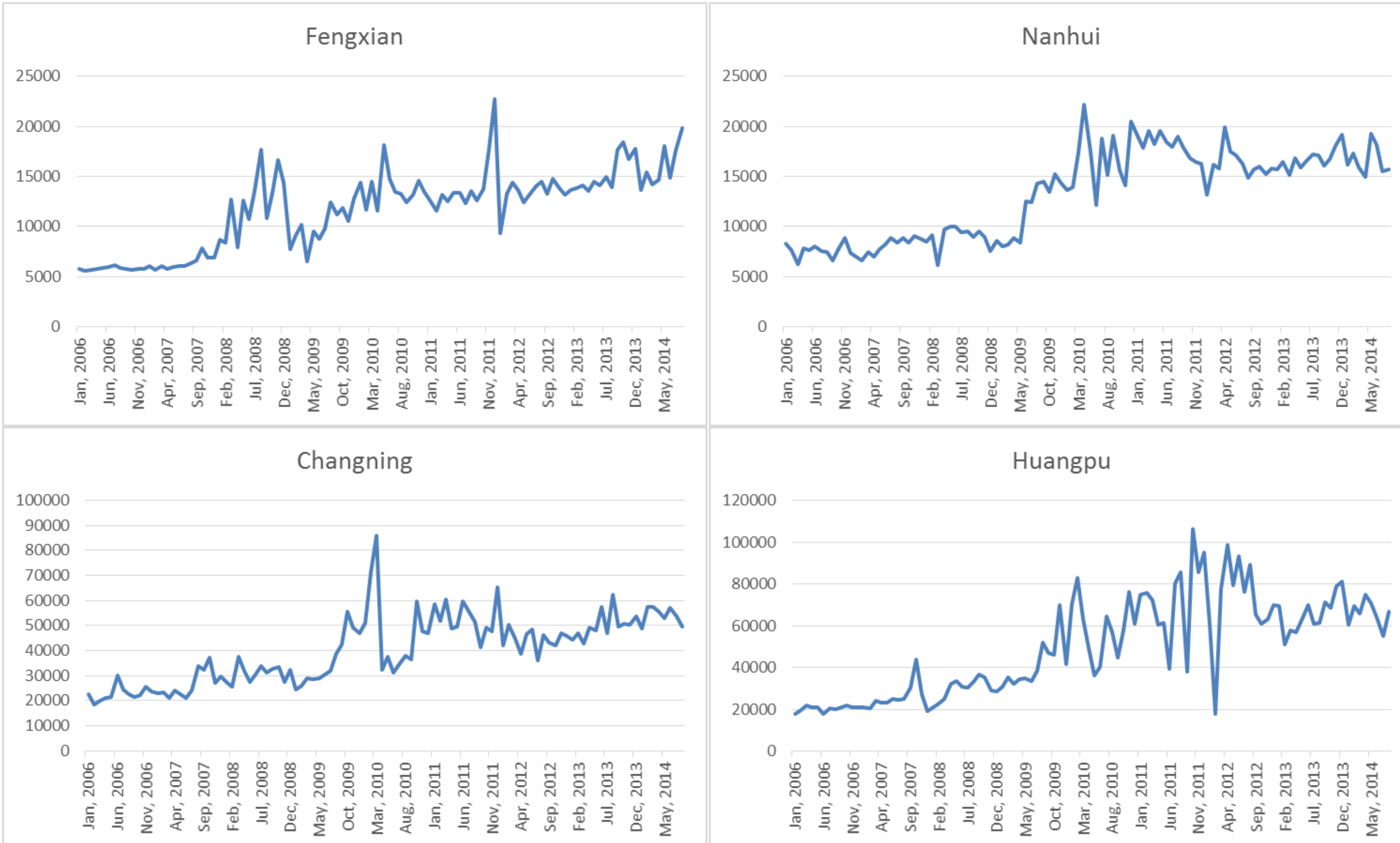
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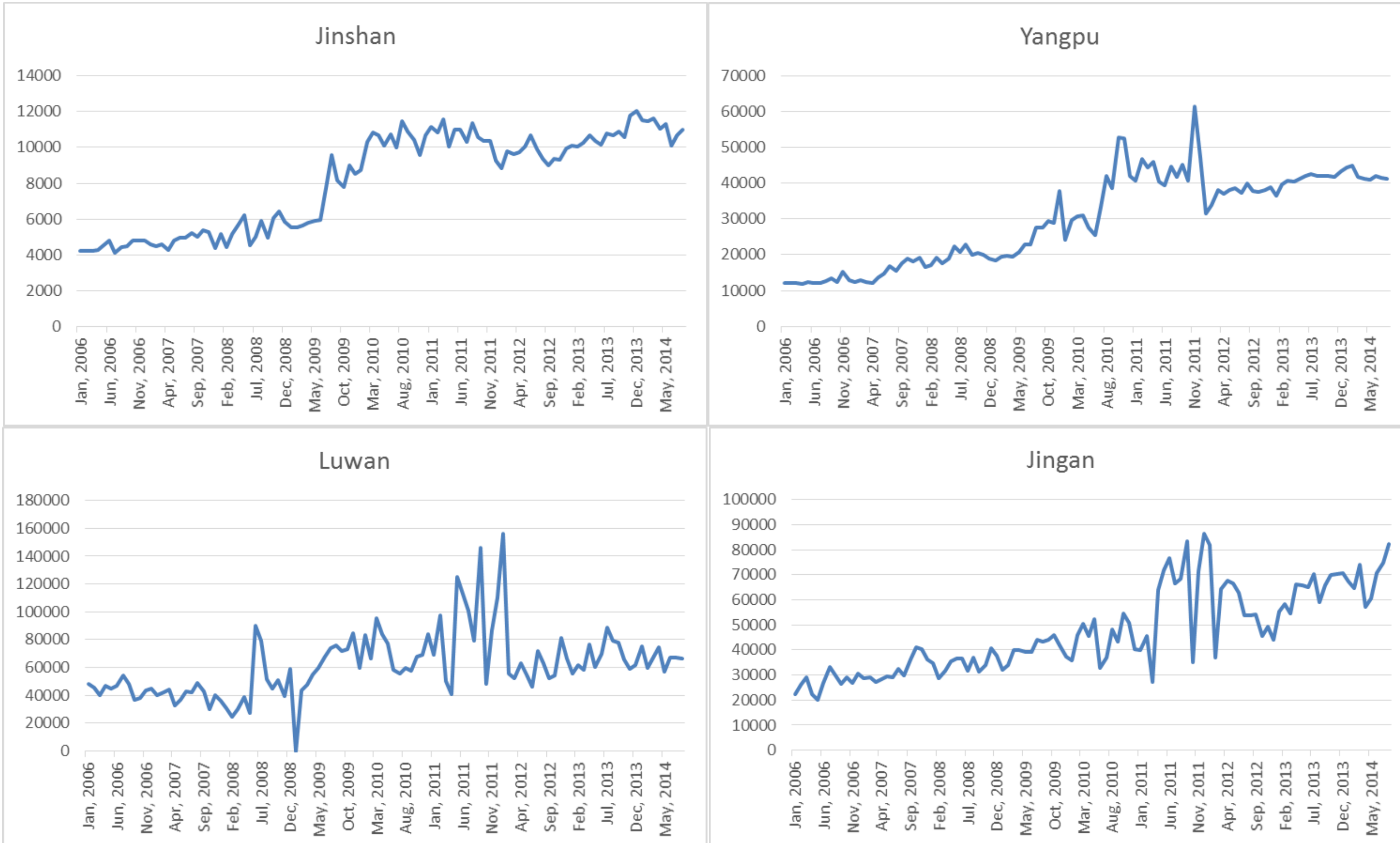
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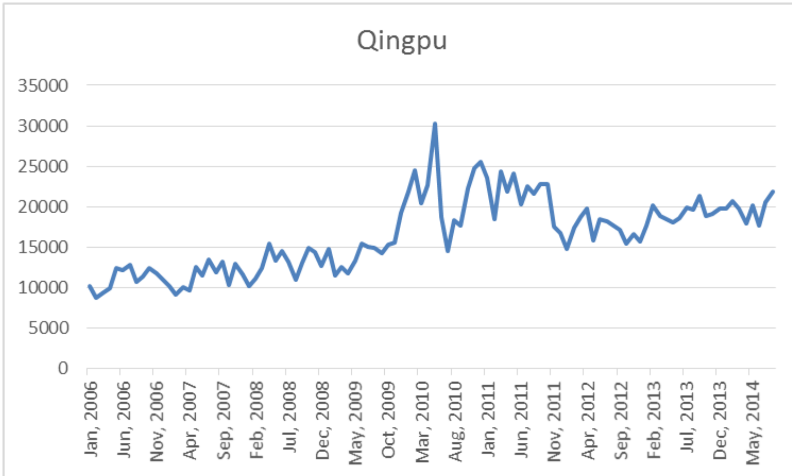
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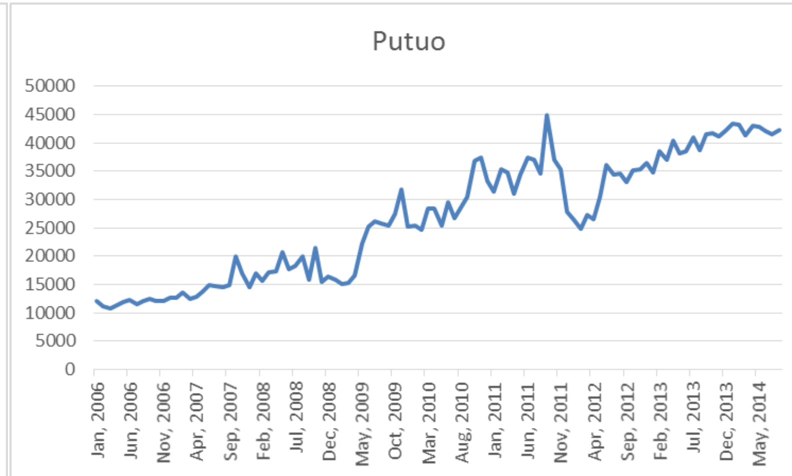
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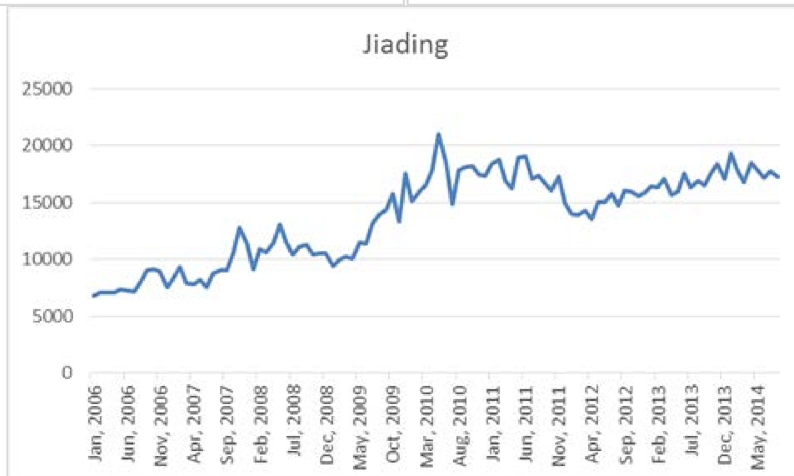
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3.4 Land Price

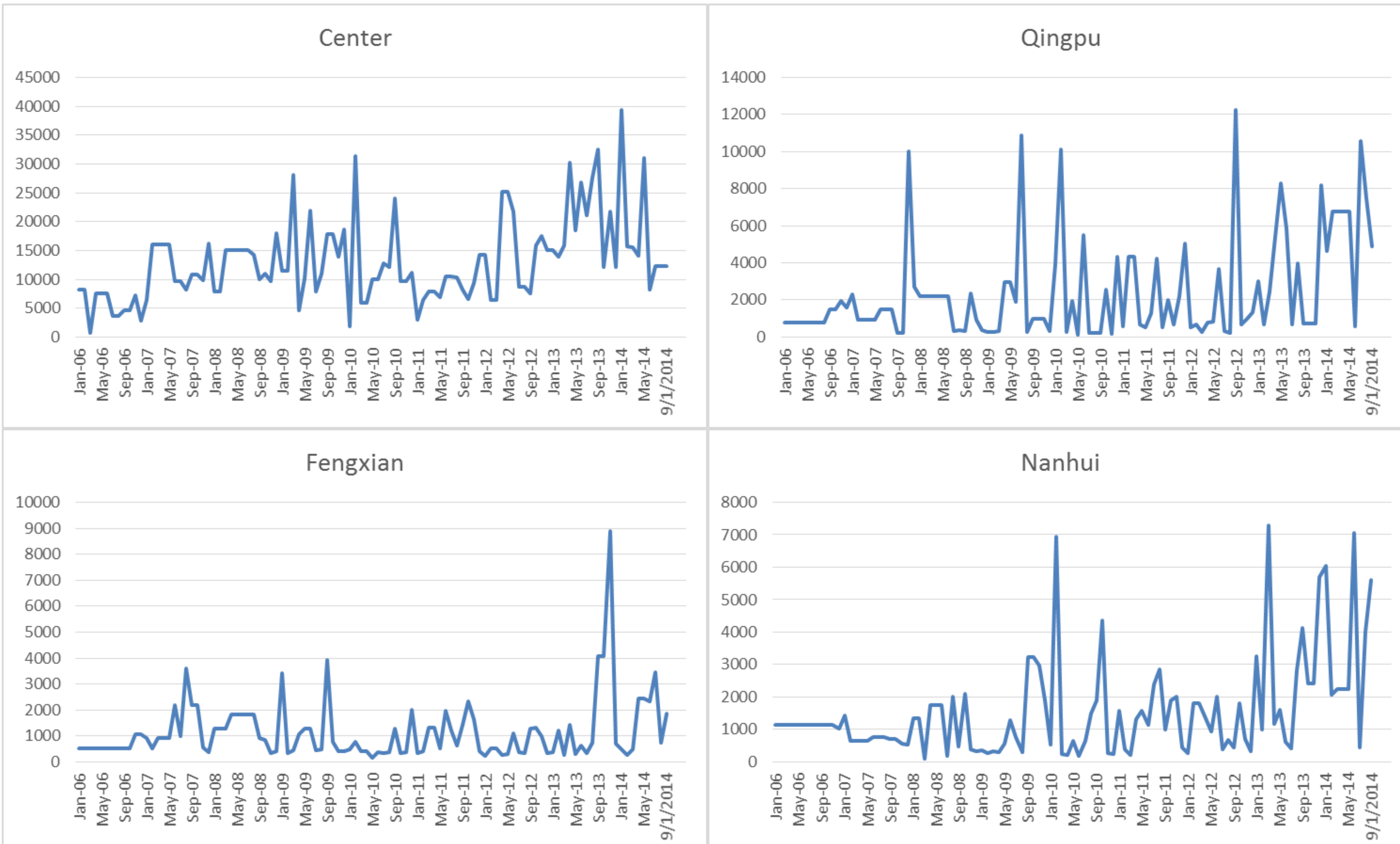
As shown by Deng, Gyourko and Wu (2012) and Wu, Gyourko and Deng (2012), the increase in housing prices is partly due to land value appreciation. However, land price data is limited at the district level. Although the sales of newly-built residential units are recorded each month for each district, land auctions do not occur each month in each district. So, I need a method to fill in the land value when no land auctions occur in a month. I will first estimate a GVAR model without the land price; then the land price will be added into the GVAR model by combining the nine small districts in the city center into a big "center district." So, the second GVAR model will be estimated with 11 districts instead of 19. If there is no land transaction in a district in a month, I will use the land price from the previous month as the land price for that month. The land price is calculated as the auction price divided by the permitted building floor space. As shown in figure 4, the land price has no obvious time trend. Considering the soaring housing prices, this result is unexpected. I will test the relationship between land price and housing price in this study to find out the role land prices play in the housing price movement during the last decade. The land price I use in this dissertation is the nominal price. The reasons to use the nominal land price are the same as those for using the nominal housing price. I have the CPI as a common variable in this study to capture inflation.

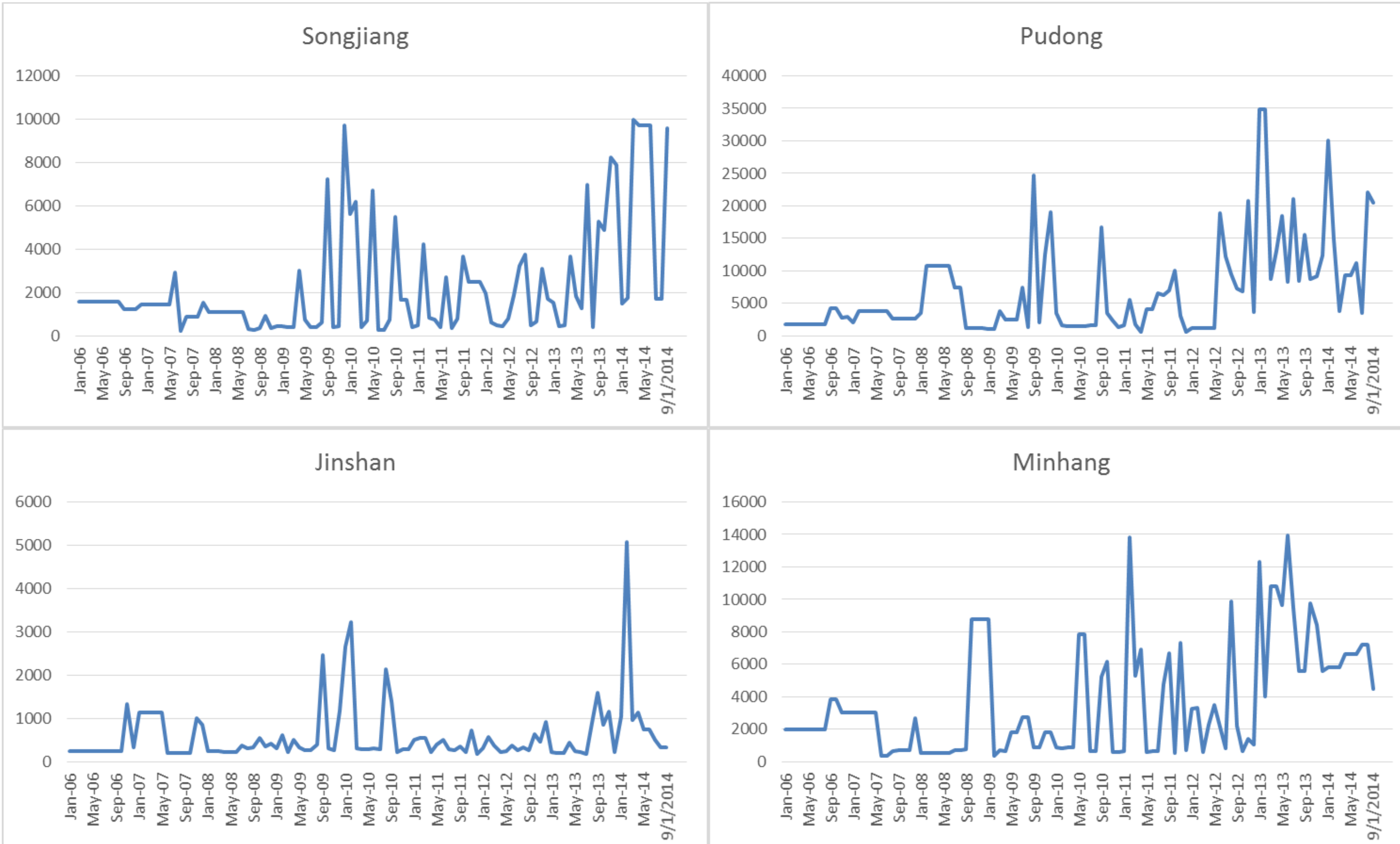
In this dissertation, land price is the average permitted building floor space per square meter nominal price of land parcels sold for the purpose of commodity residential housing construction in a given month. It is given by the total value of land parcels sold (in CNY) divided by the total sold permitted building floor space (in square meters) in a given month.

$$lp_{i,t} = \frac{total\ value\ of\ land\ sold\ (in\ CNY)_{i,t}}{total\ permitted\ building\ floor\ space\ sold\ (in\ square\ meters)_{i,t}}$$

The land price time series data are at the district level. They are at a monthly frequency, from 2006m01 to 2014m08. The data source is the China Index Academy.

Figure 4 Nominal Land Prices (Yuan per Square Meter) in 11 Districts

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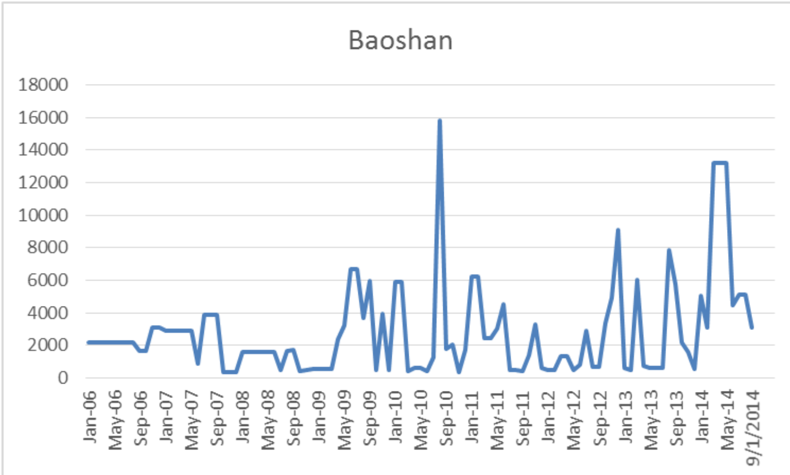
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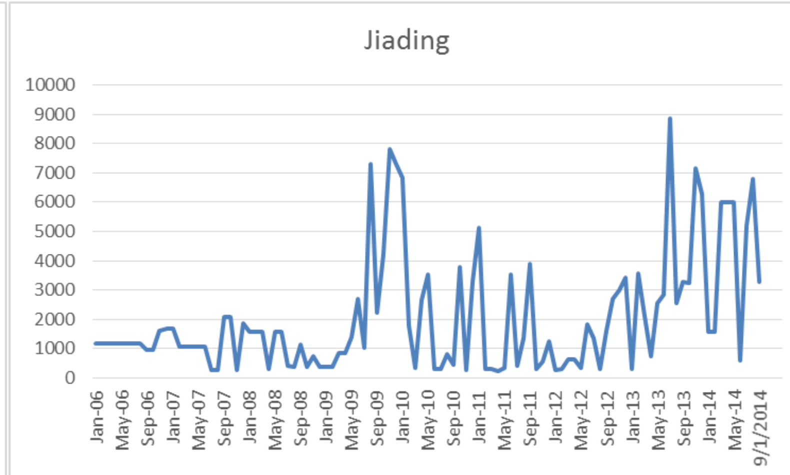
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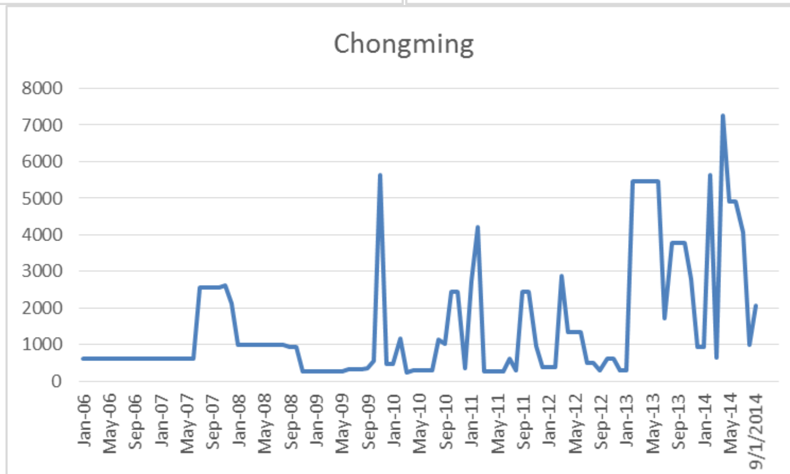
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3.5 Common Variables

The common variables used in this GVAR model include money and quasi-money supply (M2), weighted average overnight interbank offered rate, turnover of trading in Chinese stock market and long-term mortgage rate and the consumer price index (CPI). Stock market turnover is the sum of turnover of the Shanghai Stock Exchange and the Shenzhen Stock Exchange. They are the two stock exchanges operating in the People's Republic of China. The long-term mortgage rate is set by the People's Bank of China. It is an administered rate.

Except for the CPI, which is measured at the city level (Shanghai), all other variables are measured at the national level. Money and quasi money supply (M2), weighted average overnight interbank offered rate and long-term mortgage rate are available from the national financial database published by the People's Bank of China. The data source of consumer price index is the Shanghai Municipal Statistics Bureau, and the data source of nominal monthly turnover of trading in the Chinese stock market is the China National Bureau of Statistics. All these common variables are at a monthly frequency. Demographic variables such as population are not included in this model because the district-level data is not available at the monthly frequency until 2010. Table 3 is a list of the common variables and their data sources. I also tried some dummy variables for government land and real estate policies, but all were insignificant for most districts. This is probably because those policies are already captured in the weighted foreign variables.

The reasons I do not include disposable income in this dissertation are, first, the monthly Shanghai city-level disposable income data is not publicly available. Second, the

Chinese have a high savings rate. Due to the one-child policy, a young couple could expect help from their parents' savings when buying a house. This situation is very common in Shanghai. Third, in Shanghai, houses are treated more like investment products than consumption goods. So disposable income has little power to explain housing prices in Shanghai. For example, by the end of 2015, the annual per capita disposable income in Shanghai was about USD 7,700[2], when the average housing price was above USD 11,000 per square meter in 10 districts (*Jing'an*, *Huangpu*, *Luwan, Yangpu, Xuhui, Changning, Zhabei, Putuo, Hongkou,* and *Pudong)*[3].

Table 3 Common Variables and Sources

Common Variable	*Data Source*	*Symbol*
Nominal money and quasi-money supply	People's Bank of China	m_t
Weighted monthly average overnight interbank offered rate (nominal)	People's Bank of China	$ibor_t$
Nominal monthly turnover of trading in Chinese stock market	China National Bureau of Statistics	tst_t
Long-term mortgage rate (nominal)	People's Bank of China	lrh_t
Consumer price index	Shanghai Municipal Statistics Bureau	cpi_t

[2] Data Source: Shanghai Municipal Statistics Bureau
http://www.stats-sh.gov.cn/sjfb/201601/286625.html

[3] Shanghai Municipal Statistics Bureau: "2015 city real estate market overview"

Figure 5 Money and Quasi-Money Supply (in 100 Million Yuan)

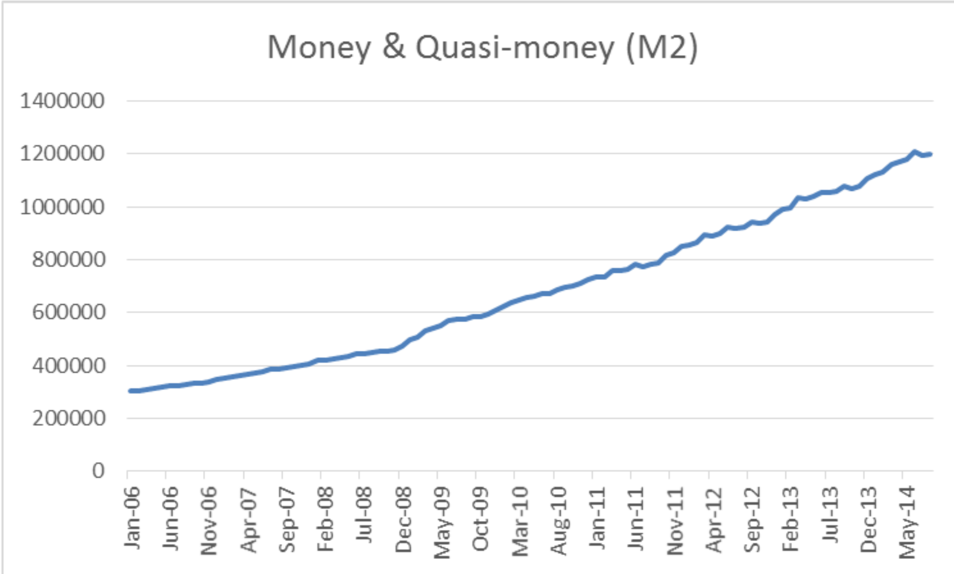


Figure 6 Weighted Monthly Average Overnight Interbank Offered Rate

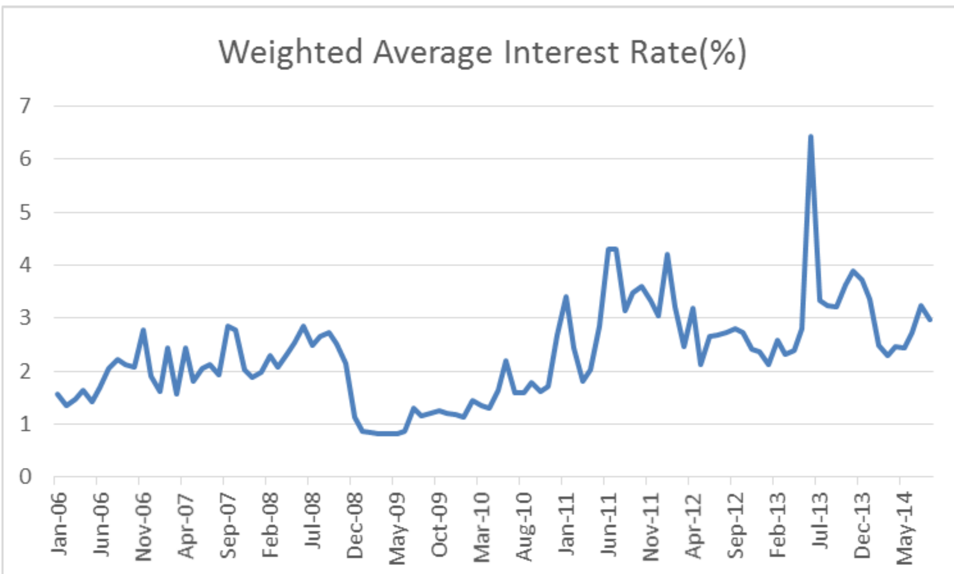


Figure 7 Monthly Turnover of Trading in Chinese Stock Market (in 100 Million Yuan)

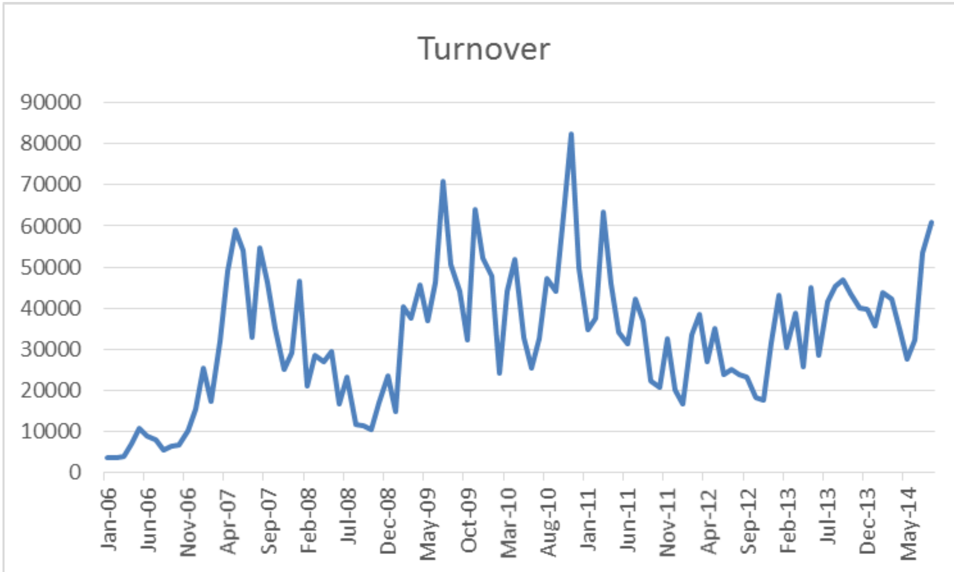


Figure 8 Individual Long-term Loan Interest Rate (over 5 years)

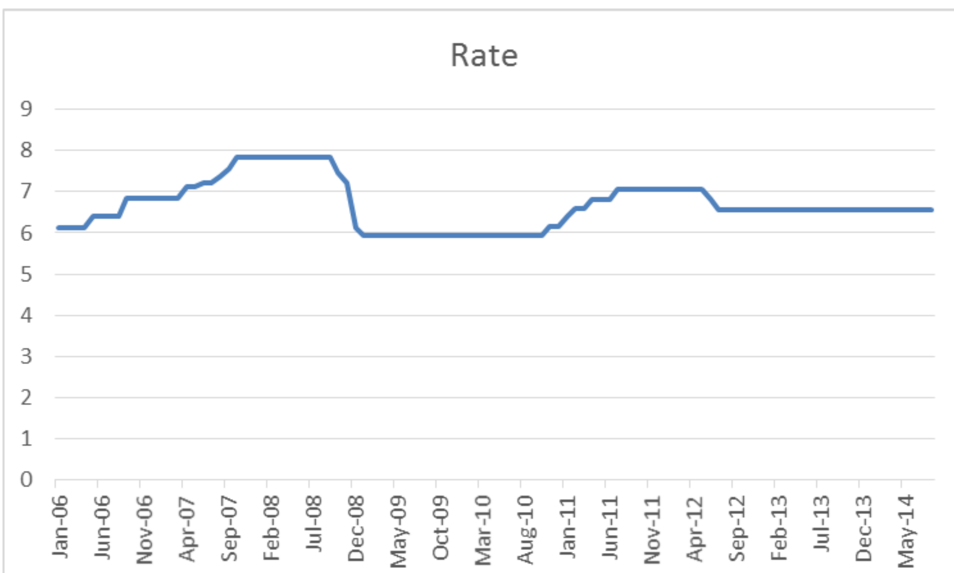
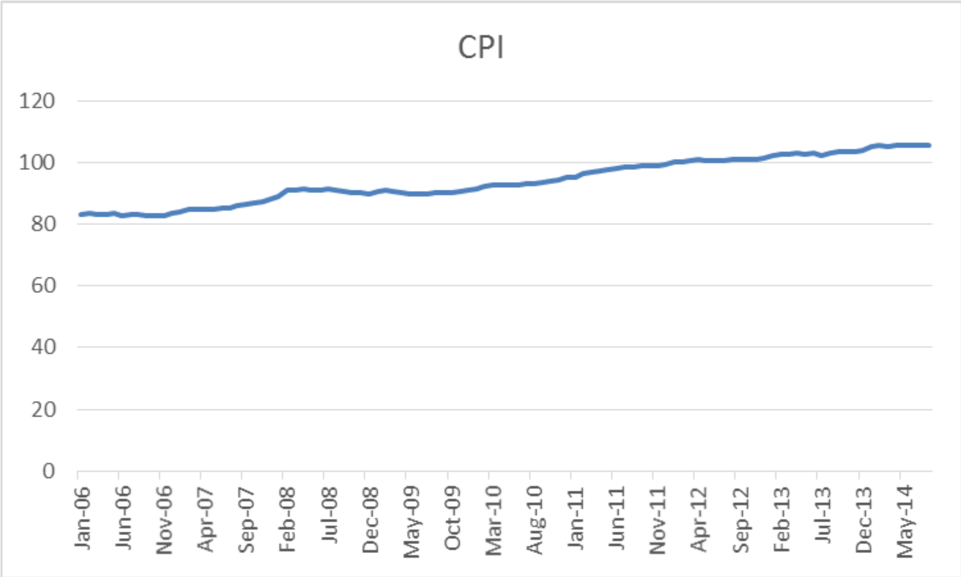


Figure 9 Consumer Price Index (Shanghai)



3.6 Weight Matrix in the GVAR Model

Another important component in the GVAR model is the weighted foreign[4] variable. To compute it, district-specific weights are required. This study calculates the weights based on commute times. It is done in two steps. First, the commute time between each district pair is calculated based on the fastest public transit from one district's center to the other's. In model #4 and model #5, the center of *center distric*t is set as the center of *Huangpu*. It is reasonable to calculate the commute time based on public transit. As shown in the 2014 White Paper on Transport Development in Shanghai, public transit is the first choice for commuting of nearly 60% of residents. The percentage is much higher in rush hours. Next, once the commute time for all district pairs is obtained, the inverse of these numbers is taken. These numbers are then rescaled. The rescaled values should add up to one for each district. The weights are time varying because of the newly-built transportation infrastructures. Since the new subway lines sharply reduce the commute time between some districts, the corresponding weights will also change. A map of the Shanghai metro network and the construction information are presented in Appendix A.

[4] The term "foreign" is used in this dissertation following the literature/terminology in the GVAR model.

Chapter 4

METHODOLOGY

4.1 An Overview of the Global VAR Model

As shown in figure 2, the housing prices in many districts of Shanghai share strong co-movements. Obviously, the housing markets are interlinked through many different channels. Four channels are identified below. First, housing price co-movement may be the by-product of the movement in standard housing market fundamentals in Shanghai (the nominal interest rate of bank loan, the mortgage rate, and construction cost, etc.). Second, the entire Shanghai area shares the same financial market regulation, which contemporarily affects the borrowing constraints in all districts. Third, if the housing price of one district is too high to be affordable, people are more likely to buy houses in the neighboring districts, pushing the prices of the latter higher. Last, the economic stimulus policy and soaring income in one district could also improve the economic status of residents in other districts by the direct channel (people who live in other districts but work in this district) and indirect channels. Even after allowing for such effects, other channels of interactions could also exist. They can be due to unobserved interactions and spillover effects not properly taken into account. It will lead to residual interdependencies. Including all these channels of interaction in forecasting and policy analysis is a challenging task for modeling a complex highly dimensional system.

High interconnection in housing price across districts calls for adequate modeling. Although a few large global models exist, they tend to be too large and complex, and cannot be used for forecasting and simulation analysis. Those large models are often incomplete and do not present a closed global system, which is required for forecasting and simulation under different count-factual scenarios. Granger and Jeon (2007) have a detailed survey of those global models.

The Global VAR (GVAR) model provides a practical global modeling framework for the quantitative analysis of the relative importance of different shocks and channels of transmission mechanisms. This approach is first introduced by Pesaran (2004) and advanced by Dees et al. (2007). It was originally developed as a tool to deal with credit risk analysis in the aftermath of the 1997 Asian financial crisis. The GVAR approach combines panel data regression, time series analysis, and factor analysis techniques. It presents a complicated, yet simple to follow, spatial-temporal structure for the analysis of the global economy. This model has been shown to be particularly suited to the analysis of the transmission of shocks from one market to other markets.

The GVAR model is composed of a large number of individual unit-specific vector error correction models (VECMs). In this dissertation, the units are the districts of Shanghai. Interactions among units are modeled through the weighted foreign variables. GVAR approach can be briefly summarized as a two-step approach (Chudik and Pesaran 2014). In the first step, individual unit-specific vector error correction models (VECMs) are estimated conditionally on domestic variables, weighted cross section averages of foreign variables, and common variables. The weighted averages of foreign variables are treated as weakly exogenous. The weak exogenous assumption is the key feature of the GVAR modeling strategy and can be tested empirically. It allows the unit model to be estimated individually and only at a later stage to be combined. This solves the problem of the curse of dimensionality, which will be illustrated in detail below. In the second step, individual unit VECMs are stacked and solved simultaneously as one large global VAR model. The following is a detailed description of the GVAR model of the Shanghai housing submarkets.

Suppose there are *N* districts in Shanghai, indexed by *i = 1, 2,…, N*. In our study, N =18 in model #1 and #2, N =19 in model #3, N =10 in model #4, and N =11 in model #5. Each district has a small scale district-specific conditional model that can be estimated separately. These district-specific conditional models contain the domestic variables of the housing market, collected in the $k_i \times 1$ vector $\mathrm{X}_{i,t}$ and district-specific cross-section averages of foreign variables, collected in the $k_i^* \times 1$ vector $\mathrm{X}_{i,t}^*$

$$\mathrm{X}_{i,t}^* = \mathrm{W}_i^{*\prime}\mathrm{X}_t \qquad \text{for } i = 1, 2, \dots, \mathrm{N} \tag{1}$$

where $\mathrm{X}_t = (\mathrm{X}_{1,t}', \mathrm{X}_{2,t}', \dots \mathrm{X}_{N,t}')'$ is a $k \times 1$ vector and W_i^* is a $k \times k_i^*$ matrix of district-specific weights. The weights are predetermined, and are meant to capture the importance of district *j* in the housing market of district i. In this study, X_t has two variables, the housing price and the land price at the monthly frequency in models #4 and #5. In models #1, #2 and #3, X_t only has one variable, housing price, also at the monthly frequency. The weight matrix is either based on the neighborhood indicator or computed from commute time, the details of which are given in Chapter 5.

Specifically, for district *i*, consider the VARX structure given by

$$\mathrm{X}_{i,t} = \sum_{l=1}^{p_i} \Phi_{i,l}\mathrm{X}_{i,t-l} + \Lambda_{i,0}\mathrm{X}_{i,t}^* + \sum_{l=1}^{q_i} \Lambda_{i,l}\mathrm{X}_{i,t-l}^* + \varepsilon_{i,t} \tag{2}$$

for $i = 1, 2, \dots, N$. Here $\Phi_{i,l}$, for $l = 1, 2, \dots, p_i$, is the coefficient of $\mathrm{X}_{i,t-l}$; $\Lambda_{i,l}$, for $l = 1, 2, \dots, q_i$ is the coefficient of $\mathrm{X}_{i,t-l}^*$. The lag orders p_i and q_i are not required to be same.

$u_{i,t}$ is a $k_i \times 1$ error vector. The process of $X^*_{i,t}$ is treated as weakly exogenous. This weakly exogenous assumption requires that district *i's* housing market does not have a dominant effect on the entire Shanghai housing market, which is expected to hold, given the relative size of each district market. The empirical and theoretical evidence will be given later. To make this VARX conducive to understanding, I have excluded the common variables here, which will be introduced to the model later.

Let $Z_{i,t} = (X'_{i,t}, X^{*\prime}_{i,t})'$. It is a $(k_i + k^*_i) \times 1$ dimensional vector of domestic and district-specific foreign variables for district i. Based on equation (1),

$$Z_{i,t} = W_i X_t \tag{3}$$

where $X_t = (X'_{1,t}, X'_{2,t}, \ldots, X'_{N,t})'$ is a $k \times 1$ vector, $k = \sum_1^n k_i$; $W_i = \begin{pmatrix} E'_i \\ W^{*\prime}_i \end{pmatrix}$ is a $(k_i + k^*_i) \times k$ weight matrix; E_i is a $k \times k_i$ dimensional matrix such that $X_{i,t} = E'_i X_t$. Then equation (2) could be re-written as

$$A_{i,0} Z_{i,t} = \sum_{l=1}^{m_i} A_{i,l} Z_{i,t-l} + \varepsilon_{i,t} \qquad for\ l = 1, 2, \ldots, m_i \tag{4}$$

where $m_i = \max(p_i, q_i)$; $A_{i,0} = (I_{k_i}, -\Lambda_{i,0})$, $A_{i,l} = (\Phi_{i,l}, \Lambda_{i,l})$. Define $\Phi_{i,l} = 0$ if $l > p_i$ and similarly $\Lambda_{i,l} = 0$ if $l > q_i$.

The model also takes into account the integration properties of the series. The GVAR model distinguishes between short run and long run relationships among districts. It interprets the long run relationship as co-integration. So individual district models (4) can be equivalently written in the error correction form, VECMX, as

$$\Delta X_{i,t} = \Lambda_{i,0} \Delta X^*_{i,t} - \Pi_i Z_{i,t-1} + \sum_{l=1}^{m_i - 1} H_{i,l} \Delta Z_{i,t-l} + \varepsilon_{i,t} \tag{5}$$

where $\Delta = 1 - \mathrm{L}$ is the first difference operator; $\Pi_i = \mathrm{A}_{i,0} - \sum_{l=1}^{m_i} \mathrm{A}_{i,l}$ and $\mathrm{H}_{i,l} = -(\mathrm{A}_{i,l+1} + \mathrm{A}_{i,l+2} + \cdots + \mathrm{A}_{i,m_i})$. It is clear that this VECMX allows for the possibility of co-integration both within the domestic variables as well as between the domestic and weighted foreign variables. These co-integration relationships are not unique. Identification of the long-run relationship[5] requires theoretical and experience based restrictions.

The estimation of district VARX models in equation (2) or the VECMX model in equation (5) is the first step of the GVAR approach. In the second step of the GVAR approach, individual district VARX/VECMX models are stacked and solved simultaneously as one large global VAR model. Based on equation (3), I can rewrite equation (4) as

$$\mathrm{A}_{i,0}\mathrm{W}_i \mathrm{X}_t = \sum_{l=1}^{m_i} \mathrm{A}_{i,l}\mathrm{W}_i \mathrm{X}_{t-l} + \varepsilon_{i,t} \tag{7}$$

Stacking these model for $i = 1, 2, \dots, N$, it becomes

[5] This dissertation focuses on the short-term dynamics of housing price due to the short span of the sample. I am not particularly interested in the long-run equilibrium of housing price. However, in the GVAR model, the district-specific models are in the error correction form, so that cointegration is allowed for. To clarify this point, suppose $\mathrm{Z}_{i,t} = (\mathrm{X}'_{i,t}, \mathrm{X}^{*\prime}_{i,t})'$ is a vector of $I(1)$ processes. γ_i is the rank of Π_i, denoted as $\gamma_i = rank(\Pi_i)$. γ_i specifics the number of cointegration relationships among variables in $\mathrm{Z}_{i,t}$. Based on equation (5), the rank of Π_i cannot be larger than k_i and Π_i can be decomposed as

$$\Pi_i = \alpha_i \beta_i' \qquad (6)$$

where α_i is a $k_i \times \gamma_i$ full column rank loading matrix, and β_i is the $(k_i + k_i^*) \times \gamma_i$ full column rank matrix of co-integrating vectors. This decomposition is not unique. Identification of α_i and β_i requires theory and experience based restrictions.

$$\mathrm{G}_0 \mathrm{X}_t = \sum_{l=1}^{m} \mathrm{G}_l \mathrm{X}_{t-l} + \varepsilon_t \tag{8}$$

where $\mathrm{G}_0 = \begin{pmatrix} \mathrm{A}_{1,0}\mathrm{W}_1 \\ \mathrm{A}_{2,0}\mathrm{W}_2 \\ \cdots \\ \mathrm{A}_{N,0}\mathrm{W}_N \end{pmatrix}$, and $\mathrm{G}_l = \begin{pmatrix} \mathrm{A}_{1,l}\mathrm{W}_1 \\ \mathrm{A}_{2,l}\mathrm{W}_2 \\ \cdots \\ \mathrm{A}_{N,l}\mathrm{W}_N \end{pmatrix}$, and $\varepsilon_t = (\varepsilon'_{1t},\ \varepsilon'_{2t}, \dots ,\ \varepsilon'_{Nt})'$.

If G_0 is invertible, one can premultiply G_0^{-1}on both sides of equation (8), and obtain

$$\mathrm{X}_t = \sum_{l=1}^{m} \mathrm{F}_l \mathrm{X}_{t-l} + \mathrm{G}_0^{-1}\varepsilon_t \quad for\ l = 1, 2, \dots, m \tag{9}$$

where $\mathrm{F}_l = \mathrm{G}_0^{-1}\mathrm{G}_l$, for $l = 1, 2, \dots, m$. Equation (9) can be solved recursively. There is no restriction placed on the covariance matrix $\sum_\varepsilon = E(\varepsilon_t \varepsilon'_t)$, unless there is a good reason to do so.

When applying the GVAR model to Shanghai housing market, observed common variables are added to the model. In particular, the conditional district models are augmented by common variables and their lagged values in addition to the vector of district-specific cross-section averages of the foreign variables. In the case of model (2), a $m_\omega \times 1$vector ω_t of common variables and its lagged values can be added so that

$$\mathrm{X}_{i,t} = \sum_{l=1}^{p_i} \Phi_{i,l}\mathrm{X}_{i,t-l} + \Lambda_{i,0}\mathrm{X}^*_{i,t} + \sum_{l=1}^{q_i} \Lambda_{i,l}\mathrm{X}^*_{i,t-l} + \mathrm{D}_{i,0}\omega_t + \sum_{l=1}^{s_i} \mathrm{D}_{i,l}\omega_{t-l} + \varepsilon_{i,t} \tag{10}$$

for $i = 1, 2, \dots, N$. The common variables are treated as weakly exogenous. As noted earlier, this assumption will be tested theoretically and empirically. For the purpose of estimation, the process of common variables can be expressed in a marginal form

$$\omega_t = \mathrm{c} + \sum_{l=1}^{s_\omega} \Phi_l^\omega \omega_{t-l} + \eta_t^\omega \tag{11}$$

which can be equivalently written in a vector error correction form as

$$\Delta\omega_t = \mathrm{c} - \Pi^\omega \omega_{t-1} + \sum_{l=1}^{s_\omega - 1} \mathrm{H}_j^\omega \Delta\omega_{t-l} + \eta_t^\omega \tag{12}$$

where $\mathrm{H}_l^\omega = -(\Phi_{l+1}^\omega + \Phi_{l+2}^\omega + \cdots + \Phi_{s_\omega}^\omega)$. Obviously, equation (12) allows for co-integration among common variables.

One can solve the entire GVAR model with common variables by combining VARX model (10) and the marginal model (11). Specifically, let $Y_t = (\omega_t', X_t')'$ be the $(k + m_\omega)\times 1$ vector of all observable variables. Based on equation (3), I can stack equation (10) or its VECMX form (combined with equation (11)), for $i = 1, 2, \dots, N$. It becomes

$$\mathrm{G}_0^y \mathrm{Y}_t = \sum_{l=1}^{m} \mathrm{G}_l^y \mathrm{Y}_{t-l} + \varepsilon_t^y \tag{13}$$

where $\varepsilon_t^y = (\eta_t^{\omega\prime}, \varepsilon_t')'$, $\mathrm{G}_0^y = \begin{pmatrix} \mathrm{I}_{m_\omega} & 0_{m_\omega \times k} \\ -\mathrm{D}_0 & \mathrm{G}_0 \end{pmatrix}$, $\mathrm{G}_l^y = \begin{pmatrix} \Phi_l^\omega & 0_{m_\omega \times k} \\ \mathrm{D}_l & \mathrm{G}_l \end{pmatrix}$, for $l = 1, 2, \dots, m$. $\mathrm{D}_l = (\mathrm{D}_{1l}', \mathrm{D}_{2l}', \dots, \mathrm{D}_{Nl}')'$ for $l = 0, 1, 2, \dots, m, m = \max(p_i, q_i, s_i, s_\omega)$. Define $\mathrm{D}_{i,l} = 0$ for $l > s_i$. If G_0 is invertible, obviously G_0^y is invertible as well. Assuming G_0^{-1} exists, then we can premultiply $\mathrm{G}_0^{y^{-1}}$on both sides of equation (13), and obtain

$$\mathrm{Y}_t = \sum_{l=1}^{m} \mathrm{F}_l^y \mathrm{Y}_{t-l} + \mathrm{G}_0^{y^{-1}} \varepsilon_t^y \tag{14}$$

where $\mathrm{G}_0^{y^{-1}} = \begin{pmatrix} \mathrm{I}_{m_\omega} & 0_{m_\omega \times k} \\ -\mathrm{G}_0^{-1}\mathrm{D}_0 & \mathrm{G}_0^{-1} \end{pmatrix}$, and $\mathrm{F}_l^y = \mathrm{G}_0^{y^{-1}} \mathrm{G}_l^y$, for $l = 1, 2, \dots, m$. This model can be solved recursively.

The GVAR model fits the purpose of my dissertation to study the dynamics of housing price at the district level in Shanghai. The GVAR approach directly models the dependence of domestic variables on both foreign and exogenous common variables. It allows the interaction among districts through two distinct channels: (1) contemporaneous dependence of domestic variables, $\mathrm{X}_{i,t}$, on foreign specific variables, $\mathrm{X}_{i,t}^{*}$, and on their lagged values; and (2) contemporaneous dependence of shocks in district *i* on the shocks in district j, which is given by the cross-district covariance. This cross-district covariance could be weak in this study, which will be tested later. These two channels capture the spillover effect of housing price among districts. Furthermore, with the use of the time-varying weight matrix, this study could also quantify the effect of transportation infrastructure on the spillover of housing price over time.

4.2 Time-Varying Weights in GVAR Modeling

The GVAR model in this study requires a time varying weight. The time varying weight could capture the effect of newly-built transportation infrastructures on the spillover of housing price. The time varying weight matrix in the GVAR model affects the calculation of foreign variables, but the estimation of this model involves the same steps as the basic GVAR model.

To illustrate the model in a conducive way, I simplify model (2) to a VARX*(1,1) model (without common variables). The following is the simplified VARX model with $p_i = 1$ and $q_i = 1$.

$$\mathrm{X}_{i,t} = \Phi_{i,1}\mathrm{X}_{i,t-1} + \Lambda_{i,0}\mathrm{X}^*_{i,t} + \Lambda_{i,1}\mathrm{X}^*_{i,t-1} + \varepsilon_{i,t} \tag{15}$$

The weight matrix $\mathrm{W}^*_{i,\tau(t)}$ (of dimension $k \times k_i^*$) is time varying but predetermined. At time t, the weighted average foreign variable vector is given by

$$\mathrm{X}^*_{i,t}\left(\mathrm{W}^*_{i,\tau(t)}\right) = \mathrm{W}^{*\prime}_{i,\tau(t)}\,\mathrm{X}_t \tag{16}$$

Putting equation (16) into equation (15), I get

$$\mathrm{X}_{i,t} = \Phi_{i,1}\mathrm{X}_{i,t-1} + \Lambda_{i,0}\mathrm{W}^{*\prime}_{i,\tau(t)}\mathrm{X}_t + \Lambda_{i,1}\mathrm{W}^{*\prime}_{i,\tau(t-1)}\mathrm{X}_{t-1} + \varepsilon_{i,t} \tag{17}$$

Here, the function $\tau(t)$ is used instead of t to index the time varying weight matrix. This is because the weights could stay unchanged (so is (t)) over several periods before they are reset.

For each choice of the weights, $\mathrm{X}^*_{i,t}\left(\mathrm{W}^*_{i,\tau(t)}\right)$ and its lagged values are constructed according to equation (16). One thing to note is that $\mathrm{X}^*_{i,t-1}$ is not always equal to the lagged value of $X^*_{i,t}$. They are equal only if the weights are fixed from the time period $t-1$ to t. For a given set of weights, equation (17) can then be tested for co-integration and estimated for each district separately.

The estimation of the district-specific parameters with a time-varying weight matrix is similar to that of a GVAR model with a fixed weight matrix.

The district-specific models are stacked and solved as a group. In the following, define E_i as the $k \times k_i$ selection matrix, such that

$$X_{i,t} = E_i' X_t$$

Then equation (17) could be rewritten in terms of X_t

$$E_i' X_t = \Phi_{i,1} E_i' X_{t-1} + \Lambda_{i,0} W^*_{i,\tau(t)} X_t + \Lambda_{i,1} W^*_{i,\tau(t-1)} X_{t-1} + \varepsilon_{i,t} \quad (18)$$

Collecting terms, equation (18) becomes

$$G_{i,t} X_t = H_{i,t} X_{t-1} + \varepsilon_{i,t} \quad (19)$$

where

$$G_{i,t} = E_i' - \Lambda_{i,0} W^*_{i,\tau(t)}$$

and

$$H_{i,t} = \Phi_{i,1} E_i' + \Lambda_{i,1} W^*_{i,\tau(t-1)}$$

Now stacking equation (19) for $i = 1, 2, \dots, N$, we get

$$G_t X_t = H_t X_{t-1} + \varepsilon_t \quad (20)$$

where $G_t = (G_{1t}', G_{2t}', \dots, G_{Nt}')'$, and $H_t = (H_{1t}', H_{2t}', \dots, H_{Nt}')'$.

Assuming G_t is nonsingular, we can premultiply ${G_t}^{-1}$on both sides of equation (20). It becomes

$$X_t = F_t X_{t-1} + \tilde{\varepsilon}_t \quad (21)$$

where $F = {G_t}^{-1} H_t$, and $\tilde{\varepsilon}_t = {G_t}^{-1} \varepsilon_t$. Equation (21) can be solved recursively.

4.3 Diagnosis of the GVAR Model

4.3.1 Weak Exogeneity Test

The weak exogeneity assumption[6] is the key feature of the GVAR modeling strategy and can be tested both empirically and statistically. This assumption allows the unit model to be estimated individually and only at a later stage to be combined together. This solves the problem of the curse of dimensionality. Following Johansen (1992) and Harbo, Johansen, Nielsen and Rahbek (1998), I perform a statistical test to check the joint significance of the estimated error correction terms in auxiliary equations of the district-specific foreign variables X_{it}^{*} and common variables ω_t. In this test, the null hypothesis is that the foreign variables and observed common variables are weakly exogenous so that the error correction terms are not statistically significant. In particular, for the g-th foreign variable in district i, it has the following auxiliary regression:

$$\Delta X_{it,g}^{*} = \alpha_{i,g} + \sum_{l=1}^{r_i} \delta_{il,g}\widehat{\mathrm{ECM}}_{it,t-l} + \sum_{l=1}^{p_i} \phi_{il,g}' \Delta X_{i,t-l} + \sum_{l=1}^{q_i} \psi_{il,g}' \Delta \widetilde{X}_{i,t-l}^{*} + \eta_{it,g}$$

where $\widehat{\mathrm{ECM}}_{it,t-l}$, $l = 1,2,\dots,r_i$, are the estimated error correction terms corresponding to the r_i cointegrating relationships found for the district i model. The test for weak exogeneity is an F-test of the joint null hypothesis that $\delta_{il,g} = 0, l = 1, 2, \dots, r_i$ in the above regression. In this dissertation, $\Delta\widetilde{X}_{i,t}^{*} = (\Delta X_{it,}^{*} \Delta m_t, \Delta cpi_t, \Delta ibor_t, \Delta lrh_t, \Delta tst_t)$ for $i = 1, 2, \dots, n$. Following Cesa-Bianchi et al. (2012), I set the lag orders p_i and q_i to be the same as the lag orders chosen in the

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[6] Following Johansen (1992) and Granger and Lin (1995), "the weak exogeniety assumption in the context of cointegrating models implies no long run feedback from $X_{i,t}$ to $X_{i,t}^{*}$, without necessarily ruling out lagged short run feedback between the two sets of variables. In this case, $X_{i,t}^{*}$ is said to be 'long run forcing' for $X_{i,t}$, which implies that the error correction terms of the individual country VECMX* models do not enter in the marginal model of $X_{i,t}^{*}$."

underlying district-specific VARX models. The lag orders p_i and q_i could also be selected by AIC.

4.3.2 Average Pairwise Cross-Section Correlations

Another important assumption of the GVAR modeling approach is that the cross-dependence of the district-specific shocks must be weak. This assumption can be shown in the equation as

$$\lim_{N\to\infty} \frac{\sum_{j=1,j\neq i}^{N} Cov(\varepsilon_{j,l}, \varepsilon_{i,s})}{N} = 0, \qquad \forall i, l, s$$

where $Cov(\varepsilon_{j,l}, \varepsilon_{i,s})$ is the covariance of the shock ε_s in district i with shock ε_l in district j. In other words, the district-specific shocks are cross-sectionally weakly correlated. The basic idea behind this assumption is straightforward. Since the district-specific model is conditional on weakly exogenous foreign variables, it is reasonable to expect that the degree of correlation of the remaining shocks across districts will be modest. The weak exogeneity test discussed earlier indirectly supports the view that the shocks from different districts could only be weakly correlated. For direct evidence on the extent to which they are correlated, the average pairwise cross-section correlations of the variables in the GVAR model is calculated for the levels and first differences of the endogenous variables in a model, as well as those of the associated residuals.

4.3.3 Parameter Stability Test

In Chapter 5, several statistical tests are reported for parameter stability. Consider the s-th equation of the estimated error correction model (Equation 5) of district i as given by

$$\Delta X_{it,s} = \hat{\mu}_{it,s} + \sum_{l=1}^{r_i} \hat{\gamma}_{ilt,s} \widehat{ECM}_{is,t-1} + \sum_{l=1}^{p_i} \hat{\varphi}'_{ilt,s} \Delta X_{i,t-l} + \sum_{l=1}^{q_i} \hat{\vartheta}'_{ilt,s} \Delta X^*_{i,t-l} + \varepsilon_{it,s}$$

Let $\theta_{it,s} = (\mu_{it,s}, \gamma_{ilt,s}, \varphi' \;, \vartheta' \;)$. The null hypothesis is $\theta_{it,s} = \theta_{i,s}$ for all time periods. The critical values of this test are calculated using the bootstrap samples obtained from the solution of the GVAR model under the null hypothesis of parameter stability. The alternative hypothesis varies and depends on which test is used. Ploberger and Kramer's (1992) maximal OLS cumulative sum (CUSUM) statistic, denoted by PK_{sub} and its mean square PK_{msq}, are based on the cumulative sum of OLS residuals. Nyblom's test (1989), denoted by $\mathfrak{H}$, tests the alternative that $\theta_{lt,s}$ follows a random walk. The heteroskedasticity-robust version of the Wald form of Quandt's(1960) likehood ratio statistic, denoted by QLR, tests for a one-time change at an unknown break point.

4.4 Evaluating Housing Price Spillover Effects

4.4.1 Contemporaneous Effects of Foreign Variables on Domestic Counterparts

In the individual district VARX models, the coefficients $\Lambda_{i,0}$ on the contemporaneous foreign variables measure the contemporaneous effect of foreign variables on domestic variables. They can be interpreted as the impact elasticity between domestic and foreign variables.

In the case of the Shanghai housing markets, the impact elasticity reflects the net effect of economic and demographic factors. It can be either positive or negative. For example, a positive impact elasticity can be observed when there is a city-wide increase in the residents' incomes. The higher income will result in higher housing prices in a district as well as in its neighbors. Thus, we expect to see a positive contemporaneous effect of foreign housing price on the domestic housing price. A positive impact elasticity could also occur when a district sees a sharp increase in its housing prices and some of its residents decide to move to a more affordable neighboring district. This will lead to an increase in the housing price of the receiving district, to which people are immigrating, and consequently a positive impact elasticity. On the other hand, a negative impact elasticity could occur when residents of a district move out to the other districts. For example, due to the massive relocation of companies from *Luwan* to other districts, the shift in population will be accompanied by a decrease in the housing price of *Luwan*, and a simultaneous increase in the housing price of districts in which companies relocate.

4.4.2 Generalized Impulse Response Function

Impulse response function examines the effect of a variable-specific shock on other variables along the time line in the GVAR model. I report the generalized impulse response functions (GIRF) in this dissertation. The method is first introduced by Koop, Pesaran, and Potter (1996) and later adapted to VAR models in Pesaran and Shin (1998). Generalized IRF measures the change in the forecast of $x_{ig,t+s}$ (the gth variable in district i) based on the information set at $t-1$ (F_{t-1}) after observing a one-time unit shock to the l^{th} innovation $\varepsilon_{jl,t}$ in district j. The GIRF can be expressed as:

$$GIRF_{ig,jl}(s) = E\left(x_{ig,t+s} \middle| \varepsilon_{jl,t} = \sqrt{\sigma_{jj,ll}}, F_{t-1}\right) - E(x_{ig,t+s}|F_{t-1})$$

where $\sigma_{jj,ll}$ is the diagonal element of the variance-covariance matrix $\sum_{\varepsilon}$ corresponding to the l^{th} equation in the j^{th}district, and s is the forecast horizon. F_{t-1} is information set at time $t-1$.

Note that the generalized impulse responses are reported in this dissertation instead of their structural counterparts. This is because the primary focus of this dissertation is the transmission mechanism of the housing price shocks. Although the orthogonality of structural shocks allows researchers to study the effect of each identified shock in isolation, the identification conditions are often controversial and false identification conditions tend to lead to false conclusions. Hence, this study will not attempt to give structural interpretations to the shocks, but instead, focus on their transmission mechanism.

4.4.3 Counter-Factual Analysis

I also conduct a set of counterfactual simulation exercises to quantify the changes in the transmission of housing price shocks before and after the construction of new transportation infrastructures. While keeping the set of variables unchanged and solving the GVAR model with the same time varying weight matrix, I use two different sets of weight matrices to do the simulation test. The two weight matrices are based on commute time in January 2006 and December 2014, respectively. These simulation tests attest to what extent the new transportation infrastructures could have altered the impact and transmission of housing price shocks and, hence, changed the relationships among house submarkets in Shanghai. A detailed description can be found in Chapter 5.

Chapter 5

EMPIRICAL RESULTS

5.1 Introduction

This section discusses model specifications and empirical results. The methodology described in Chapter 4 is applied to district-level housing price in Shanghai using the monthly data. I will estimate five GVAR models with different weight matrices (fixed, time-varying), numbers of districts and variable sets. Due to the limited availability of land price data, I will also combine some districts into one larger district to check the interactions between housing price and land price. Table 4 is a summary of the models.

Table 4 Summary of Models

<table>
<tr><th>Model #</th><th># of Equations per Districts</th><th># of Districts</th><th>Weight Matrix</th><th>Domestic Variables</th><th>Foreign Variables</th><th>Common Variables</th></tr>
<tr><td>1</td><td>1</td><td>18</td><td>Fixed</td><td>$hp_{i,t}$</td><td>$hps_{i,t}$</td><td rowspan="5">m_t
cpi_t
$ibor_t$
lrh_t
tst_t</td></tr>
<tr><td>2</td><td>1</td><td>18</td><td>Time-Varying</td><td>$hp_{i,t}$</td><td>$hps_{i,t}$</td></tr>
<tr><td>3</td><td>1</td><td>19</td><td>Time-Varying</td><td>$hp_{i,t}$</td><td>$hps_{i,t}$</td></tr>
<tr><td>4</td><td>2</td><td>10</td><td>Fixed</td><td>$hp_{i,t}$
$lp_{i,t}$</td><td>$hps_{i,t}$
$lps_{i,t}$</td></tr>
<tr><td>5</td><td>2</td><td>11</td><td>Time-Varying</td><td>$hp_{i,t}$
$lp_{i,t}$</td><td>$hps_{i,t}$
$lps_{i,t}$</td></tr>
</table>

5.2 GVAR Model with a Fixed-Weight Matrix

First, I consider a GVAR model specification with a fixed-weight matrix. The fixed-weight matrix is constructed based on the neighborhood connections. It sets the relational value to 1 if two districts are contiguous; otherwise, the relational value equals 0. These numbers are then rescaled. The rescaled values should add up to one for each district. The logic behind this fixed-weight matrix is straightforward: contiguity provides a useful guide to determine the neighbors for each district; neighboring districts usually have more characteristics in common and share a similar location and public goods (roads, subway lines, and shopping centers, etc.). This fixed-weight model is estimated using data from 18 districts. It excludes district *Chongming*, which is an island and had no bridge to any other districts until 2009. The district names, their abbreviations, and their neighbor districts are listed in Table 5. The fixed-weight matrix is given in Table 6.

Table 5 Districts and Abbreviations

Districts	Abbreviation	Neighbors
Changning	CN	*Jing'an, Putuo, Xuhui, Minhang, Jiading*
Luwan	LW	*Jing'an, Huangpu, Xuhui, Pudong*
Qingpu	QP	*Songjiang, Jinshan, Jiading*
Jing'an	JA	*Changning, Luwan, Huangpu, Putuo, Xuhui, Zhabei*
Huangpu	HP	*Luwan, Jinan, Hongkou, Pudong, Zhabei*
Putuo	PT	*Changqing, Jinan, Zhabei, Baoshan, Jiading*
Fengxian	FX	*Nanhui, Songjiang, Minhang, Jinshan*
Nanhui	NH	*Fengxian, Pudong, Minhang*
Songjiang	SJ	*Qingpu, Fengxian, Minhang, Jinshan*
Hongkou	HK	*Huangpu, Pudong, Yangpu Zhabei, Baoshan*
Xuhui	XH	*Changing, Luwan, Jing'an Pudong, Minhang*
Pudong	PD	*Luwan, Huangpu, Nanhui, Hongkou, Xuhui, Minhang, Yangpu, Baoshan*
Minhang	MH	*Changning, Fengxian, Nanhui, Songjiang, Xuhui, Pudong, Jiading*
Jinshan	JS	*Qingpu, Fengxian, Songjiang*
Yangpu	YP	*Hongkou, Pudong, Baoshan*
Zhabei	ZB	*Jinan, Huangpu, Putuo, Hongkou Baoshan*
Baoshan	BS	*Putuo, Hongkou, Pudong, Yangpu, Zhabei, Jiading*
Jiading	JD	*Changing, Putuo, Minhang, Baoshan*

Table 6 The Fixed-Weight Matrix

	Changning	Luwan	Qingpu	Jingan	Huangpu	Putuo	Fengxian	Nanhui	Songjiang	Hongkou	Xuhui	Pudong	Minhang	Jinshan	Yangpu	Zhabei	Baoshan	Jiading
Changning	0	0	0	0.166667	0	0.2	0	0	0	0	0.2	0	0.142857	0	0	0	0	0.2
Luwan	0	0	0	0.166667	0.2	0	0	0	0	0	0.2	0.111111	0	0	0	0	0	0
Qingpu	0	0	0	0	0	0	0	0	0.25	0	0	0	0	0.333333	0	0	0	0.2
Jingan	0.2	0.25	0	0	0.2	0.2	0	0	0	0	0.2	0	0	0	0	0.2	0	0
Huangpu	0	0.25	0	0.166667	0	0	0	0	0	0.2	0	0.111111	0	0	0	0.2	0	0
Putuo	0.2	0	0	0.166667	0	0	0	0	0	0	0	0	0	0	0	0.2	0.166667	0.2
Fengxian	0	0	0	0	0	0	0	0.333333	0.25	0	0	0	0.142857	0.333333	0	0	0	0
Nanhui	0	0	0	0	0	0	0.25	0	0	0	0	0.111111	0.142857	0	0	0	0	0
Songjiang	0	0	0.333333	0	0	0	0.25	0	0	0	0	0	0.142857	0.333333	0	0	0	0
Hongkou	0	0	0	0	0.2	0	0	0	0	0	0	0.111111	0	0	0.333333	0.2	0.166667	0
Xuhui	0.2	0.25	0	0.166667	0	0	0	0	0	0	0	0.111111	0.142857	0	0	0	0	0
Pudong	0	0.25	0	0	0.2	0	0	0.333333	0	0.2	0.2	0	0.142857	0	0.333333	0	0.166667	0
Minhang	0.2	0	0	0	0	0	0.25	0.333333	0.25	0	0.2	0.111111	0	0	0	0	0	0.2
Jinshan	0	0	0.333333	0	0	0	0.25	0	0.25	0	0	0	0	0	0	0	0	0
Yangpu	0	0	0	0	0	0	0	0	0	0.2	0	0.111111	0	0	0	0	0.166667	0
Zhabei	0	0	0	0.166667	0.2	0.2	0	0	0	0.2	0	0	0	0	0	0	0.166667	0
Baoshan	0	0	0	0	0	0.2	0	0	0	0.2	0	0.111111	0	0	0.333333	0.2	0	0.2
Jiading	0.2	0	0.333333	0	0	0.2	0	0	0	0	0	0	0.142857	0	0	0	0.166667	0

(The weight vector for each district given by the rows of this matrix)

5.2.1 Model #1: The Single-Equation GVAR Model with a Fixed-Weight Matrix, 18 Districts

This GVAR model serves as the benchmark in this dissertation. Following Holy et al. (2010), each district model consists of a single housing price equation while a fixed-weight matrix W is used to calculate the cross-section weighted average of foreign housing price. Each district model includes one domestic variable, the logarithm of nominal housing price $hp_{i,t}$, one foreign variable, the logarithm of the weighted average of nominal foreign housing price $hps_{i,t}$, and five common variables: m_t is the logarithm of the nominal national money and the quasi-money supply (M2); CPI_t is the logarithm Shanghai's CPI which equals 100 in January 2012; $ibor_t$ is the nominal monthly average overnight interbank offered rate; lrh_t is the nominal long term mortgage rate to households; and tst_t is the monthly turnover of stock trading.

$$\mathrm{X}_{i,t} = \sum_{l=1}^{p_i} \Phi_{i,l}\mathrm{X}_{i,t-l} + \Lambda_{i,0}\mathrm{X}_{i,t}^{*} + \sum_{l=1}^{q_i} \Lambda_{i,l}\mathrm{X}_{i,t-l}^{*} + \mathrm{D}_{i,0}\omega_t + \sum_{l=1}^{s_i} \mathrm{D}_{i,l}\omega_{t-l} + \varepsilon_{i,t}$$

for $i = 1, 2, \ldots, 18$. p_i and q_i are the lag orders for domestic and foreign variables, respectively. $\mathrm{X}_{i,t} = hp_{i,t}$ is the logarithm of housing price; $\mathrm{X}_{i,t}^{*} = hps_{i,t}$ is the logarithm of the weighted average foreign housing price; ω_t= $(m_t, cpi_t, ibor_t, lrh_t, tst_t)$ is the vector of common variables.

Next, I present and discuss some statistical tests for this model. These tests include unit root test, lag order selection, cointegration rank selection, weak exogeneity of foreign and common variables, and parameter stability. In addition, I also discuss the impulse response functions of a price shock to some selected districts. All the test results are represented in Appendix C.

5.2.1.1 The Unit Root Test

The unit root test examines the integration properties of domestic, foreign and common variables. Augmented Dickey-Fuller (ADF) tests are performed for each district-specific model. The lag orders employed in the ADF tests are selected by the Akaike information criterion (AIC). The results of the unit root test are summarized in Tables 24 through 27 in Appendix C. Domestic and foreign housing prices are $I(1)$ processes for nearly all districts, except the domestic housing price of *Changning*, *Luwan*, *Hongkou*, and *Jing'an*. The common variables are all $I(1)$ processes except *ibor* which is $I(0)$.

5.2.1.2 Lag Orders Selection

After the orders of integration have been determined, the lag orders of the GVAR are chosen based on AIC. Details on the lag order selection are reported in Appendix C. The lag orders selected for each individual VECM and corresponding residual serial correlation F-statistics are presented in Table 25 of Appendix C. I impose some constraints on the lag order selection following Cesa-Bianchi et al. (2012). The maximum lag orders of the domestic and district-specific foreign variables are set to two for all districts ($p_i \leq 2, q_i \leq 2$). This restriction helps improve the forecast performance of the model and smooths out the ragged response pattern following a price shock in some districts.

5.2.1.3 Cointegration Ranks

I then proceed to the cointegration analysis. This analysis could help to distinguish between short-run and long-run relations. It interprets the cointegrating vector, if it exists, as long-run relations. Since the sample period in this study is short (nine years) and the Shanghai housing market has experienced drastic changes over these years, I do not expect to detect any long-run relation in this study. This study mainly focuses on examining the short-run dynamics of the housing market, while allowing for the existence of long-run relations.

The cointegration rank for each district-specific model is tested using Johansen's trace test. The critical values are calculated following MacKinnon, Haug, and Michelis (1999). I choose the trace test instead of the maximal eigenvalue test because the former has better performance for small samples. I also set the maximum rank to two. This is due to the concern of overestimation of the number of cointegrating relationships when the test is based on asymptotic critical values. It is also expected to improve the stability of the model. The results of the trace tests are presented in Appendix C.

5.2.1.4 Weak Exogeneity Test

The weak exogeneity test is then performed on this model. The weak exogeneity is the main assumption in the construction of the GVAR model as discussed in Chapter 4, section 4.3. In this test, I set the lag orders p_i and q_i to be the same as the lag orders found in the underlying district-specific VARX models following Cesa-Bianchi et al. (2012). The results of the weak exogeneity test are presented in Table 30 in Appendix C. The results show 4 out of 108 variables failing the weak exogeneity test. Considering the 5% significance level of the test, this result is acceptable.

5.2.1.5 Average Pairwise Cross-Section Correlations

Another important assumption of GVAR modeling is that the cross-dependence of the district-specific shocks must be weak. The details of this test are discussed in Chapter 4, section 4.3. The basic idea behind this assumption is straightforward. Since the district-specific model is conditional on weakly exogenous foreign variables, it is reasonable to expect that the degree of correlation of the remaining shocks across districts to be modest. The average pairwise cross-section correlations are calculated for the levels and first differences of the endogenous variables of the individual district VARX models, as well as those of the associated residuals. To calculate the average pairwise cross-section correlations for each variable of each district, I first compute the pairwise correlation of that district with remaining districts, then find the average value across districts. It is expected that the average correlation between the levels of *hp* is high because the housing price is closely connected among districts while the average correlation of the associated residuals is weak. My findings confirm this expectation. The results of the tests are provided in Appendix C Table 32.

5.2.1.6 Parameter Stability Test

I then test the parameter stability. The mathematics of this test are illustrated in Chapter 4 section 4.3. The test statistics and the corresponding 5% critical values are presented in Appendix C. As can be seen in Table 33 of Appendix C, the assumption of stability holds for nearly all districts. I will compare the results of these tests with those of the time-varying weight model to see whether using the time-varying weight improves parameter stability.

5.2.1.7 Contemporaneous Effects of Foreign Variables on Domestic Counterparts

In the individual district VARX models, the coefficients $\Lambda_{i,0}$ on the contemporaneous foreign variables measures the contemporaneous effect of foreign variables on domestic variables. They can be interpreted as the impact elasticity between domestic and foreign variables, i.e. the instantaneous percentage change in the housing price of one district given a one percent increase in other districts' housing prices.

Table 7 reports the impact elasticities with the corresponding standard deviations (in parentheses). In Table 7, I divide the districts into three groups according to the impact elasticities: the high elasticity group (with an elasticity greater than 0.7), the low elasticity group (with an elasticity smaller than 0.3) and the medium elasticity group (with an elasticity between 0.3 and 0.7). Districts in the high and the medium elasticity groups are significantly influenced by the price movements in other markets, while districts in the low elasticity group are only affected in a modest way and the effects are insignificant. In this fixed-weight model, no district is in the high elasticity group. The districts in the low elasticity group are nearly all in the outskirts (except *Yangpu* and *Hongkou*). I will compare this result with the result in Model #2, which applies a time-varying weight.

Table 7 MODEL #1: Contemporaneous Effects of Foreign Housing Price on Domestic Housing Price

High Elasticity Group	
District	*hp*
None	

Medium Elasticity Group	
District	*hp*
CHANGNING	0.64
	(0.23)
JING'AN	0.62
	(0.18)
QINGPU	0.57
	(0.18)
PUDONG	0.56
	(0.17)
MINHANG	0.49
	(0.19)
LUWAN	0.45
	(0.20)
HUANGPU	0.37*
	(0.23)
JIADING	0.36
	(0.12)

Low Elasticity Group	
District	*hp*
SONGJIANG	0.26
	(0.14)
YANGPU	0.25
	(0.13)
FENGXIAN	0.23*
	(0.21)
NANHUI	0.22
	(0.11)
JINSHAN	0.21
	(0.08)
BAOSHAN	0.06*
	(0.11)
HONGKOU	0.00*
	(0.20)

XUHUI	0.35
	(0.12)
ZHABEI	0.33
	(0.09)
PUTUO	0.31
	(0.13)

* Not significant at the 5% level

5.2.1.8 Generalized Impulse Response Functions (GIRFs)

To examine the spatial and temporal transmission of a housing price shock, I conduct a set of impulse response analyses. Three housing price shocks are considered separately: a shock to one of the urban centers (taking *Huangpu* as an example), a shock to one of the emerging districts (taking *Pudong* as an example), and a shock to one of the suburbs (taking *Nanhui* as an example). Here, I do not attempt to interpret these price shocks structurally. Given that the focus is on the transmission mechanism of a price shock, identification of the source of the shock is not central to this analysis. The GIRFs for a one percent positive shock in *Huangpu, Pudong,* and *Nanhui* housing prices are presented in Figures 10 through 12, respectively. As shown in the GIRFs, all shocks have an immediate impact on the housing price of the neighboring districts. Neighboring districts with similar conditions have nearly the same responses to a given shock (such as *Zhabei* and *Yangpu* to *Pudong* housing price shocks, or *Changning* and *Putuo* to *Huangpu* housing price shocks). The difference mainly lies in the size of the responses. A price shock from *Pudong* has bigger effects on all other districts than a shock from *Huangpu* or *Nanhui*. The reason would be that the housing submarket of *Pudong* has an important role in Shanghai as a whole. The number of housing transactions in *Pudong* is more than twice the transaction number of *Huangpu* and *Nanhui* together. While a price shock in *Huangpu* takes time to spread to other districts, a shock from *Pudong* affects nearly all districts immediately. A housing price shock from *Nanhui* has a significant effect on the districts in similar locations (the outskirt of Shanghai). There are also some unexpected results. First, most shock effects are transitory. Second, the shock effects are smaller than expected. It will be interesting to see if the results improve after adding time-varying weight and district-specific control variables (Model #2 and Model #5).

Figure 10 MODEL #1: GIRF One Percent Positive Shock to the *Huangpu* Housing Price

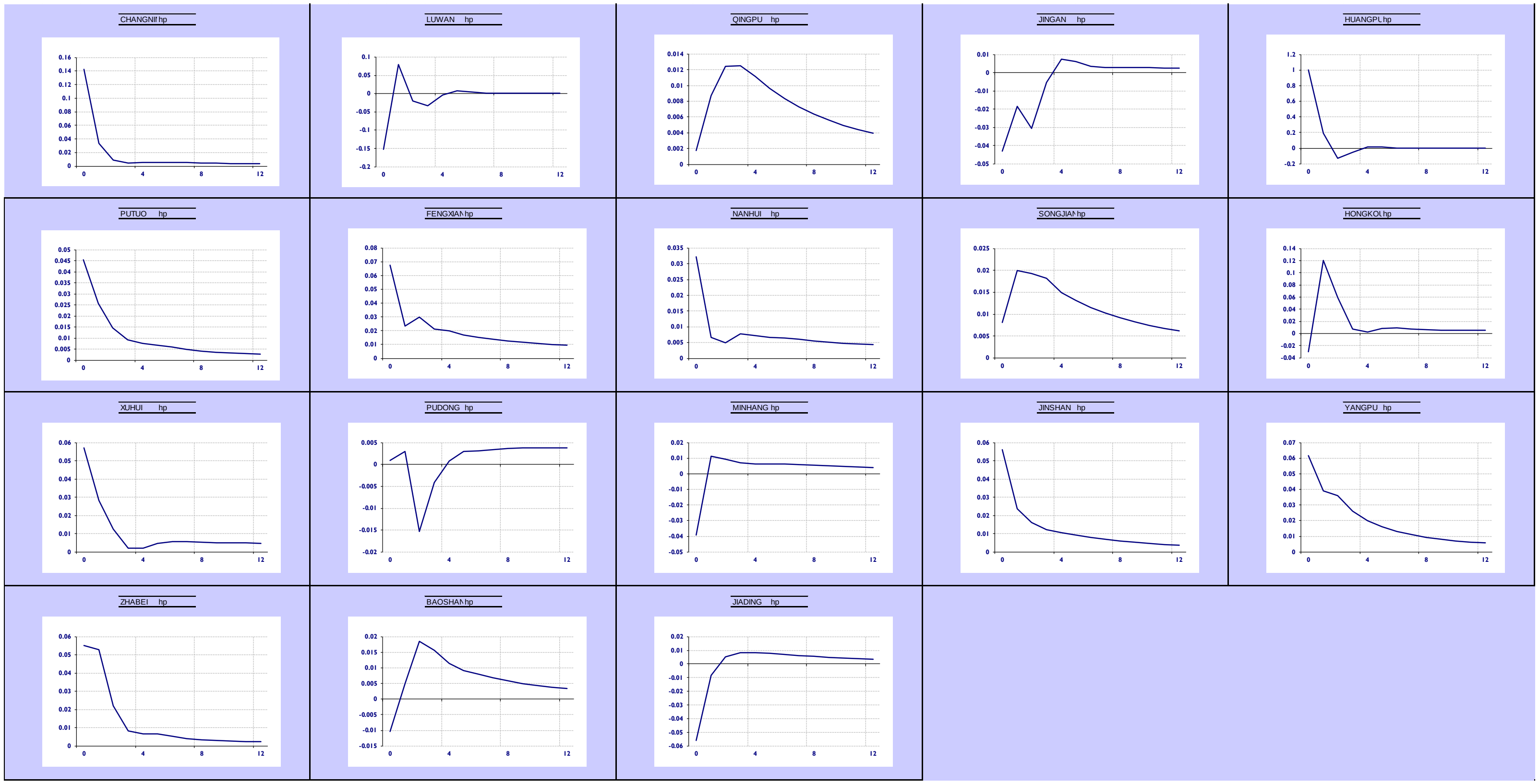


Figure 11 MODEL #1: GIRF One Percent Positive Shock to the *Pudong* Housing Price

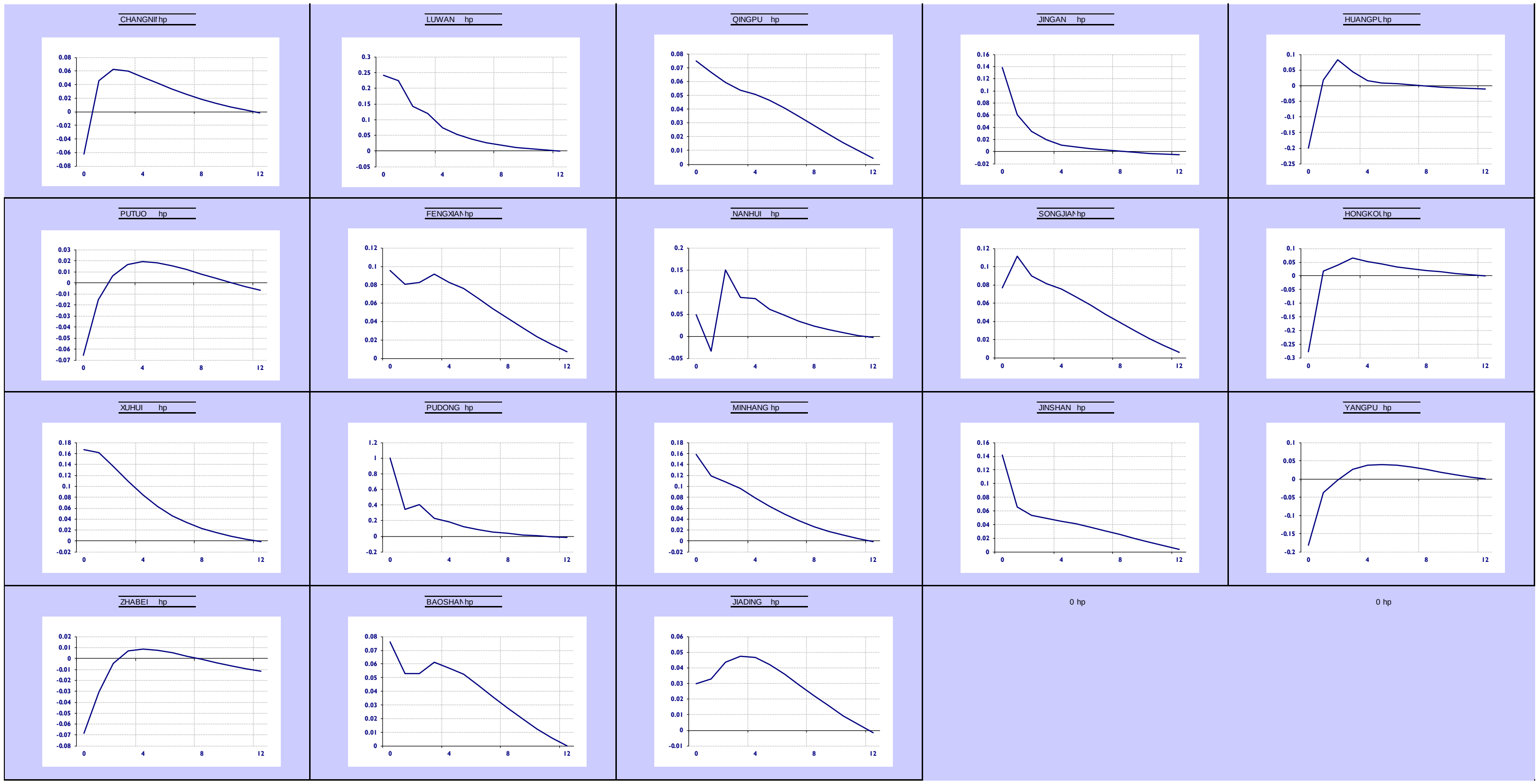
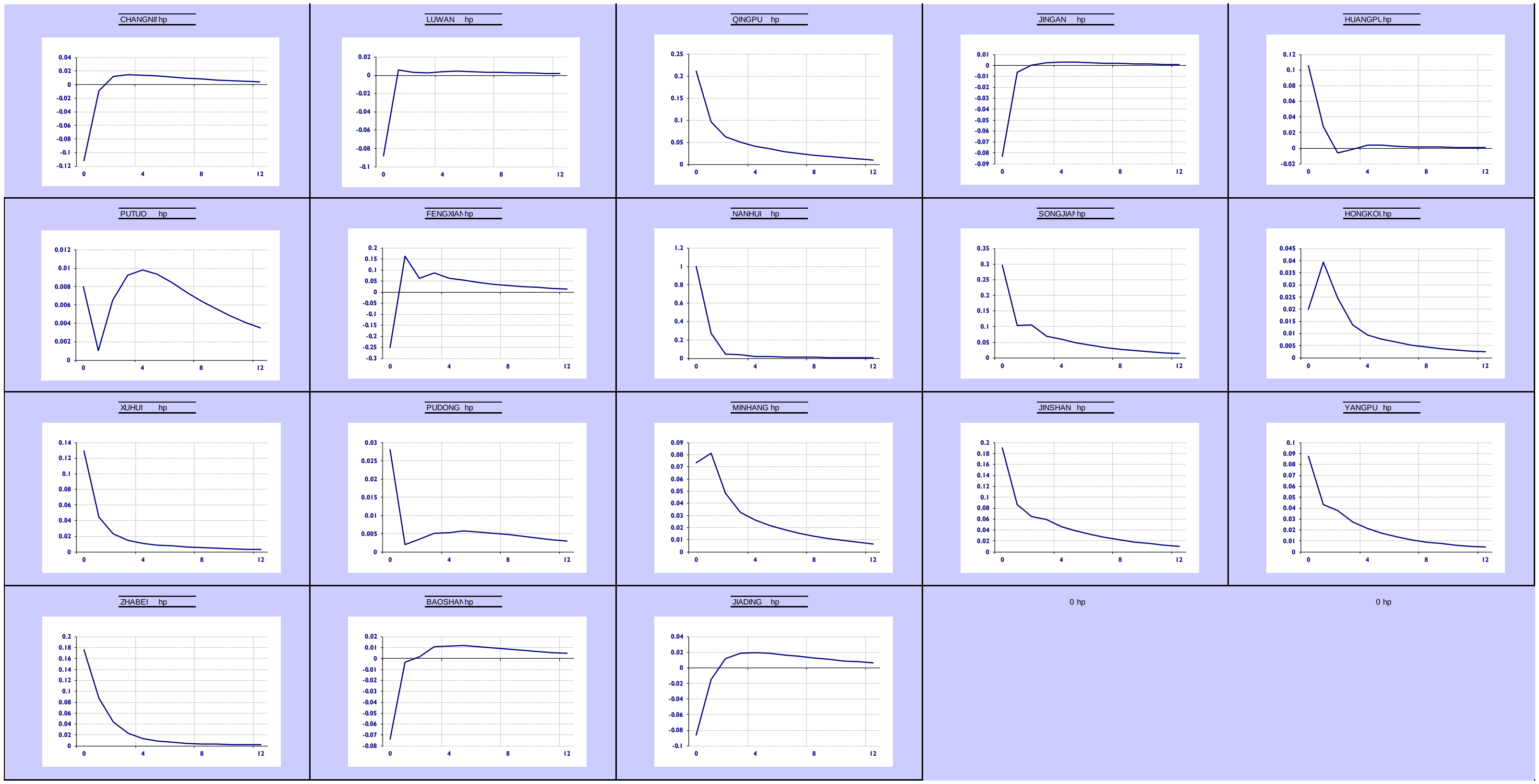


Figure 12 MODEL #1: GIRF One Percent Positive Shock to the *Nanhui* Housing Price



5.3 The GVAR Model with a Time-Varying Weight Matrix

I then consider models with a time varying weight matrix. The idea of using a time-varying weight matrix in this dissertation is based on the following considerations. Although the contiguity relationship does not change with time, the commute time between districts evolves significantly during the sample period. Shanghai has constructed several large transportation infrastructures in the last decade, such as new subway lines and the Yangtze River Bridge. These transportation infrastructures greatly shortened the commute time between some districts. For example, the newly-built Shanghai Yangtze River Bridge reduces the commute time between district *Chongming* and the city center from over 2 hours to 45 minutes. It is reasonable to speculate that the construction of the new transportation infrastructures plays an important role in changing the co-movement relationship of the Shanghai housing markets.

To show the relevance of a time-varying weight matrix, Figure 4 depicts the evolution of the Shanghai metro system from 2006 to 2014. I also take three districts (*Huangpu*, *Pudong,* and *Nanhui*) as examples to show the change in the commute time between districts. The details are given in Tables 8 and 10.

Figure 13 The Evolution of the Shanghai Metro System from 2005 to 2014

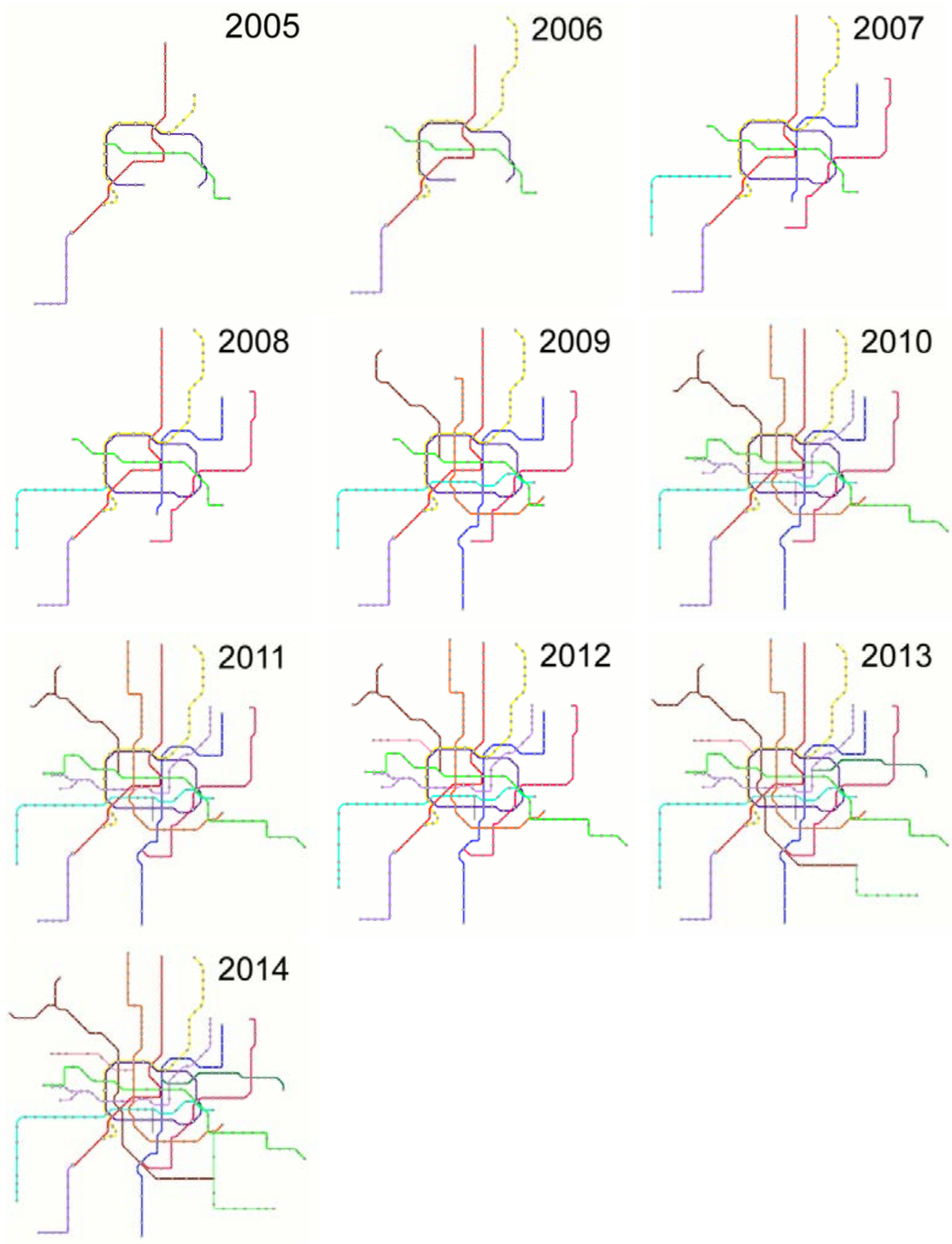


Table 8 Commute Time in Minutes between *Huangpu* and Other Districts

District	*Huangpu*	
	2006m1	2014m8
Changning	36	25
Luwan	9	5
Qingpu	75	75
Jing'an	15	14
Putuo	45	34
Fengxian	125	116
Nanhui	146	82
Songjiang	148	80
Hongkou	26	30*
Xuhui	29	26
Pudong	31	30
Minhang	75	75
Jinshan	207	122
Yangpu	28	19
Zhabei	30	35*
Baoshan	77	55
Jiading	149	95

* The increase is due to bus route changes.

Table 9 Commute Time in Minutes between *Pudong* and Other districts

District	*Pudong*	
	2006m1	2014m8
Changning	48	37
Luwan	37	34
Qingpu	154	125
Jing'an	26	26
Huangpu	31	30
Putuo	55	49
Fengxian	160	126
Nanhui	117	62
Songjiang	157	92
Hongkou	47	47
Xuhui	44	43
Minhang	90	90
Jinshan	221	136
Yangpu	53	43
Zhabei	45	45
Baoshan	98	72
Jiading	159	109

Table 10 Commute Time in Minutes between *Nanhui* and Other districts

District	*Nanhui*	
	2006m1	2014m8
Changning	163	89
Luwan	148	86
Qingpu	270	178
Jing'an	141	78
Huangpu	146	82
Putuo	171	96
Fengxian	118	118
Songjiang	272	140
Hongkou	162	99
Xuhui	162	76
Pudong	117	62
Minhang	206	134

Jinshan	213	213
Yangpu	168	95
Zhabei	161	98
Baoshan	213	124
Jiading	275	157

In order to capture the effect of newly-built transportation infrastructures, I employ a GVAR model with a time-varying weight matrix. The time varying weight model is expected to improve parameter stability, which in turn improves the accuracy of the counterfactual simulation. I will test the parameter stability later in this section. Since this is a model with the time-varying weight, the first thing is to calculate a time-varying weight.

The calculation of the time-varying weight matrix is based on commute time. The calculation involves three steps: First, the commute time between each district pair is computed for each month. Once the commute time for all district pairs at all time points is obtained, it then takes the inverse of these commute time. In the third step, these inverted numbers are rescaled. The rescaled values should add up to one for each district in each month. Finally, it will produce 116 weight matrices, one for each month between 2006m01 and 2014m08.

Obviously, the key step in the weight calculation is to find the commute time between districts. To compute the commute time, the fastest public transit from one district's center to others' will be used. It is reasonable to calculate the commute time based on public transit. As shown in the 2014 White Paper on Transport Development in Shanghai, nearly 65% of residents select public transit as their first choice in commuting. The percentage is much higher in rush hours. The commute time has three components: time on the bus, time on the subway and transfer time. The bus time is computed based on the schedules published by bus companies. The subway time is based on schedules published by Shanghai *Shentong Metro Group*. The transfer time is calculated as the number of transfers multiplied by the average transfer time. Based on the information available, I use 6 minutes as the average time for one transfer in this dissertation. So the transfer time (in minutes) equals the number of transfers multiplied by 6. One thing worth pointing out is that the bus schedule does not take traffic conditions into account. In rush hours, the actual bus time could be much longer. It should be equal to the scheduled time multiplied by an index of the traffic condition. This index reflects the longer expected commute time due to traffic congestion. So the commute time between districts could be computed as (in min.):

$$\begin{aligned}\text{Commute Time}\\ &= (\text{Bus Time} \times \text{Traffic Index}) + \text{Subtrain Time}\\ &+ (\text{Number of Transfers} \times 6)\end{aligned}$$

The commute between districts could require taking both buses and subways and transferring several times, or just one bus/subway line and no transfer. So the bus time, subway time, and transfer times could be 0 in this equation.

After computing the commute time between each pair of districts for every month, I get the time-varying weight matrix by following the steps described above. Table 11 shows the different weight matrices in 2006m1 and 2014m8, respectively. Tables 12 through 14 illustrate the changes in weights of *Huangpu, Pudong,* and *Nanhui* between 2006m1 to 2014m8.

Table 11 The different weight matrices in 2006m1 and 2014m8

$2006m1^{*}$

Districts	changn	luw	qingp	jingan	huangp	put	fengx	nanh	songj	hongk	xuh	pud	minh	jinsh	yangp	zhab	baosh	jiad	chongm
changn	0.000	0.047	0.063	0.095	0.058	0.149	0.059	0.061	0.061	0.066	0.110	0.074	0.068	0.056	0.050	0.055	0.058	0.064	0.049
luw	0.067	0.000	0.091	0.149	0.234	0.064	0.069	0.067	0.061	0.068	0.120	0.096	0.089	0.060	0.070	0.135	0.058	0.056	0.050
qingp	0.030	0.031	0.000	0.033	0.028	0.026	0.043	0.037	0.107	0.028	0.024	0.023	0.039	0.056	0.028	0.028	0.049	0.060	0.049
jingan	0.134	0.148	0.096	0.000	0.140	0.109	0.064	0.071	0.060	0.076	0.125	0.136	0.078	0.058	0.068	0.103	0.066	0.065	0.050
huangp	0.082	0.231	0.082	0.139	0.000	0.073	0.059	0.068	0.054	0.097	0.091	0.114	0.068	0.055	0.100	0.086	0.068	0.058	0.050
put	0.134	0.041	0.049	0.070	0.047	0.000	0.051	0.058	0.057	0.068	0.080	0.064	0.052	0.050	0.049	0.060	0.059	0.115	0.049
fengx	0.024	0.019	0.035	0.018	0.017	0.023	0.000	0.084	0.063	0.018	0.027	0.022	0.077	0.098	0.018	0.020	0.027	0.036	0.048
nanh	0.018	0.014	0.023	0.015	0.014	0.019	0.063	0.000	0.029	0.016	0.016	0.030	0.025	0.054	0.017	0.016	0.024	0.031	0.050
songj	0.023	0.016	0.083	0.016	0.014	0.023	0.059	0.037	0.000	0.018	0.023	0.023	0.058	0.081	0.018	0.017	0.027	0.035	0.047
hongk	0.078	0.056	0.068	0.063	0.081	0.089	0.053	0.061	0.057	0.000	0.066	0.075	0.059	0.052	0.232	0.112	0.100	0.062	0.049
xuh	0.123	0.094	0.057	0.100	0.072	0.099	0.076	0.061	0.071	0.063	0.000	0.080	0.112	0.064	0.055	0.083	0.057	0.064	0.049
pud	0.061	0.056	0.040	0.080	0.068	0.060	0.046	0.085	0.051	0.054	0.060	0.000	0.057	0.052	0.053	0.057	0.053	0.054	0.050
minh	0.039	0.036	0.046	0.032	0.028	0.033	0.111	0.048	0.090	0.029	0.057	0.039	0.000	0.072	0.027	0.034	0.038	0.047	0.047
jinsh	0.014	0.011	0.030	0.011	0.010	0.014	0.064	0.047	0.056	0.011	0.015	0.016	0.032	0.000	0.013	0.013	0.020	0.025	0.048
yangp	0.053	0.052	0.063	0.051	0.075	0.058	0.048	0.059	0.050	0.210	0.052	0.067	0.050	0.051	0.000	0.112	0.116	0.055	0.050
zhab	0.063	0.109	0.067	0.084	0.070	0.076	0.058	0.062	0.053	0.109	0.085	0.079	0.068	0.056	0.121	0.000	0.106	0.059	0.052
baosh	0.033	0.023	0.058	0.026	0.027	0.037	0.039	0.047	0.042	0.048	0.029	0.036	0.037	0.044	0.062	0.052	0.000	0.106	0.163
jiad	0.022	0.013	0.043	0.016	0.014	0.044	0.031	0.036	0.032	0.018	0.019	0.022	0.028	0.033	0.018	0.018	0.063	0.000	0.049
chongm	0.003	0.002	0.006	0.002	0.002	0.003	0.007	0.010	0.007	0.002	0.002	0.003	0.005	0.011	0.003	0.003	0.010	0.008	0.000

* The weight vector for each district given by the rows of this matrix

$2014m8^*$

Districts	changn	luw	qingp	jingan	huangp	put	fengx	nanh	songj	hongk	xuh	pud	minh	jinsh	yangp	zhab	baosh	jiad	chongm
changn	0.000	0.049	0.068	0.161	0.064	0.110	0.058	0.066	0.070	0.068	0.122	0.083	0.067	0.064	0.060	0.068	0.066	0.071	0.060
luw	0.065	0.000	0.058	0.098	0.320	0.088	0.065	0.066	0.065	0.072	0.105	0.090	0.082	0.069	0.099	0.128	0.072	0.066	0.062
qingp	0.024	0.015	0.000	0.028	0.021	0.022	0.040	0.035	0.073	0.025	0.021	0.025	0.036	0.049	0.018	0.026	0.036	0.049	0.045
jingan	0.195	0.089	0.095	0.000	0.114	0.110	0.061	0.066	0.069	0.080	0.110	0.118	0.072	0.064	0.085	0.097	0.072	0.071	0.062
huangp	0.086	0.320	0.081	0.126	0.000	0.077	0.060	0.066	0.065	0.074	0.089	0.103	0.063	0.059	0.120	0.070	0.069	0.063	0.063
put	0.089	0.053	0.051	0.074	0.047	0.000	0.055	0.067	0.067	0.070	0.080	0.063	0.067	0.059	0.051	0.064	0.067	0.098	0.058
fengx	0.018	0.015	0.035	0.015	0.014	0.021	0.000	0.055	0.037	0.016	0.023	0.024	0.068	0.077	0.015	0.019	0.023	0.032	0.046
nanh	0.022	0.017	0.033	0.018	0.016	0.027	0.059	0.000	0.037	0.020	0.030	0.045	0.035	0.034	0.020	0.021	0.028	0.038	0.048
songj	0.029	0.020	0.085	0.024	0.020	0.034	0.050	0.046	0.000	0.025	0.038	0.033	0.056	0.067	0.023	0.027	0.034	0.043	0.051
hongk	0.065	0.052	0.067	0.063	0.053	0.082	0.050	0.058	0.059	0.000	0.058	0.065	0.055	0.057	0.190	0.106	0.152	0.064	0.061
xuh	0.113	0.073	0.056	0.084	0.061	0.091	0.070	0.085	0.086	0.056	0.000	0.072	0.103	0.078	0.051	0.079	0.059	0.067	0.060
pud	0.058	0.047	0.049	0.068	0.053	0.054	0.056	0.093	0.056	0.047	0.054	0.000	0.053	0.053	0.053	0.054	0.053	0.055	0.062
minh	0.030	0.028	0.046	0.027	0.021	0.037	0.100	0.048	0.061	0.026	0.050	0.034	0.000	0.057	0.024	0.032	0.034	0.045	0.051
jinsh	0.019	0.015	0.041	0.016	0.013	0.022	0.075	0.030	0.048	0.018	0.025	0.023	0.038	0.000	0.016	0.020	0.025	0.033	0.044
yangp	0.056	0.070	0.047	0.066	0.084	0.058	0.047	0.056	0.052	0.186	0.051	0.072	0.050	0.051	0.000	0.106	0.075	0.056	0.061
zhab	0.060	0.084	0.066	0.071	0.046	0.069	0.054	0.056	0.058	0.097	0.074	0.068	0.062	0.058	0.099	0.000	0.078	0.060	0.064
baosh	0.037	0.030	0.057	0.033	0.029	0.046	0.042	0.047	0.046	0.089	0.036	0.043	0.043	0.047	0.045	0.050	0.000	0.073	0.054
jiad	0.026	0.018	0.050	0.021	0.017	0.043	0.038	0.041	0.037	0.024	0.026	0.028	0.036	0.039	0.022	0.025	0.046	0.000	0.048
chongm	0.008	0.006	0.016	0.006	0.006	0.009	0.019	0.018	0.015	0.008	0.008	0.011	0.014	0.019	0.008	0.009	0.012	0.017	0.000

* The weight vector for each district given by the rows of this matrix

Table 12 The weight matrices of *Huangpu* in 2006m1 and 2014m8

District	*Huangpu*	
	2006m1	2014m8
Changning	0.059	0.064
Luwan	0.234	0.320
Qingpu	0.028	0.021
Jing'an	0.140	0.114
Putuo	0.047	0.047
Fengxian	0.017	0.014
Nanhui	0.014	0.020
Songjiang	0.014	0.020
Hongkou	0.081	0.053
Xuhui	0.073	0.062
Pudong	0.068	0.053
Minhang	0.028	0.021
Jinshan	0.010	0.013
Yangpu	0.075	0.084
Zhabei	0.070	0.046
Baoshan	0.027	0.029
Jiading	0.014	0.017

Table 13 The weight matrices of *Pudong* in 2006m1 and 2014m8

District	*Pudong*	
	2006m1	2014m8
Changning	0.074	0.084
Luwan	0.096	0.091
Qingpu	0.023	0.025
Jing'an	0.137	0.119
Huangpu	0.115	0.103
Putuo	0.065	0.063
Fengxian	0.022	0.025
Nanhui	0.030	0.050
Songjiang	0.023	0.034
Hongkou	0.076	0.066
Xuhui	0.081	0.072
Minhang	0.039	0.034
Jinshan	0.016	0.023
Yangpu	0.067	0.072
Zhabei	0.079	0.069
Baoshan	0.036	0.043
Jiading	0.022	0.028

Table 14 The weight matrices of *Nanhui* in 2006m1 and 2014m8

District	*Nanhui*	
	2006m1	2014m8
Changning	0.062	0.068
Luwan	0.068	0.070
Qingpu	0.037	0.034
Jing'an	0.071	0.077
Huangpu	0.069	0.073
Putuo	0.059	0.063
Fengxian	0.085	0.051
Songjiang	0.037	0.043
Hongkou	0.062	0.061
Xuhui	0.062	0.079
Pudong	0.086	0.097
Minhang	0.049	0.045
Jinshan	0.047	0.028
Yangpu	0.060	0.063
Zhabei	0.062	0.061
Baoshan	0.047	0.049
Jiading	0.037	0.038

5.3.1 Model #2: The Single-Equation GVAR Model with a Time-Varying Weight Matrix, 18 Districts

This model has the same variable sets as Model #1, except that the foreign housing price is constructed using a time-varying weight. This model contains 18 districts (it does not include *Chongming*). The VECM of each district includes 5 common variables.

The regression equation of this model is

$$\mathrm{X}_{i,t} = \sum_{l=1}^{p_i} \Phi_{i,l}\mathrm{X}_{i,t-l} + \Lambda_{i,0}\mathrm{X}_{i,t}^{*} + \sum_{l=1}^{q_i} \Lambda_{i,l}\mathrm{X}_{i,t-l}^{*} + \mathrm{D}_{i,0}\omega_t + \sum_{l=1}^{s_i} \mathrm{D}_{i,l}\omega_{t-l} + \varepsilon_{i,t}$$

For $i = 1, 2, \ldots, 18$. $\mathrm{X}_{i,t} = hp_{i,t}$ is the logarithm of housing price; $\mathrm{X}_{i,t}^{*} = hps_{i,t}$ is the logarithm of weighted average foreign housing price. $\omega_t = (m_t, cpt_t, ibor_t, lrh_t, tst_t)$ is the vector of common variables; $\mathrm{X}_{i,t}^{*}$ is a function of the time-varying weight $\mathrm{W}_{i,\tau(t)}$.

$$\mathrm{X}_{i,t}^{*}\left(\mathrm{W}_{i,\tau(t)}^{*}\right) = \sum_{j=1}^{N} \mathrm{W}_{ij,\tau(t)}^{*}\mathrm{X}_{j,t} = \mathrm{W}_{i,\tau(t)}^{*\prime}\mathrm{X}_t$$

where $\mathrm{X}_t = (\mathrm{X}_{1,t}', \mathrm{X}_{2,t}', \ldots, \mathrm{X}_{18,t}')'$ is a 18×1 vector of the endogenous variables and $\mathrm{W}_{i,\tau(t)}^{*} = (\mathrm{W}_{i1,\tau(t)}, \mathrm{W}_{i2,\tau(t)}, \ldots, \mathrm{W}_{i18,\tau(t)})'$ is the weight vector that is used to calculate the foreign variable for district i at time t. An index $\tau(t)$ is used instead of t to indicate the time-varying weight matrix, because the weight could stay unchanged and be used over several periods before it is reset. If a fixed set of weights are used over the entire sample period then $\tau(t)$ will be unchanged with t.

5.3.1.1 Unit Root Test

The results of the unit root tests are presented in Appendix D Table 36 through Table 38. As expected, the variables *hp* and *hps* in most of the district-specific models are integrated at order one, I(1). There are several exceptions. *hp* in *Changning*, *Luwan*, *Jing'an* and *Hongkou* reject the null hypothesis of a unit root. As discussed in Model #1, the common variables *m*, *cpi*, *lrh* and *tst* are also I(1) except *lbor* which is I(0).

5.3.1.2 Lag Orders Selection

The lag orders, p_i and q_i of the individual districts' VARX(p_i, q_i) models are selected according to the Akaike information criterion (AIC). The maximum lag orders of the domestic and district-specific foreign variables are set to two in all districts ($p_i \leq 2, q_i \leq 2$). Note that the same constraints are imposed on Model #1. The AIC statistics and the selected orders are presented in Appendix D Tables 40 and 41. With the use of the time-varying weight, there is an improvement over Model #1 for *Jinshan*. Its residual serial correlation *F*-statistic becomes insignificant at the 5% level.

5.3.1.3 Cointegration Ranks

I then proceed to the cointegration analysis. This analysis follows the same method used in Model #1. The cointegration rank for each district-specific model is tested using Johansen's trace test statistics. The critical values are calculated following MacKinnon, Haug and Michelis (1999). I choose the trace test instead of the maximal eigenvalue test because the former has better performance for small samples. The results of the trace tests are presented in Appendix D.

5.3.1.4 Weak Exogeneity Test

The error correction forms of the individual district VARX models are derived after lag orders and cointegration ranks are selected. However, I need to test the assumption of weak exogeneity before solving the whole GVAR model. This assumption is required for consistent estimation of the individual district VARX model. The results of weak exogeneity tests are presented in Appendix D. As shown in Table 44, the weak exogeneity assumption holds for 103 out of 108 variables. Considering the 5% significance level, this result is acceptable.

5.3.1.5 Average Pairwise Cross-Section Correlations

Another important assumption of GVAR modeling is that the cross-sectional dependence of the district-specific shocks must be weak. The details of this test are discussed in Chapter 4, section 4.3. The basic idea behind this assumption is straightforward. Since the district-specific model is conditional on weakly exogenous foreign variables, it is reasonable to expect that the degree of correlation of the remaining shocks across districts to be modest. The average pairwise cross-section correlations are calculated for the levels of the endogenous variables of the individual district VARX models, as well as those of the associated residuals. To calculate the average pairwise cross-section correlations for each variable of each district, I first compute the pairwise correlation of that district with remaining districts, then get the average value across districts. It is expected that the average correlation between the levels of *hp* is high because the housing price is closely connected among districts while the average correlation of the associated residuals is weak. My findings confirm this expectation. The results of the tests are provided in Appendix D Table 45.

5.3.1.6 Parameter Stability Test

I then test the parameter stability. Parameter stability is required in order to obtain reliable results from counterfactual simulations. In order to make the tests more conclusive, I conduct four different statistical tests to check the parameter stability: Ploberger and Kramer's (1992) maximal OLS cumulative sum (CUSUM) statistic, denoted by PK_{sub}; its mean square PK_{msq}; Nyblom test (1989), denoted by $\mathfrak{H}$ and the heteroskedasticity-robust version of Wald's form of Quandt's(1960) likehood ratio statistic, denoted by QLR. The test statistics and the corresponding 5% critical values are presented in Appendix D Table 46. Nearly all individual district VARX models pass the tests, with only a few exceptions. *Yangpu* in Model #2 passes the PK_{sub} test, which is an improvement over Model #1.

5.3.1.7 Contemporaneous Effects of Foreign Variables on Domestic Counterparts

In the individual district VARX models, the coefficients $\Lambda_{i,0}$ on the contemporaneous foreign variables measure the contemporaneous effect of foreign variables on domestic variables. They can be interpreted as the impact elasticity between domestic and foreign variables: the instantaneous percentage change in the housing prices of one district given a one percent increase in other districts' housing prices.

Table 15 reports the impact elasticities with the corresponding standard deviations (in parentheses). In Table 15, I divide the districts into three groups according to the impact elasticities: the high elasticity group (with an elasticity greater than 0.7), the low elasticity group (with an elasticity smaller than 0.3) and the medium elasticity group (with an elasticity between 0.3 and 0.7). Districts in the high and the medium elasticity groups are significantly influenced by price movements in other markets, while districts in the low elasticity group are only affected in a modest way and the effects are insignificant. Districts in the same elasticity group are found to share many common features. Two districts, *Yangpu* and *Chongming* in the high elasticity group, are the ones near the urban center. They were not closely connected with districts in the urban center in the past because of the long commute time; however, things have changed. Due to newly built subway lines, the commute time between the urban center and *Changning* and *Yangpu* has been reduced from over one hour to less than half an hour. They are two of Shanghai's emerging regions. These two districts have experienced high economic growth and stable population in the past ten years (for example, the population of *Yangpu* was 1.25 million in 2006 and 1.32 million in 2014). *Fengxian* was probably the most undeveloped area in Shanghai. It also experienced high economic growth. It has no subway lines to other districts. There are four districts in the low elasticity group. Three of them (*Songjiang*, *Jiading*, and *Baoshan*) are on the outskirts. *Luwan* is a district that calls for special attention. The negative impact elasticity is probably due to changes in the demographics. *Luwan* is small and in the old town. Only a few new sales happened each month. Its population has decreased by about 30% in the past decade as many companies in *Luwan* have moved to the outskirt districts. The negative effect is not significant at the 5% level. Compared to the results in Model #1, many districts have higher impact elasticities. *Luwan*, *Pudong*, *Minhang* and *Jiading* are the exceptions. I will recheck these impact elasticities in Model #5 which contains an extra district-specific variable (land price). Compared to Model #1, Model #2's results make more sense. It shows a closer relationship among these housing submarkets, which can be observed in Shanghai: these submarkets have similar housing price movement pattern, especially in the short term.

Table 15 MODEL #2: Contemporaneous Effects of Foreign Housing Price on Domestic Housing Price

High Elasticity Group	
District	*Impact Elasticity*
YANGPU	0.80 (0.15)
FENGXIAN	0.80 (0.25)
CHANGNING	0.78 (0.21)

Medium Elasticity Group	
District	*Impact Elasticity*
JING'AN	0.61 (0.24)
JINSHAN	0.46 (0.14)
QINGPU	0.44 (0.20)
PUDONG	0.43

Low Elasticity Group	
District	*Impact Elasticity*
SONGJIANG	0.25* (0.21)
JIADING	0.17* (0.15)
HONGKOU	0.13* (0.26)
BAOSHAN	0.03*

	(0.17)
MINHANG	0.42
	(0.20)
HUANGPU	0.41
	(0.18)
PUTUO	0.34
	(0.15)
XUHUI	0.31
	(0.18)
ZHABEI	0.32
	(0.12)
NANHUI	0.31*
	(0.20)

	(0.11)
LUWAN	−0.05*
	(0.21)

* Not significant at the 5% level.

5.3.1.8 Generalized Impulse Response Functions (GIRFs)

The GVAR model summarized in Appendix D presents a complicated set of dynamic and interacting housing market relations in Shanghai. Each estimated parameter only provides a partial view of these relationships. Therefore, to have a complete understanding, I employ the generalized impulse response functions (GIRFs) to trace the effects of housing price shocks over time and across districts. The GIRF is introduced by Koop et al. (1996) and adapted to the VAR model in Pesaran and Shin (1998), and Pesaran and Smith (1998). In using the GIRFs, I am not attempting to interpret the price shocks structurally. Given that the focus of this study is on the ripple effects of price shocks on different districts, the issue of identification of shock sources is not central to this analysis. Due to the considerable variations between districts (such as geographic location, economic situation, attractiveness to new immigrants and affordability), it is expected that price shocks of the same size but to different districts could have very different outcomes in terms of the propagation speed and size of the impact. To illustrate the differences in the ripple effects, I choose three very different but typical districts, *Pudong*, *Huangpu*, and *Nanhui*.

Pudong is an emerging district in Shanghai. It has experienced skyrocketing economic growth in the last two decades and is now Shanghai's financial center. It has a strong attraction to immigrants. The population of *Pudong* has increased by 65% in the past nine years. It has also seen many newly-built apartment complexes each month during the sample period, so housing supply has been kept at a steady level.

Huangpu is in the old town of Shanghai and has the best geographic location. It sits right on the *Huangpu River* and is also the business center of Shanghai. *Huangpu* has the highest average housing price in Shanghai and only a few newly-built residential units are seen each month. The population of *Huangpu* has decreased by 30% in the past 15 years due to residential areas being converted into commercial centers and expensive newly-built residential units.

Nanhui is in the outskirts of Shanghai. A large number of new houses are built in *Nanhui* every month. It was not closely connected with other districts in the past because of the long commute time (except for *Pudong, Fengxian,* and *Minhang*, with which *Nanhui* shares borders). However, things have changed nowadays. Newly built subway lines greatly shorten the commute time between *Nanhui* and other districts. This makes it possible for people, who work in the urban center, to live in *Nanhui*. *Nanhui* is not the ideal location for most homeowners, but the low price attracts home buyers to the area.

Figure 14 displays the GIRFs for a one percent positive housing price shock to these three districts. As presented in the figure, a *Pudong* housing price shock affects the housing price of other districts immediately upon impact. It has a sizeable positive effect on districts in the urban center (*Luwan*, *Xuhui*, *Minhang*). All the districts in the outskirts are affected in a modest way. One thing to note is that the shock has a negative effect on the districts connected to *Pudong* by bridges (*Huangpu*, *Hongkou,* and *Yangpu*, and possibly *Zhabei*, which is next to *Huangpu* and *Hongkou* and quite near the bridges to

Pudong. These districts sit to the west of the *Huangpu River* and *Pudong* sits to the east of the *Huangpu River*). A possible explanation is the following: *Pudong* has a sufficient housing supply; a strong housing demand in *Pudong* may reflect a diversion in the housing demand in nearby districts that have similar locations (*Huangpu*, *Zhabei,* and *Hongkou*) or districts that have similar economic performance and commute time to the city center (*Putuo* and *Changning*). So, in the short run, responses in the nearby districts are negative because of the competition effect. In the medium run, the increasing price in *Pudong* may have a positive effect on these districts by some channels, distinguishing the short-term responses from the medium-term ones. Compared to Model #1, the impacts on the neighboring districts (*Xuhui*, *Minhang,* and *Baoshan*) are over 35% larger, whereas the impacts on the outskirt districts (*Fengxian, Nanhui, Songjiang, Jinshan*) are smaller.

Compared to *Pudong*, a *Huangpu* housing price shock has a weaker effect on other districts. The effects on most districts are small and dissipate quickly. This result is expected given the small size of the *Huangpu* housing market. Compared to Model #1, a *Huangpu* housing price shock has a bigger impact on nearly all districts. For most districts, the impacts are more than twice the ones in Model #1.

The effect of a housing price shock in *Nanhui* is quite different from that in *Huangpu*. It has a sizable effect on nearly all districts in the outskirts of Shanghai immediately (no matter whether they share borders with *Nanhui* or not). These results may reflect the similar developments in the economy and demography in *Nanhui* and other districts in the outskirts. Compared to Model #1, the impacts on *Songjiang, Minhang*, and *Jinshan* are significantly larger. On the other hand, the blooming *Nanhui* housing market has an obviously negative effect on the housing markets of *Luwan, Jing'an,* and *Huangpu.* These negative relationships can be due internal immigration. Residents move to the outskirts from the city center because of companies' relocation and cheaper cost of living. This shock has little effect on districts close to the city center, except *Zhabei*. Even in *Pudong* (they share a common border), the effect is quite small (0.025). The impact on *Xuhui* also becomes trivial, which is consistent with expectation.

5.3.1.9 Counterfactual Analysis

I conduct counterfactual simulation exercises to evaluate the effect of the newly-built transportation infrastructures on the spillover effects of a housing price shock. In this analysis, the GVAR model is estimated with the time-varying weight matrix described earlier in this section, but the GIRFs are constructed using a different set of weight matrices. These weight matrices are based on commute time in January 2006, which corresponds to the beginning of the sample period. I then calculate the GIRF by giving a one percent positive housing price shock to districts *Huangpu*, *Pudong*, and *Nanhui*. These counterfactual GIRFs are presented in Figure 14 through Figure 16. By comparing these GIRFs with those reported in the last section (Figure 10 though Figure 12, where GIRFs are based on commute time in December 2014), I can infer to what extent the newly-built infrastructures affect the spillover effect. The newly-built transportation infrastructures increase the impact of a *Huangpu* housing price shock, especially on districts that do not share a border with *Huangpu*. The effects on *Huangpu*'s neighbors (*Luwan*, *Hongkou, Zhabei*, and *Jing'an*) do not change, which is expected, because the commute time between *Huangpu* and its neighbors does not change over time.

The impacts of a *Nanhui* housing price shock do not increase with the new transportation infrastructures. Its impact remains the same on districts in the outskirts except for *Fengxian*. As nearly all new subway lines aim at connecting districts to the city center, the new infrastructures strengthen the connections between the city center and other districts, while they weaken the relationships among the housing submarkets in the outskirts. The impact of this shock to *Hongkou*, *Yangpu*, *Putuo*, *Xuhui* and *Pudong* decrease a lot. All of these districts are close to the city center. New subway lines have been built to connect them directly to the city center during the sample period. The commute time has been reduced to less than 30 minutes because of new transportation construction.

The new transportation infrastructures have a mixed effect on the spillover effect of a *Pudong* housing price shock to the city center. On average, its instantaneous impact remains the same, but its medium-run impact becomes stronger. I will compare these results with the counterfactual analysis in Model #5, which contains an extra district-specific control variable, i.e. land price.

Figure 14 MODEL #2: GIRFs of a One Percent Positive Shock to the *Pudong* Housing Price

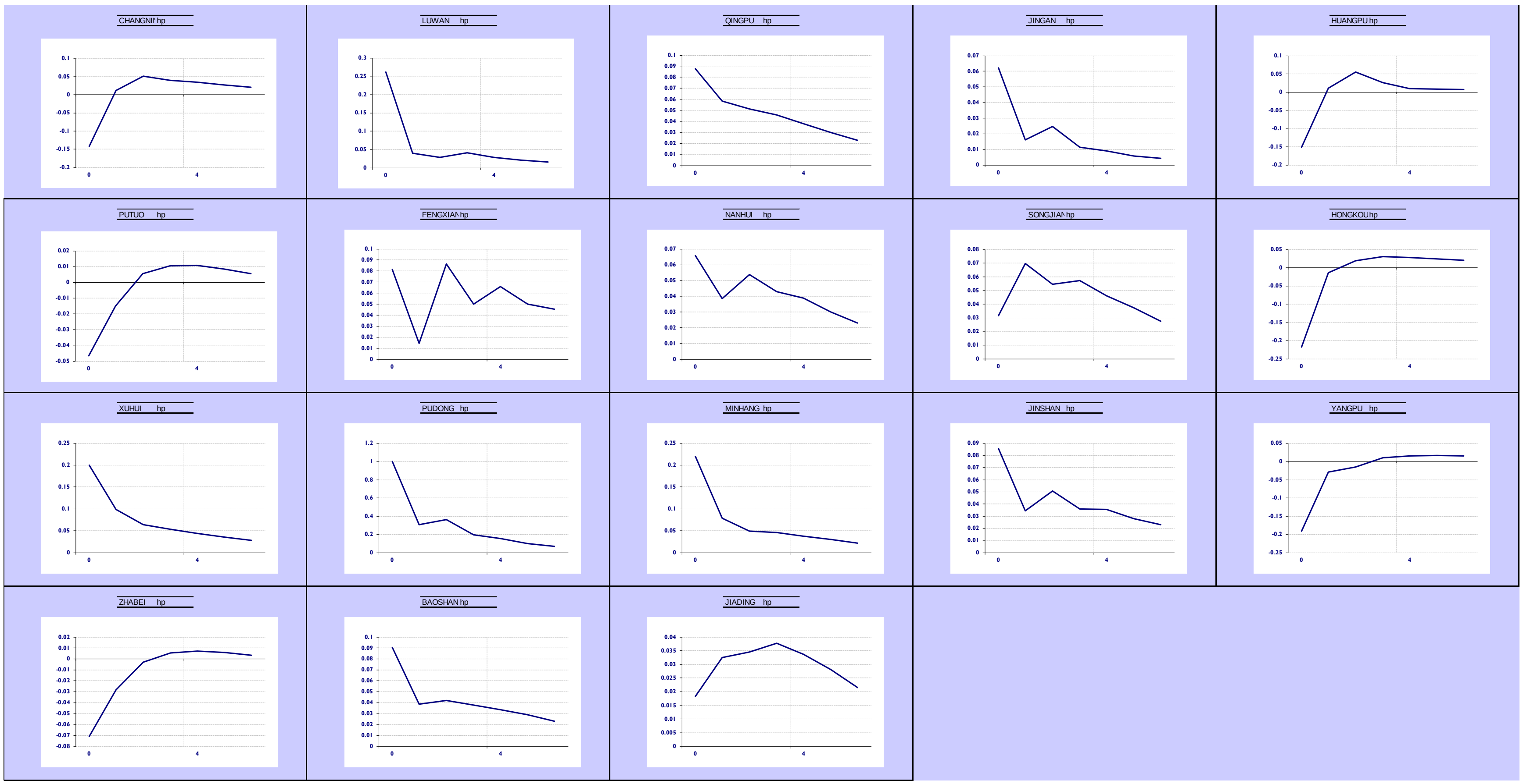


Figure 15 MODEL #2: GIRFs of a One Percent Positive Shock to the *Huangpu* Housing Price

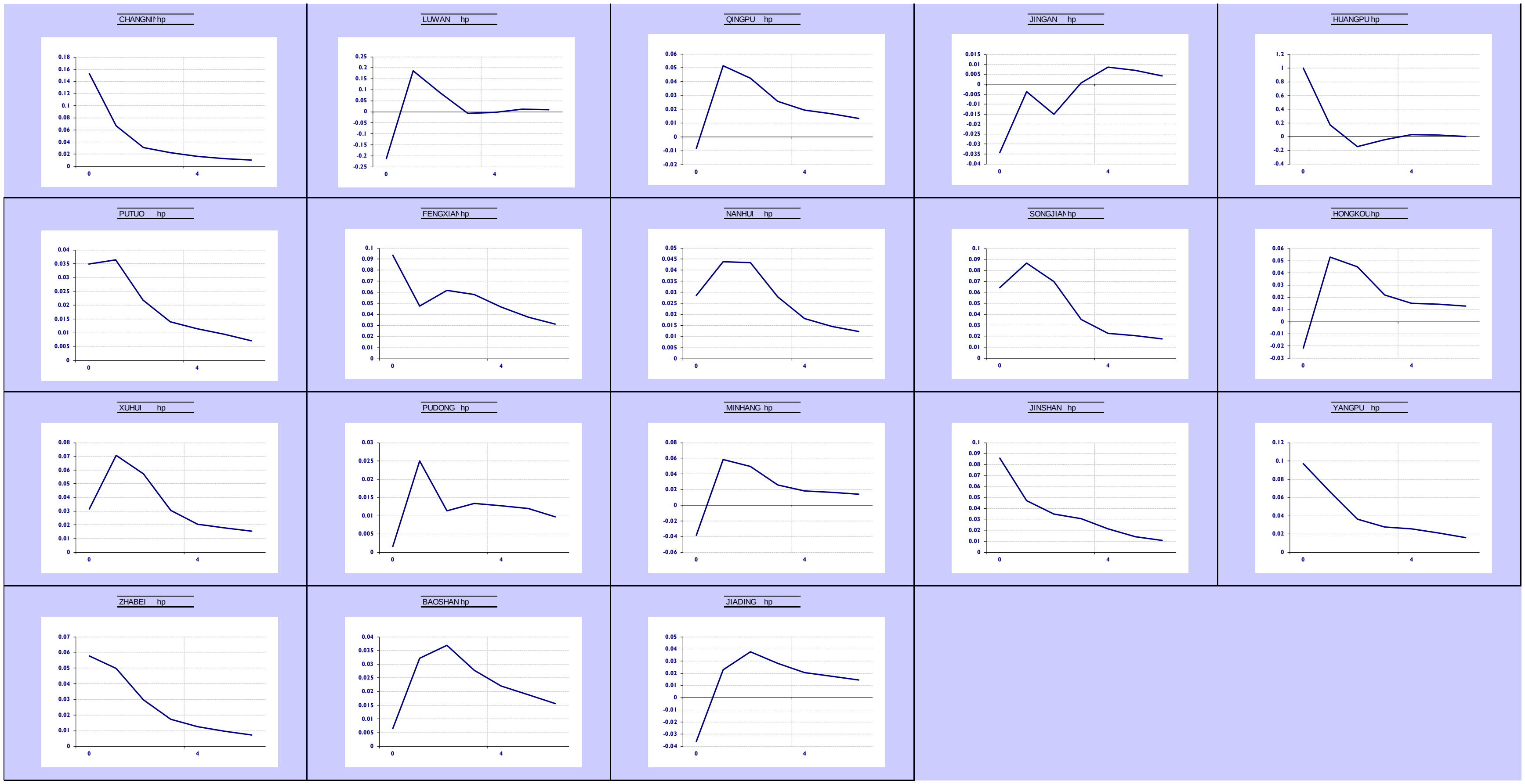


Figure 16 MODEL #2: GIRFs of a One Percent Positive Shock to the *Nanhui* Housing Price

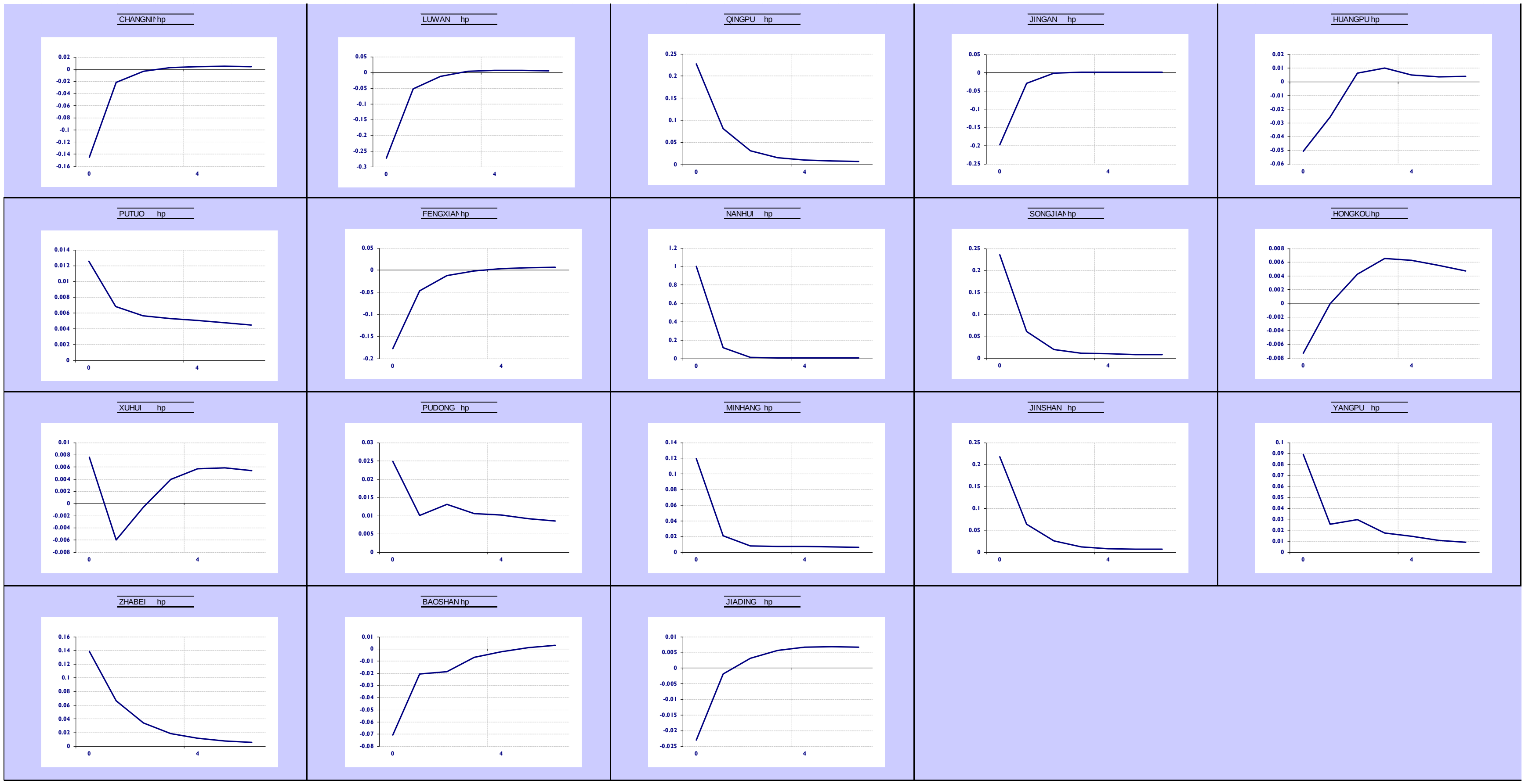
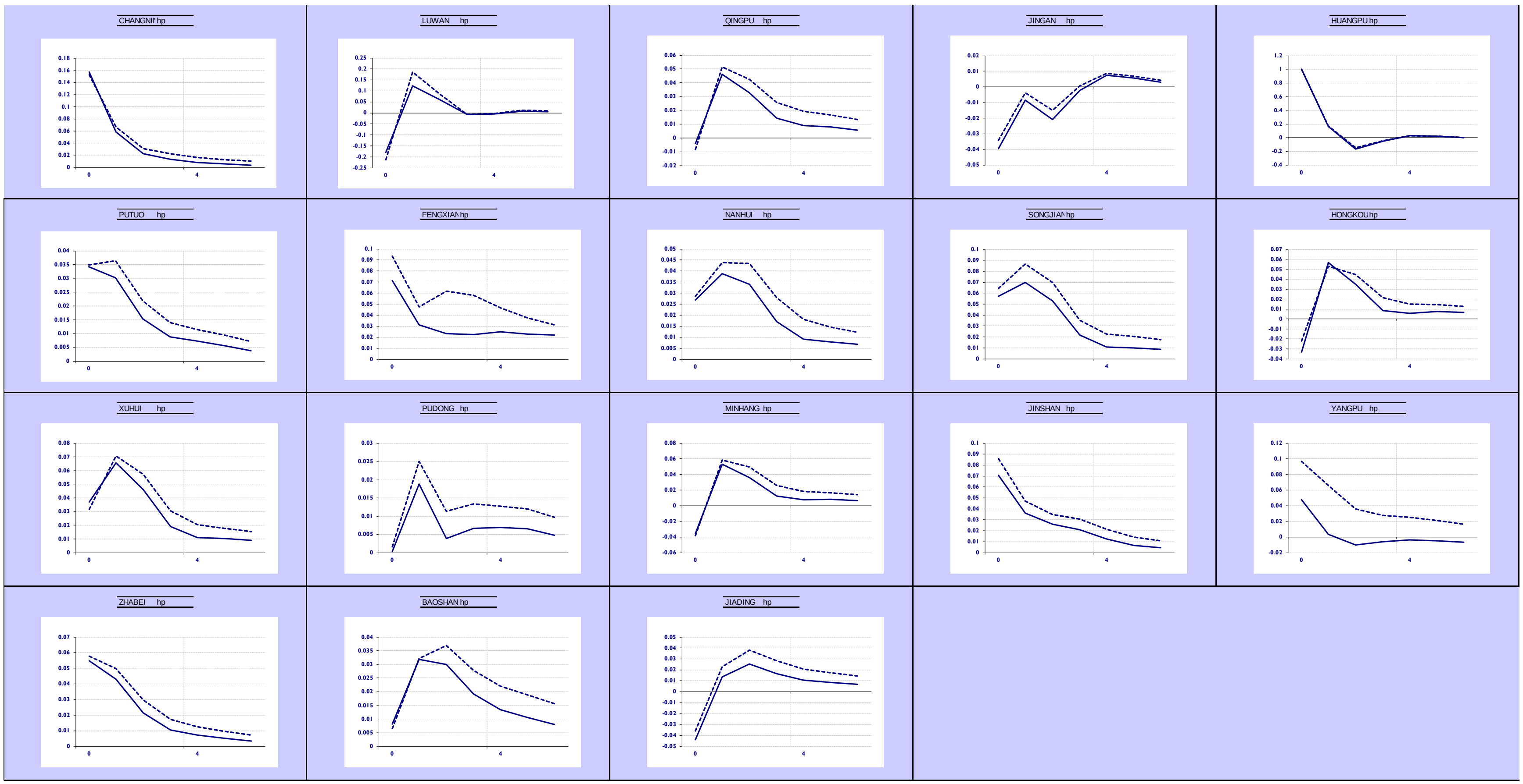
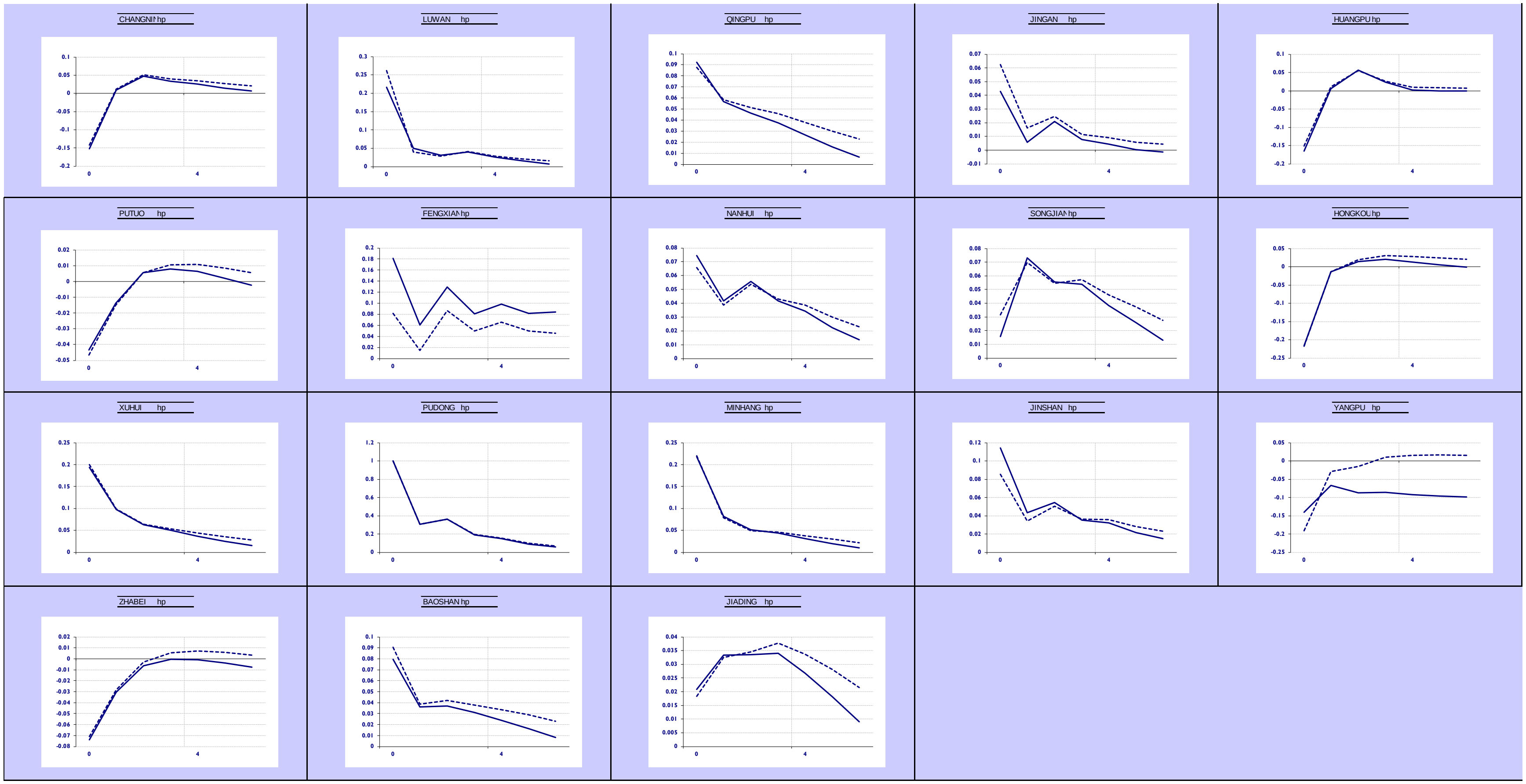


Figure 17 MODEL #2 Counterfactual Analysis: GIRFs of a One Percent Positive Shock to the *Huangpu* Housing Price



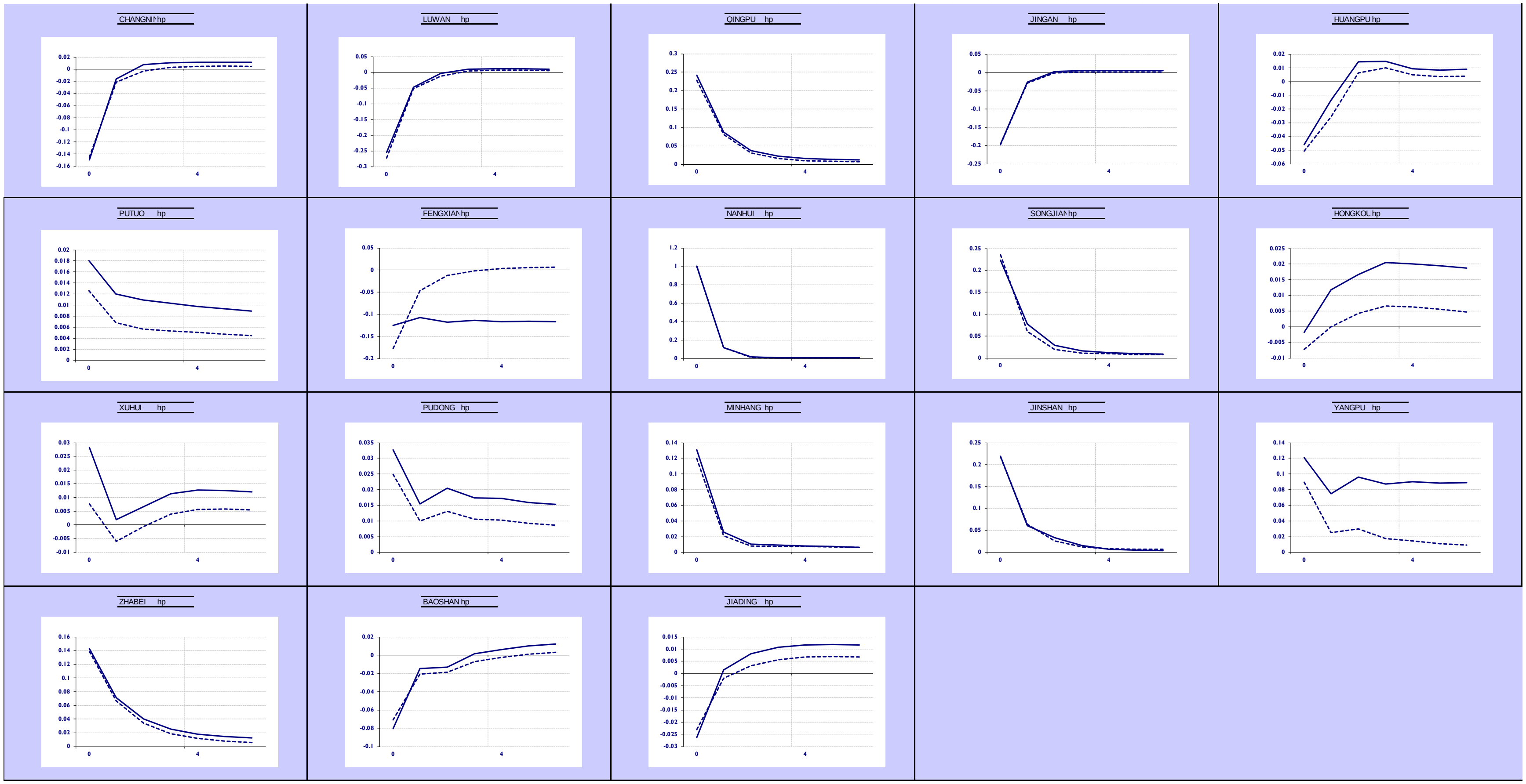
(--- Dec 2014, — Jan 2006)

Figure 18 MODEL #2 Counterfactual Analysis: GIRFs of a One Percent Positive Shock to the *Pudong* Housing Price



(--- Dec 2014, — Jan 2006)

Figure 19 MODEL #2 Counterfactual Analysis: GIRFs of a One Percent Positive Shock to the *Nanhui* Housing Price



(--- Dec 2014, — Jan 2006

5.3.2 Model #3: A Single-Equation GVAR Model with a Time-Varying Weight Matrix, 18 Districts Plus *Chongming*

Model #3 is similar to Model #2, except that it includes one more district, *Chongming*, in the model. *Chongming* is a very special district in Shanghai. It is an island that had no bridge to any other districts until November 2009 when the Shanghai *Yangtze River Bridge* opened. Before this bridge was built, residents in *Chongming* had to take a ferry to the port in *Baoshan* before they could go to other districts. This ferry was time-consuming and sometimes canceled due to inclement weather. These problems made it nearly impossible for people to live in *Chongming* and work in other districts. Since the transportation to *Chongming* was inconvenient, demand for vacation homes in Chongming was also very low. It is reasonable to speculate that the housing price of *Chongming* was affected by other house markets only modestly in the past. Large price gaps existed between *Chongming* and other districts. However, the newly-built *Yangtze River Bridge* took *Chongming* out of isolation. It connects *Chongming* to *Pudong* which is on the south bank of the river. The construction lasted from 2005 to 2009 and the bridge opened in November 2009. It cost 1.84 billion U.S. dollars. This project was financed in the form of build–operate–transfer (BOT). An entity, Shanghai *Yangtze River Tunnel and Bridge Construction Development Co., Ltd.*, bore the majority of the construction costs and will bear the cost of daily operations and maintenance for 25 years. In return, it is entitled to all revenues generated by the bridge for 25 years. The title of the bridge will then be transferred to the Shanghai government. Right now, it costs 50 RMB (7.2 U.S. dollars) for a passenger car and is free for a bus.

The shortened commute time is expected to strengthen the connection between *Chongming* and districts in the urban center. It is now possible for people to live in *Chongming* and work in other districts. *Chongming* experienced a soaring housing price shortly after the bridge opening (see Table 16). Model #3 investigates to what extent the *Yangtze River Bridge* affected *Chongming*'s housing price.

I use two different methods to calculate the vector matrix of *Chongming* before the bridge opening. The first method is based on commute time between *Chongming* and all the other districts (Type I). Before the bridge opened, the commute time is the sum of the time to take the ferry to *Baoshan* and the time to other districts from the ferry terminal. Only *Baoshan* has ports to go to *Chongming*. After the bridge opened, the commute time is computed based on the travel time across the bridge. The second weight matrix (Type II) is based on the observation that before the opening of the bridge, it was nearly impossible for *Chongming* residents to have a round trip to other districts except for *Baoshan* within one day. In constructing this weight matrix, I assume that *Chongming* is directly affected only by *Baoshan* before the bridge opened, so this weight matrix has a value of 1 for *Baoshan* and 0 for all other districts. After the bridge opening, the weight matrix is computed based on commute time across the bridge. Both weight matrices are time varying, which is expected to capture the effect of the newly-built bridge on commute time and spillover effect. The time-varying weight also helps parameter stability. Table 17 presents the weight vectors of *Chongming* before and after the bridge opening. The GIRFs are presented in Appendix E. The housing price shocks of *Huangpu, Pudong* or *Nanhui* have the same impact on other districts no matter which weight matrix is used, but the impact on *Chongming* is different. With the second weight matrix, *Chongming* is more sensitive to the housing price shocks originated from the city center (*Huangpu*).

A one percent housing price shock to *Chongming* has little effect on the housing price of other districts (less than 0.1%). The small responses can be explained by the long commute time between *Chongming* and other districts even after the opening of the bridge, which implies small weights received by *Chongming* in other districts' weight vectors.

Table 16 Average Price per Square Meter in *Chongming* in Nominal Yuan

2009	Price	2010	Price
Jan	8,171	Jan	22,694
Feb	6,356	Feb	12,025
Mar	5,186	Mar	15,916
Apr	6,143	Apr	25,685
May	5,060	May	14,528
Jun	5,446	Jun	11,140
Jul	5,405	Jul	22,498
Aug	6,348	Aug	14,455
Sep	8,763	Sep	14,245
Oct	7,443	Oct	13,945
Nov*	13,173	Nov	15,841
Dec	19,147	Dec	14,568

*The bridge opened on 31 October 2009

Table 17 The Weight Vectors of *Chongming* in 2009m10 and 2009m11

District	*Chongming*		
	2009m10 method #1	2009m10 method #2	2009m11 method #1 & #2
Chanqning	0.049	0	0.062
Luwan	0.050	0	0.063
Qingpu	0.049	0	0.045
Jing'an	0.050	0	0.064
Huangpu	0.050	0	0.063
Putuo	0.049	0	0.058
Fengxian	0.048	0	0.047
Nanhui	0.050	0	0.045
Songjiang	0.047	0	0.051
Hongkou	0.049	0	0.061

Xuhui	0.049	0	0.062
Pudong	0.050	0	0.064
Minhang	0.047	0	0.052
Jinshan	0.048	0	0.038
Yangpu	0.050	0	0.060
Zhabei	0.052	0	0.066
Baoshan	0.163	1	0.055
Jiading	0.049	0	0.043

Following the same method and tests described in Model #2, I check the parameter stability of the model, estimate contemporaneous effects of foreign variables and evaluate the GIRFs of *Chongming* following a price shock to other districts. The results of these tests and others (unit root, lag orders, etc.) are presented in Appendix E. It is expected that the housing price of *Chongming* is significantly affected by other housing submarkets, since it is in the outskirts. Compared to *Huangpu* and *Nanhui*, *Pudong* should have a larger impact on the housing price of *Chongming*. As can be seen, although the housing price of *Chongming* is very volatile during the sample period, none of these tests finds evidence of parameter instability in the *Chongming* VECM. The time-varying weight helps to achieve parameter stability. The foreign housing price has a high contemporaneous effect on *Chongming*. The impact elasticity is high, at 1.26 with a standard deviation 0.57. This could explain why *Chongming* experienced a price hike in November 2009 and subsequent months. This also shows the importance of transportation infrastructure in housing price interactions.

5.3.2.1 Counterfactual Analysis

In this counterfactual analysis, the GVAR model is estimated with the time-varying weight matrix (Type I or Type II). Then, I check the impact of housing price shocks for *Huangpu*, *Pudong*, and *Nanhui* or *Chongming* with different weights -- the weight of 2009m10 and the weight of 2009m11. The differences in the GIRFs due to the different weight matrices measure the impact of the new bridge.

The results are plotted in Figure 20. As shown in the plots, the bridge strengthens the impact of *Huangpu* on *Chongming* significantly. Using the Type II weight matrix, the impact increases by nearly 200%. Compared to a *Huangpu* shock, the impacts of *Pudong* and *Nanhui* shocks are less affected by the bridge.

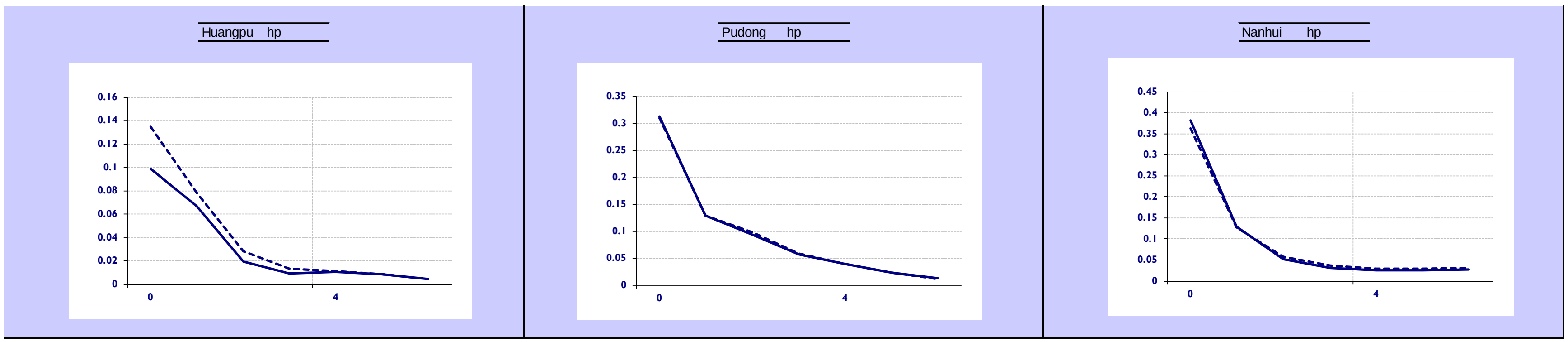
The results from this model could contribute to a widely debated topic in China – the introduction of a property tax. Local governments favor property tax because of its stability as a major revenue source. In recent years, Chinese local governments have relied heavily on land transaction revenue. In some areas, land revenue contributes to over 70% of the local government's total revenue. However, this revenue is unsustainable. Some developed regions, like Shanghai, have already reached a high level of urbanization. They do not have much lands reserved to sell in the future. In addition, the soaring housing price aggravates income inequality which has become a sharp social problem in China in the last decade. Collecting property taxes can create an alternative financial lifeline to local governments while at the same time slowing the rise in housing prices and mitigating income inequality.

In 2011, Shanghai launched a pilot program to impose a property tax at the city level. In this pilot program, the Shanghai city government imposes a 0.6% property tax on a family’s second house/apartment (the first house/apartment is exempted from property tax). This property tax can serve as a tool in wealth re-distribution. For example, since the *Yangtze River Bridge* increased the housing price in *Chongming*, the Shanghai government will collect more property tax from homeowners in *Chongming*. The increased tax can be used in reimbursing the bridge’s construction costs or be distributed to residents whose property value has been harmed by the new bridge. This paper could provide some empirical guidance for this discussion. In particular, property tax places an appropriate burden on property owners who benefit from new infrastructures and other public services. The owner of higher value property will pay a higher property tax. The higher user cost of property will cut back on speculation. The adjusted property tax can also suppress housing market speculation and narrows income inequality. The Shanghai pilot program is supposed to spread to other main cities that are also suffering from high housing prices.

Besides property tax, special assessment tax is another hot topic in China. A special assessment tax levy is a form of remuneration. A public project can create a benefit in properties lying within a special geographic area (a special assessment district), so the governmental unit can demand a special assessment tax from property owners to fund this public project. Special assessment taxes are also collected on a property tax bill. Compared to property tax, a special assessment tax has two advantages in China. First, China is experiencing a huge scale of infrastructure construction in this century. Housing price changes a lot due to the newly built infrastructure; however, property tax usually has a lag time of property valuation whereas a special assessment tax is immediate. Second, special assessment taxes fund public projects directly, while property tax is used to fund general or day-to-day government operations. This dissertation can support the discussion of special assessment taxes in an econometric way.

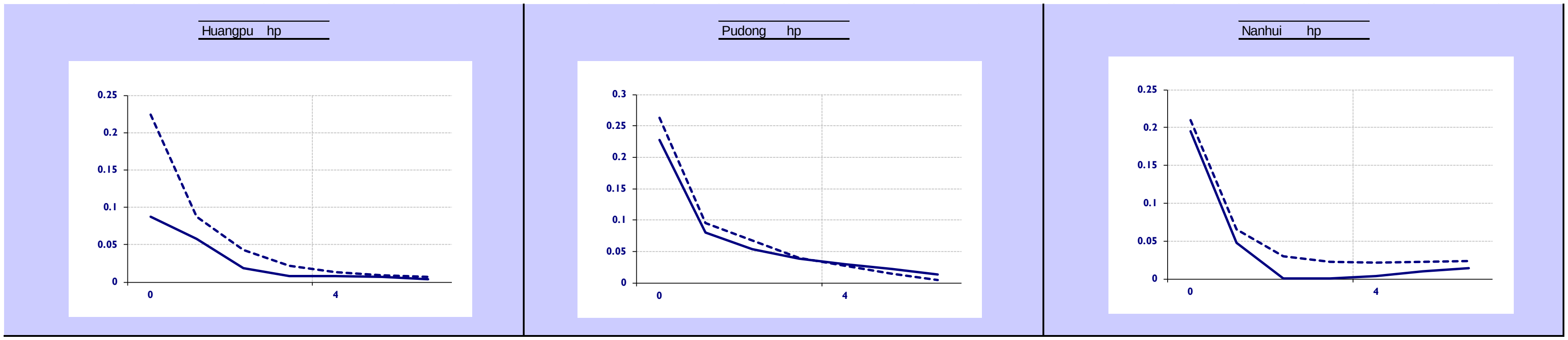
Figure 20 Model #3: Comparing the Impact of Housing Price Shocks on *Chongming* Before and After the Bridge Opened

Type I Weight Matrix



(--- Weight of 2009m11, —Weight of 2009m10)

Type II Weight Matrix



(--- Weight of 2009m11, —Weight of 2009m10)

5.4 The Two-Equation GVAR Model

In this section, I estimate two two-equation GVAR models, one with a fixed-weight matrix, the other with time-varying weights. The two endogenous variables are the log of nominal housing price and the log of nominal land price at the district level. Land price is added to the individual district VARX model to capture the housing price fluctuations that are due to the supply side cost. In doing so, I can isolate the housing price fluctuations caused by housing price spillover from other districts. Other variables included in this model are the same as those described in Models #1 through #3. All the variables in this model are listed in Table 4.

The role of land price in the soaring housing price is a hotly debated topic in China. It is widely believed that the high housing prices in Shanghai and other Chinese cities are driven significantly by the soaring land price. By giving shocks to both housing price and land price and checking their response functions, this two-equation GVAR can be used to show whether it is the increased land price pushing the housing price higher or *vice versa*.

To include the land price in the model, I have to modify the models used in the previous sections. The land price data is limited at the district level. Although the sales of newly-built residential units are recorded each month for each district, land auctions do not occur every month. This data limitation is more serious for districts in the city center because of their smaller sizes. To solve this problem, I combine the nine districts in and near the city center into a big "center district" that I call *Center*. After the combination, the land auctions can be observed nearly every month for each district. The new GVAR model is estimated with 11 districts with *Chongming,* or 10 districts without *Chongming*. However, even after this combination, there still are some districts that experience no land auction in some specific months. If this situation happens, I take the land price of the prior month as the price for that specific month.

5.4.1 Model#4: A Two-Equation GVAR Model with a Fixed-Weight Matrix, 10 Districts

I first estimate a two-equation GVAR model, with one equation for housing price and the other for land price using a fixed-weight matrix. This is a baseline model. The fixed-weight matrix is based on neighborhood connections. The district name and their neighboring districts are presented in Table X. It sets the relational value to 1 if two districts are contiguous; otherwise, the relational value equals 0. These numbers are then rescaled. The rescaled values add up to 1 for each district. After putting all these calculated numbers together, I get the fixed-weight matrix. The contiguity provides useful guidance for determining the relationship among districts. It is reasonable to believe that districts that share a common border have a much closer relationship. This fixed-weight model includes 10 districts. It excludes district *Chongming*, because it is an island and had no bridge to any other districts until November 2009. The fixed-weight matrix is presented in Appendix F. The GVAR model is given by

$$\mathrm{X}_{i,t} = \sum_{l=1}^{p_i} \Phi_{i,l}\mathrm{X}_{i,t-l} + \Lambda_{i,0}\mathrm{X}^*_{i,t} + \sum_{l=1}^{q_i} \Lambda_{i,l}\mathrm{X}^*_{i,t-l} + \mathrm{D}_{i,0}\omega_t + \sum_{l=1}^{s_i} \mathrm{D}_{i,l}\omega_{t-l} + \mu_{i,t}$$

for $i = 1, 2, \ldots, 10$. p_i and q_i are the lag orders for domestic and foreign variables, respectively. $\mathrm{X}_{i,t} = (hp_{i,t}, lp_{i,t})$ is the vector of logarithms of housing price and land price ; $\mathrm{X}^*_{i,t} = (hp^*_{i,t}, lp^*_{i,t})$ is the vector of the logarithm of weighted foreign housing price and land price; ω_t= $(m_t, cpi_t, ibor_t, lrh_t, tst_t)$ is the vector of common variables. The statistical results are presented in Appendix G.

Table 18 Districts and Neighbors

Districts	Neighbors
CENTER	*Qingpu, Pudong, Minhang, Baoshan, Jiading*
QINGPU	*Center, Songjiang, Jiading*
FENGXIAN	*Nanhui, Songjiang, Minhang, Jinshan*
NANHUI	*Fengxian, Pudong, Minhang*
SONGJIANG	*Qingpu, Fengxian, Minhang, Jinshan*
PUDONG	*Center, Nanhui, Minhang*
MINHANG	*Center, Fengxian, Nanhui, Songjiang, Pudong*
JINSHAN	*Fengxian, Songjiang*
BAOSHAN	*Center, Jiading*
JIADING	*Center, Qingpu, Baoshan*

As shown in Table 19, the estimated contemporaneous effects of foreign variables on domestic counterparts are similar but much higher in Model #4 than those reported in Model #1. Compared to land price, housing price is more closely related across districts. However, for those districts in the very outskirt areas (*Nanhui*, *Songjiang,* and *Jinshan*), land price, instead of the housing price, is affected more by its foreign counterparts. I will discuss the details of these contemporaneous effects later in the two-equation GVAR model with a time-varying weight.

Two sets of GIRFs are reported for Model #4. One is for housing price shocks, and the other is for land price shocks. In each case, a one percent positive shock is given to *Center*, *Pudong* and *Nanhui,* respectively. The results are presented in Appendix G. In general, land price shocks have little effect on the housing price. Even for the district where the land price shock originates, the effect on housing price is still very small and, therefore, can be ignored. On the other hand, housing price shocks have a substantial effect on land price. A one percent positive housing price shock can lead to over a 3 percent increase in the land price of some districts. This finding contradicts the common perception that higher housing prices in China are caused by increasingly expensive land prices. Based on results of this model, the soaring housing price pushes the land price high, but the fluctuation of land price has nearly no effect on housing price. I will check this point further in the time-varying model. In this GIRF, a *Pudong* housing price shock has a permanent and positive effects on other districts' housing prices. Compared to Model #1, these effects are lasting and larger in degree. A *Center* housing price shock only has temporary effects on other districts' housing prices and those effects become negative with time (but the negative value is small). This finding is counter-intuitive. The result is reversed in Model #5. It can be taken as evidence that the use of the time-varying weights can better capture the dynamics of the Shanghai housing market. A *Nanhui* housing price shock has a mostly positive but transitory effect on other district housing prices. Compared to Model #1, these two models have the nearly same result. I will compare these results with the results of Model #5, which has a time-varying weight.

Table 19 MODEL #4: Contemporaneous Effects of Foreign Variables on Domestic Counterparts

District	*hp*	*lp*
CENTER	0.313	-0.013^{*}
	(0.103)	(0.101)
QINGPU	0.605	0.156^{*}
	(0.184)	(0.181)
FENGXIAN	0.292^{*}	0.173^{*}
	(0.212)	(0.111)
NANHUI	0.345	0.442
	(0.113)	(0.139)
SONGJIANG	0.256	0.588
	(0.140)	(0.146)
PUDONG	0.501	0.271
	(0.142)	(0.141)

MINHANG	0.615	0.294
	(0.174)	(0.154)
JINSHAN	0.193	0.368
	(0.072)	(0.081)
BAOSHAN	0.361	0.347
	(0.103)	(0.157)
JIADING	0.362	0.245
	(0.127)	(0.124)

* Not Significant at the 5% level

5.4.2 Model#5: A Two-Equation GVAR Model with a Time-Varying Weight Matrix, 10 Districts

Then I estimate a model with the same set of variables as Model #4 while the cross-section average of foreign variables is constructed using time-varying weights. This time-varying weight matrix is based on commute time using the same method used in Models #2 and #3, so it evolves with new infrastructure. The statistical results are presented in Appendix H.

Here, I focus on discussing the estimated contemporaneous effects of foreign variables on domestic counterparts, GIRFs, and counterfactual analysis.

Table 20 Contemporaneous Effects of Foreign Variables on Domestic Counterparts

District	*hp*	*lp*
CENTER	0.293	0.078
	(0.103)*	(0.113)
QINGPU	0.771	0.385
	(0.225)	(0.256)
FENGXIAN	0.498	0.260
	(0.264)	(0.163)
NANHUI	0.645	0.837
	(0.196)	(0.194)
SONGJIANG	0.395	0.431
	(0.198)	(0.227)
PUDONG	0.749	0.580
	(0.254)	(0.187)
MINHANG	0.752	0.226
	(0.210)	(0.198)
JINSHAN	0.426	0.664
	(0.126)	(0.154)
BAOSHAN	0.303	0.584
	(0.098)	(0.231)
JIADING	0.342	0.258
	(0.141)	(0.179)

*( ) Standard error

5.4.2.1 Contemporaneous Effects of Foreign Variables on Domestic Counterparts

Compared to Models #3 and #4, the estimated contemporaneous effects based on Model #5 are similar qualitatively, but much larger quantitatively. The foreign impact increases on all districts except *Center*. This large increased contemporaneous effect shows new infrastructure enhances the relationship among housing submarkets. Compared to land price, the contemporaneous effect of housing price is larger for many districts. However, for districts in the outskirt areas (*Nanhui*, *Songjiang*, *Baoshan,* and *Jinshan*), the land price, instead of the housing price, is affected more by its foreign counterparts. This finding is also consistent with Model #4. The land price of the *Center* district is barely affected contemporaneously by the land price of other districts. This could be explained by the unique position of the *Center* district: it has the most important effect on the housing market of Shanghai. It has the most expensive housing and land price and the biggest housing market in Shanghai. No other districts can play an alternative role to the *Center* district. Also, the land available for residential development is much more limited in Center than in other districts.

5.4.2.2 Generalized Impulse Response Function (GIRF)

Housing Price Spillover: The Effect on Housing Price

The GIRFs are shown in Appendix H. It has two types of shock: the housing price shock and the land price shock. I give a one percent positive shock of each type to *Center, Pudong* and *Nanhui*, respectively. A housing shock to *Pudong* has a positive effect on all other districts. Compared to Model #4, these effects are not permanent and dissipate over time, but they have a large effect on many districts (*Qingpu*, *Fengxian, Nanhui*, *Songjiang*, *Minhang*, and *Jiading*). Compared to the results in Model #2, the effects are stronger for nearly all districts, which suggests a more important position for *Pudong* in the Shanghai housing market.

The housing price shock to *Center* has a permanent and positive effect on all other districts' housing prices. Compared to Model #4, these effects are positive and last over time. Compared to Model #2, the shock has larger positive effects on other housing markets. The results from Model#5 are more consistent with the observation and expectation that an increase in the *Center* housing price also stimulates other housing markets. From these comparisons, we can infer that the use of time-varying weight can better capture the dynamics of the Shanghai housing market.

A one percent *Nanhui* housing price shock has mostly positive but transitory effects on other districts' housing prices. It significantly affects the housing price of districts in the outskirts (*Qingpu* and *Jinshan*). The results are very similar to the ones based on Model #4, but it has a smaller effect on some districts (*Qingpu*, *Fengxian,* and *Songjiang*). Compared to Model #2, the shock has much smaller effects on *Qingpu*, *Songjiang*, and *Minhang*, all of which are in the outskirts.

Housing Price Spillover: The Effect on Land Price

As shown in the figures, a housing price shock not only has a significant effect on the land price of the district in which the shock originates, but also on the land price of some other districts as well. A housing price shock affects the land price of nearly all districts immediately. A one percent positive shock to the *Pudong* housing price increases its own land price by about 1%. It has a negative effect on the land price of *Center*, *Qingpu, Fengxian, Nanhui, Minhang* and *Chongming*. This negative impact could be due to competition among these housing submarkets. Real estate companies have limited capital. As the booming housing market of *Pudong* attracts a large portion of capital from real estate companies, capital invested in other districts decreases. The *Center* housing price shock increases the *Center* land price by around 0.6% and pushes the land price of five other districts higher by over 1.5%. The *Nanhui* housing price shock increases the land price of *Nanhui* by over 3%, *Pudong* land price by 0.5%, *Fengxian* by 1.5% *Jinshan* by 0.3%, and Baoshan by 0.3%. It has a negative effect on the land price of *Minghang*, *Qingpu*, and *Jiading*. These three districts are adjacent to each other and to the west of *Nanhui*.

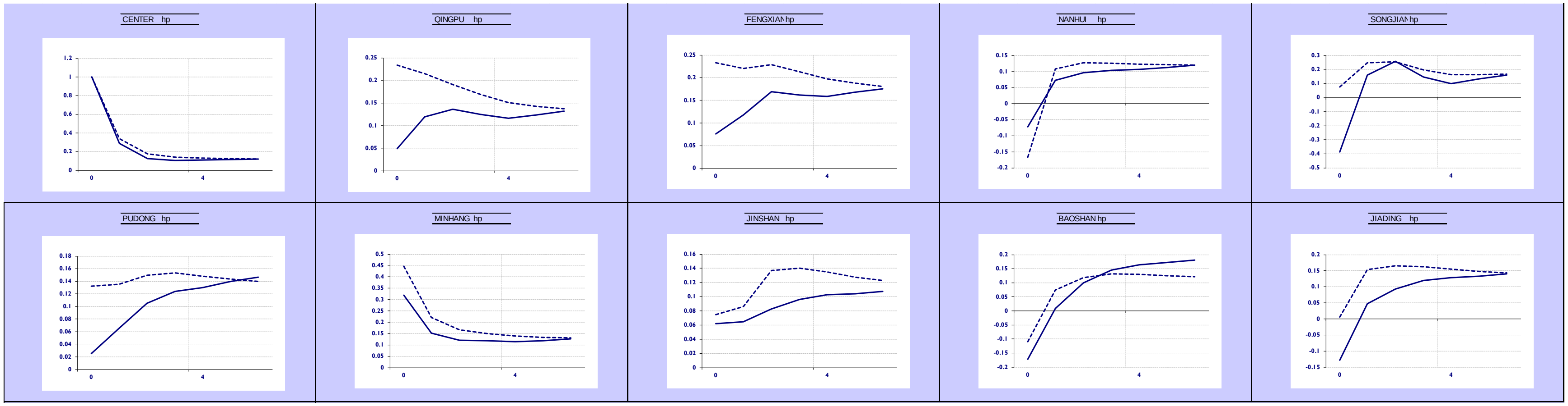
Effect of a Land Price Shock on Housing Price

On the other hand, the land price shock has little effect on the housing price. This result suggests that the soaring housing price in Shanghai is not driven by changes in land price. This is consistent with the observations and the findings in Liang Zhong (2015). It is also supported by many local newspaper reports (*21st Century Business Herald*, 2016; *First Finance*, 2016; etc.). As I will show later in this chapter, broad money supply (M2), rather than land price, is a main driving force behind the soaring housing price in Shanghai.

5.4.2.3 Counterfactual Analysis

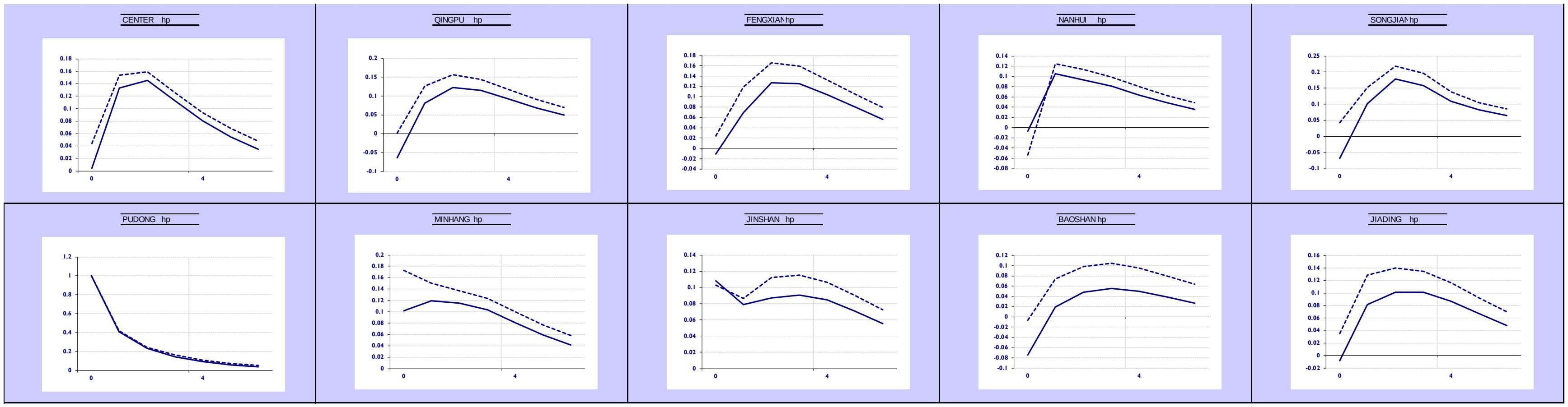
Figures 21 through 23 present the counterfactual simulation analysis. As presented in the plots, the new transportation infrastructures strengthen the impact of the *Center* and *Pudong* housing submarkets on others. At the same time, there is a weakened impact on the *Nanhui* housing submarket. This result is expected, because nearly all new subway lines aim at connecting districts to *Center* and *Pudong.* As a result, *Center* and *Pudong* receive larger weights and hence exert a larger impact on other districts in 2014m12 than in 2006m1. The estimated impact of this model is in line with, but much higher than the results in Model #2.

Figure 21 MODEL #5 Counterfactual Analysis: GIRFs of a One Percent Positive Shock to the *Center* Housing Price - Effects on Housing Price



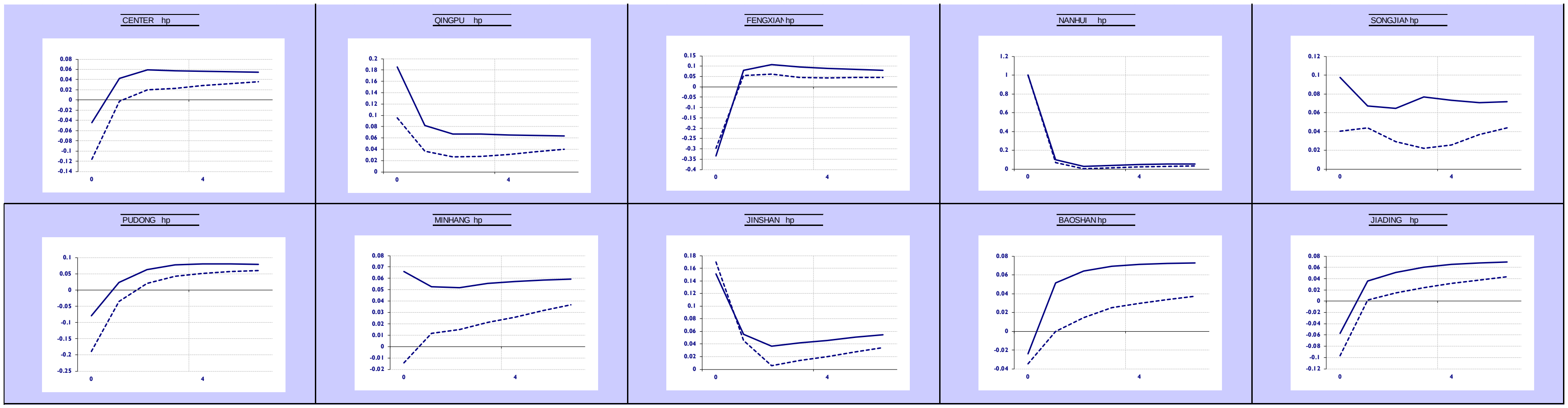
(--- Dec 2014, — Jan 2006)

Figure 22 MODEL #5 Counterfactual Analysis: GIRFs of a One Percent Positive Shock to the *Pudong* Housing Price - Effects on Housing Price



(--- Dec 2014, — Jan 2006)

Figure 23 MODEL #5 Counterfactual Analysis: GIRFs of a One Percent Positive Shock to the *Nanhui* Housing Price - Effects on Housing Price



(--- Dec 2014, — Jan 2006)

5.4.2.4 The Effect of M2 on Housing Price

Next, I inspect the impact of M2 on housing price. M2 is an exogenous global variable in this model. It increased from CNY 303.57 billion to CNY 1228.37 billion during the sample period (2006m1 - 2014m12). It is widely believed that M2 has an important effect on housing price. In this section, I will quantify this impact. Similar to the previous GIRFs, here I give a one percent positive shock to M2 and examine its effect on housing price. Figure 24 presents the GIRFs. Note that I do not examine the effect of M2 on land price, because they have no direct relationship. The land in Shanghai is sold by auction. Only registered real estate companies can take part in the auction. So land price is expected to be directly affected by business loans and shadow banking. The data of these two variables is of poor quality. So here, I only examine the effect of M2 on housing price.

As shown in the figure, the long-term (12 months) effects of an M2 shock are positive on all districts except *Fengxian*[7]. The impacts are persistent. They are small initially and increase with time. On average, a one percent positive shock to M2 will increase *Center*, *Pudong*, *Songjiang* and *Baoshan* housing prices by 2.6 percent, *Qingpu* and *Jiading* housing prices by 1.6 percent, and *Nanhui* housing price by over 3.6 percent. The transaction value of the Shanghai housing market is about 1.1 trillion CNY (equivalent to USD 175 billion) in 2014. Given the scale of the Shanghai housing market,

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[7] The M2 shock has a negative effect on *Fengxian* housing price. *Fengxian* is unique in the Shanghai housing market in the sense that it is in the outskirts and the only district that has no subway lines to other districts throughout the sample period.

it is evident that a significant share of new M2 flows into the housing market. The housing market plays a money cistern role.

Next, I compare the model's prediction with market observations in a historical example. During the Financial Crisis of 2007–2008, the Chinese government launched an economic stimulus plan in an attempt to minimize the impact of the global financial crisis. The State Council of the People's Republic of China announced the stimulus package of CNY 4 trillion (USD 586 billion) on November 9th, 2008. Money supply (M2) soared in the following five months (Nov. 2008 to Mar. 2009, Figure5).

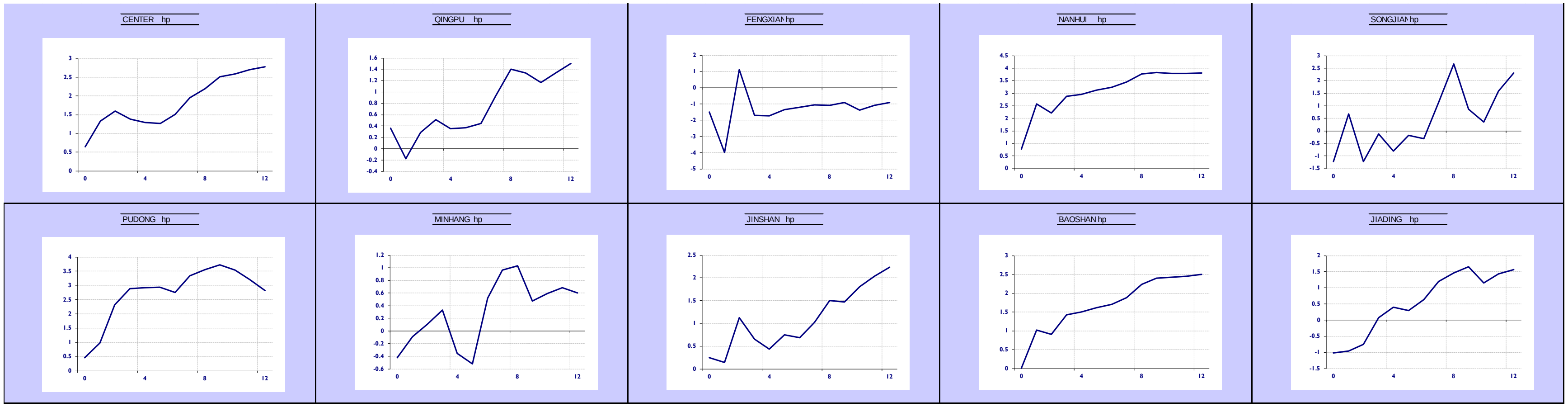
To see to what extent M2 shocks can explain the increase in the Shanghai housing price, first I model M2 as an ARIMA(1,1,3) process with monthly seasonal dummies. The M2 shocks are computed as the difference between the actual M2 and its one-month-ahead forecast value for each month from Nov. 2008 to Mar. 2009. Then I use the estimated M2 shocks and the GIRFs to calculate the cumulative impact on each district's housing price. Table 21 summarizes the actual and the predicted housing price changes for each district in 2009. It is clear that the five months' M2 shocks alone could explain a big portion of housing price increases during 2009.

Table 21 Historical Example: The Predicted vs. Actual Housing Price Changes (Unit: CNY)

District	hp 2009m1	hp $2009m12$	Actual Δhp	Predicted Δhp
CENTER	19157.76	31878.76	66.4%	27%
QINGPU	13353	17467	30.8%	14%
FENGXIAN	7005	11599	65.6%	-11%
NANHUI	7780	13107	68.5%	39%
SONGJIANG	12697	17210	35.5%	14%
PUDONG	15943	34943	119.2%	35%
MINHANG	13765	19657	42.8%	6%
JINSHAN	4988	7773	55.8%	19%
BAOSHAN	9680	16708	72.6%	25%

JIADING	8529	15978	87.3%	16%

Figure 24 MODEL #5: GIRFs of a One Percent Positive Shock to M2 - Effects on Housing Price



5.4.2.5 An Alternative Counterfactual Analysis

Based on Model #5, I conduct another set of counterfactual simulation exercises to evaluate the effect of the newly-built infrastructures on housing price. These simulations are different from the ones reported earlier in this section. They are based on GVAR models using two different sets of fixed weight matrices. These two weight matrices are based on commute time in January 2006 and December 2014, respectively. I then compare the GIRFs of these two models by giving an identical housing price shock.

By this simulation exercise, I can quantify how new transportation infrastructures may have altered the impact and transmission of a housing price shock, and consequently changed the relationships among house submarkets in Shanghai. The variables included in this simulation test are listed in Table 22.

Table 22 The list of variables

District-specific VARX Model		Common Variables
Domestic	Foreign	
$hp_{i,t}$ $lp_{i,t}$	$hp^*_{i,t}$ $lp^*_{i,t}$	m_t cpi_t $ibor_t$ lrh_t tst_t

A *Center* Housing Price Shock

Figure 25 presents GIRFs of a one percent housing price shock to *Center*, using Jan. 2006 and Dec. 2014 weights, respectively. For most districts, the responses to the shock with the Dec. 2014 weight are about 20% to 30% larger than the responses with Jan. 2006 weight. However, the new transportation infrastructures weaken the impacts of the *Center* housing price shock to *Baoshan* and *Chongming*. A possible explanation is that the new subway line (line 7) and the *Yangzi River Bridge* closely connect these two districts with *Pudong*, which dilutes the impact of *Center* on them. (*Center* has no direct subway lines to *Baoshan* and *Chongming*, but *Pudong* has a new subway line to Baoshan since 2009m12 and a new bridge to Chongming since 2009m11).

A *Pudong* Housing Price Shock

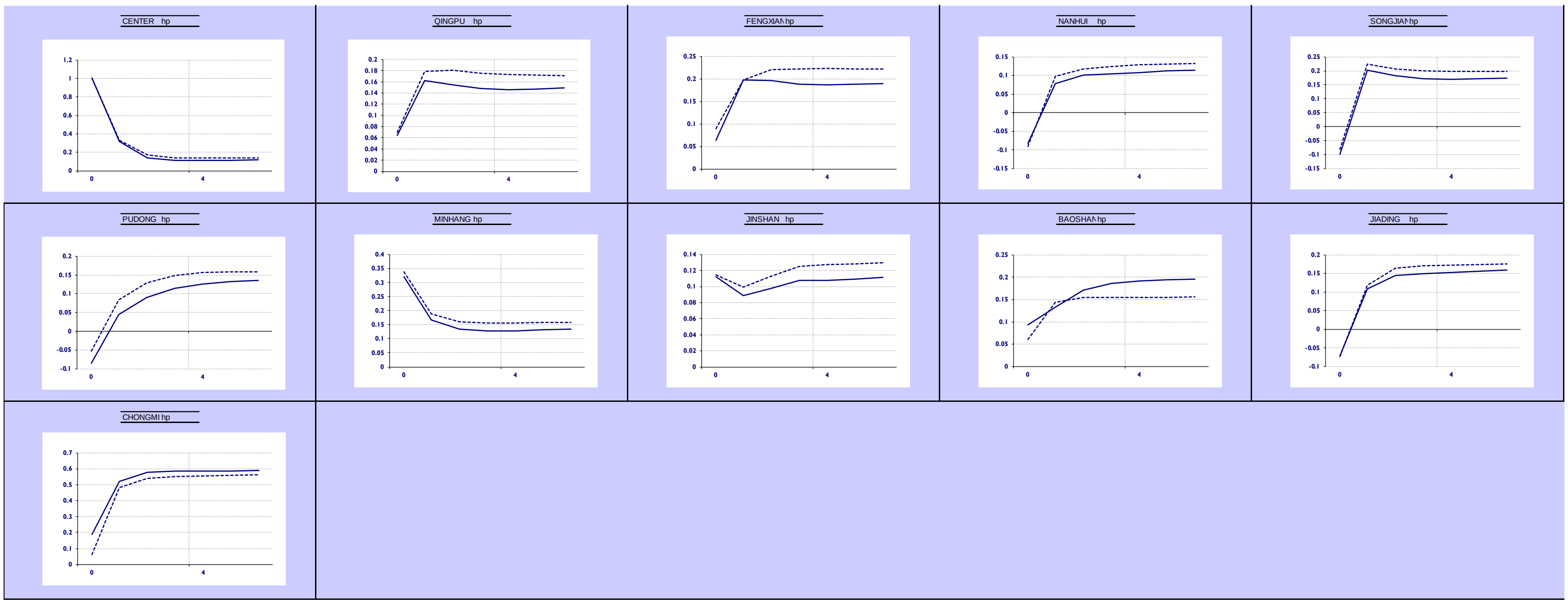
Figure 26 presents the GIRFs of a one percent shock to the *Pudong* housing price. In the intermediate run, the responses of all districts associated with the Dec. 2014 weight is over 15% larger than the responses associated with the Jan. 2006 weight. The most dramatic changes happen in *Baoshan* and *Chongming.* Six months after the shock, the response in *Baoshan* more than triples and the response in *Chongming* switches from negative to positive. The new subway lines and bridge greatly increase the impact of *Pudong* on these two districts.

A *Nanhui* Housing Price Shock

Figure 27 presents the GIRFs for a one percent shock to the *Nanhui* housing price. Although the new transportation infrastructures increase the impacts of *Center* and *Pudong* on *Nanhui*, with the Dec. 2016 weight, the impact of a *Nanhui* housing price shock falls considerably on all other districts, especially in the very short term. This supports the findings in Model #2. The new subway lines strengthen the connections between *Center* / *Pudong* and other districts but, at the same time, they weaken the relationships among the house submarkets of the outskirts (nearly all new subway lines aim at connecting districts to *Center* / *Pudong*).

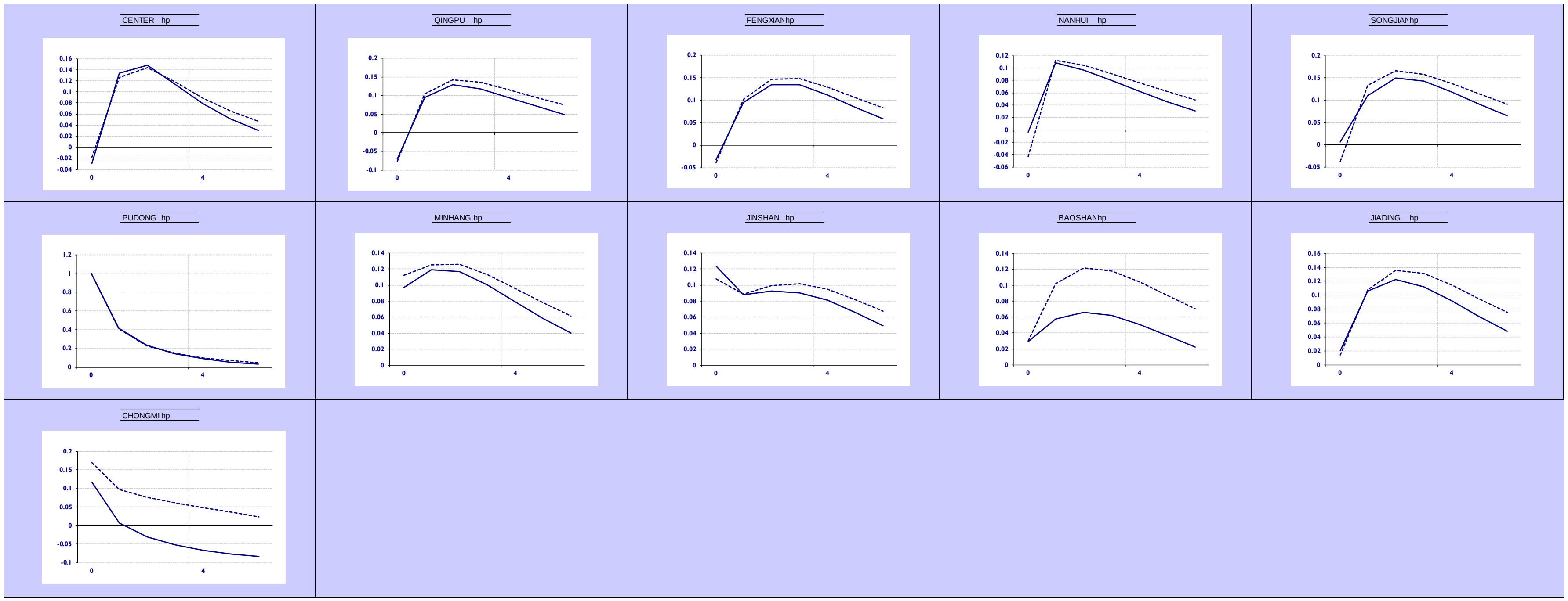
The above counterfactual exercises show that the new transportation infrastructures have changed the housing price spillover pattern of Shanghai at the district level. It increases the impacts of *Center* and *Pudong* on other districts in a measurable level, while, at the same time, it weakens the relationship among districts in outskirt areas.

Figure 25 Model #5: GIRFs of One Percent Positive Shock to the *Center* Housing Price



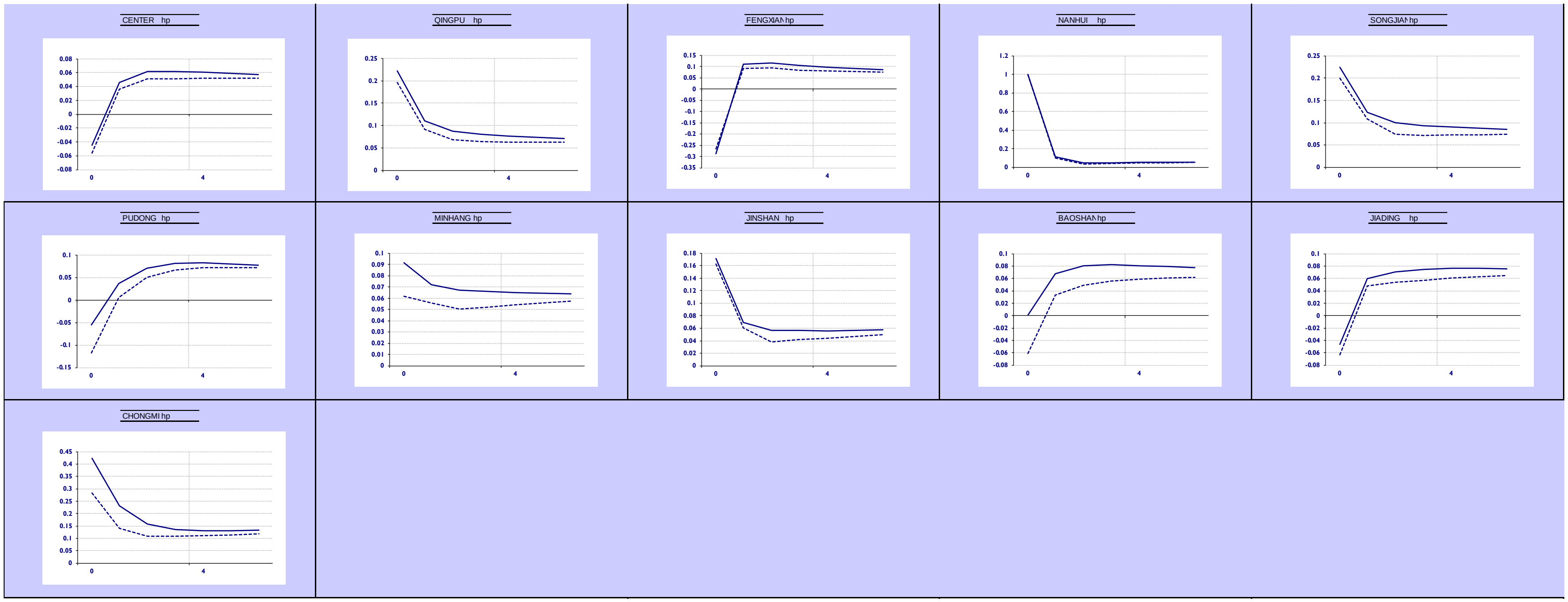
(--- Dec. 2014, — Jan. 2006)

Figure 26 Model #5: GIRFs of One Percent Positive Shock to the *Pudong* Housing Price



(--- Dec. 2014, — Jan. 2006)

Figure 27 Model #5: GIRFs of One Percent Positive Shock to the *Nanhui* Housing Price



(--- Dec. 2014, — Jan. 2006)

Chapter 6

CONCLUSION

In this dissertation, I investigate the housing price spillover effect in the Shanghai housing market. More specifically, I focus on the transmission mechanism of district-level housing price shocks among 18 housing submarkets (19 in Model #3, and 10 in Models #4 and #5). The analysis is based on a time-varying GVAR model using monthly district-level housing market data and macroeconomic data. The GVAR model provides a practical global modeling framework to quantify the relative importance of different shocks and channels of transmission mechanisms in a large system containing many housing submarkets.

To the best of my knowledge, this is the first paper to quantify the transmission mechanism among housing submarkets in a large metropolitan area. It is also the first paper to investigate the evolution of this transmission mechanism against a background of rapid infrastructure development. The GVAR model with a time-varying weight is shown to be flexible and informative. This is the first time that this model is used in studying housing markets.

The time-varying weight matrix in this dissertation is based on commute time between the districts. Shanghai experienced large-scale infrastructure construction in the last decade, and the commute time between districts evolved as a result. It is reasonable to suspect that the transmission mechanism has changed along with the transportation infrastructures. A time-varying weight has the potential to capture this feature. I also conducted a series of counterfactual exercises with different sets of the weights of 2006m1 and 2014m12 to quantify the impact of new infrastructures on the transmission mechanism. Compared to the fixed-weight models, the GIRFs of time-varying models are more consistent with the market observations. It has three main advantages:

1. A time-varying weight based on commute time more accurately quantifies the relationship between districts, while a fixed weight with only 0 and 1 cannot exactly quantify these relationships.
2. The models in this dissertation are estimated over the period 2006m1 to 2014m12, which has seen major transportation construction in Shanghai. It is evident that the housing location preference and price transmission mechanism have changed during the period. A time-varying weight has the potential to capture these changes.
3. Time-varying weight models can be used in the counterfactual analysis. Using alternative weight matrices, these models allow one to study the effect of new transportation infrastructure on the housing price transmission mechanism.

I found that a housing price shock in a district in the city core or *Pudong* has a substantial effect on all other districts. This impact became stronger in the last decade with new infrastructure construction. On the other hand, the effect of a housing price shock in *Nanhui* is limited to districts in the outskirts. The effect on *Center* and *Pudong* is minimal. Moreover, this impact is weakened by new infrastructures. This is due to the fact that nearly all new subway lines aim at connecting districts to *Center* and *Pudong*. As a result, *Center* and *Pudong* receive larger weights and hence exert larger impacts on other districts over time.

This dissertation found that a housing price shock has a significant positive effect on land price. However, a land price shock has little effect on housing price. This result suggests that the soaring housing price in Shanghai is not driven by the land costs to real estate companies. This finding is corroborated by many local newspaper reports and provides the quantitative evidence against a widely held belief that the high housing prices in Shanghai and other major Chinese cities are driven significantly by the soaring land price.

This dissertation also studies the effect of M2 on housing price. A positive M2 shock has a significant effect on housing price. This impact is positive and lasting. Chinese M2 increased from CNY 30,357.2 billion to CNY122,837.5 billion during the study period (2006m1 – 2014 m12). It can explain a significant portion of housing price movements during the same period. It also shows that without government housing price control policy, the housing price would be much higher than it is now.

The findings in this dissertation also have an implication on public finance. Property tax is a hotly debated topic in China. A new line of public transportation could sharply increase the housing prices in some districts. At the same time, it could also harm other housing submarkets. Property tax can serve as a tool of wealth redistribution in this process. Homeowners, whose property values are positively affected by these newly-built transportation infrastructures, should be required to pay an increased property tax. The increased tax revenue can be used to reimburse the infrastructure construction costs or be distributed to residents whose property value has been harmed by those constructions. In doing so, it can narrow income inequality, which has widened dramatically over the past decade. This dissertation could provide some empirical guidance to the property tax discussion. In addition, as property tax raises the user cost of home ownership for property owners who benefit from new infrastructure and other public services, it can suppress housing market speculations.

Future research is needed to improve the existing GVAR framework. The existing GVAR framework is a closed system, not allowing the addition of a district into the system in the middle of the sample period. So the number of districts in the model cannot change over time. Hopefully, this concern can be solved in future research.

REFERENCES

Bibliography

Aneett, A. 2005. "Euro Area Policies: Selected Issues." *IMF Country Report* No. 05/266.

Baker, K. 2004. "Review of Housing Supply." *Final Report* HM Treasury.

Black, Angela, Patricia Fraser, and Martin Hoesli. 2006. "House Prices, Fundamentals and Bubbles." *Journal of Business Finance & Accounting* 33 (9-10): 1535-1555.

Case, Karl E. and Robert J. Shiller. 1989. "The Efficiency of the Market for Single-Family Homes." *The National Bureau of Economic Research*.

———. 1987. "Prices of Single Family Homes since 1970: New Indexes for Four Cities." *The National Bureau of Economic Research*.

Cesa-Bianchi, Ambrogio, M. Hashem Pesaran, Alessandro Rebucci, TengTeng Xu, and Roberto Chang. 2012. "China's Emergence in the World Economy and Business Cycles in Latin America [with Comment]." *Economía*: 1-75.

Chudik, Alexander and M. Hashem Pesaran. 2014. "Theory and Practice of GVAR Modeling." *The university of Southern California, Center for Applied Financial Economics (CAFE) Research Paper Series* (14.04).

Costello, Greg, Patricia Fraser, and Nicolaas Groenewold. 2011. "House Prices, Non-Fundamental Components and Interstate Spillovers: The Australian Experience." *Journal of Banking & Finance* 35 (3): 653-669.

Dees, Stephane, Filippo di Mauro, M. Hashem Pesaran, and L. Vanessa Smith. 2007. "Exploring the International Linkages of the Euro Area: A Global VAR Analysis." *Journal of Applied Econometrics* 22 (1): 1-38.

Deng, Yongheng, Joseph Gyourko, and Jing Wu. 2012.*Land and House Price Measurement in China*.

Gallent, Nick and Kwang Sik Kim. 2001. "Land Zoning and Local Discretion in the Korean Planning System." *Land Use Policy* 18 (3): 233-243.

Girouard, Nathalie, Mike Kennedy, Paul Van Den Noord, and Christophe André. 2006. "Recent House Price Developments: The Role of Fundamentals." *OECD Publishing* No. 475.

Glaeser, Edward L., Joseph Gyourko, and Albert Saiz. 2008a. "Housing Supply and Housing Bubbles." *Journal of Urban Economics* 64 (2): 198-217.

Glaeser, Edward L., Joseph Gyourko, and Raven Saks. 2005. "Why have Housing Prices Gone Up?" *National Bureau of Economic Research* No. w11129.

———. 2003. "Why is Manhattan so Expensive? Regulation and the Rise in House Prices." *National Bureau of Economic Research* No. w10124.

Glaeser, Edward L., Joseph Gyourko, and Raven E. Saks. 2006. "Urban Growth and Housing Supply." *Journal of Economic Geography* 6 (1): 71-89.

Glaeser, Edward L., Matthew E. Kahn, and Jordan Rappaport. 2008. "Why do the Poor Live in Cities? The Role of Public Transportation." *Journal of Urban Economics* 63 (1): 1-24.

Glaeser, Edward, Wei Huang, Yueran Ma, and Andrei Shleifer. 2017. "A Real Estate Boom with Chinese Characteristics." *Journal of Economic Perspectives* 31 (1): 93-116.

Glaeser, Edward L., Joseph Gyourko, and Albert Saiz. 2008b. "Housing Supply and Housing Bubbles." *Journal of Urban Economics* 64 (2): 198-217.

Granger, Clive WJ and Yongil Jeon. 2007. "Evaluation of Global Models." *Economic Modelling* 24 (6): 980-989.

Gros, Daniel. 2006. *Bubbles in Real Estate?: A Longer-Term Comparative Analysis of Housing Prices in Europe and the US* CEPS.

Guilford, Gwynn. 2015. "The most Egregious Examples from the Chinese Government's Long, Sordid History of Data-Doctoring." *Quartz*.

Gürkaynak, Refet S. 2008. "ECONOMETRIC TESTS OF ASSET PRICE BUBBLES: TAKING STOCK*." *Journal of Economic Surveys* 22 (1): 166-186.

Gyourko, Joseph, Christopher Mayer, and Todd Sinai. 2006. "Superstar Cities." *National Bureau of Economic Research* No. w12355.

Harbo, Ingrid, Søren Johansen, Bent Nielsen, and Anders Rahbek. 1998. "Asymptotic Inference on Cointegrating Rank in Partial Systems." *Journal of Business & Economic Statistics* 16 (4): 388-399.

Himmelberg, Charles, Christopher Mayer, and Todd Sinai. 2005.*Assessing High House Prices: Bubbles, Fundamentals, and Misperceptions*.

Hirata, Hideaki, M. Ayhan Kose, Christopher Otrok, and Marco E. Terrones. 2012. "Global House Price Fluctuations: Synchronization and Determinants." *National Bureau of Economic Research* No. w18362.

Holly, Sean, M. Hashem Pesaran, and Takashi Yamagata. 2011. "The Spatial and Temporal Diffusion of House Prices in the UK." *Journal of Urban Economics* 69 (1): 2-23.

Holz, Carsten A. 2014. "The Quality of China's GDP Statistics." *China Economic Review* 30: 309-338.

Johansen, Søren. 1992. "Testing Weak Exogeneity and the Order of Cointegration in UK Money Demand Data." *Journal of Policy Modeling* 14 (3): 313-334.

Klyuev, Vladimir. 2008. *What Goes Up must Come Down? House Price Dynamics in the United States* International Monetary Fund.

Knoll, Katharina, Moritz Schularick, and Thomas Michael Steger. 2017. "No Price Like Home: Global House Prices, 1870-2012." *American Economic Review* 107 (2): 331-353.

Koch-Weser, Iacob N. 2013. "The Reliability of China's Economic Data: An Analysis of National Output." *US-China Economic and Security Review Commission Staff Research Project*: 4.

Koop, Gary, M. Hashem Pesaran, and Simon M. Potter. 1996. "Impulse Response Analysis in Nonlinear Multivariate Models." *Journal of Econometrics* 74 (1): 119-147.

Krainer, John and Chishen Wei. 2004. "House Prices and Fundamental Value." *FRBSF Economic Letter* (Oct 1).

Lee, Kevin, M. Hashem Pesaran, and Ron Smith. 1998. "Growth Empirics: A Panel Data Approach--A Comment." *Quarterly Journal of Economics*: 319-323.

MacKinnon, James G., Alfred A. Haug, and Leo Michelis. 1999. "Numerical Distribution Functions of Likelihood Ratio Tests for Cointegration." *Journal of Applied Econometrics* 14 (5): 563-577.

Manski, Charles F. 2000.*Economic Analysis of Social Interactions*.

———. 1993. "Identification of Endogenous Social Effects: The Reflection Problem." *The Review of Economic Studies* 60 (3): 531-542.

Mayer, Christopher J. and C. Tsuriel Somerville. 2000. "Land use Regulation and New Construction." *Regional Science and Urban Economics* 30 (6): 639-662.

Meen, Geoffrey. 2005. "On the Economics of the Barker Review of Housing Supply." *Housing Studies* 20 (6): 949-971.

———. 2002. "The Time-Series Behavior of House Prices: A Transatlantic Divide?" *Journal of Housing Economics* 11 (1): 1-23.

Mikhed, Vyacheslav and Petr Zemčík. 2009. "Do House Prices Reflect Fundamentals? Aggregate and Panel Data Evidence." *Journal of Housing Economics* 18 (2): 140-149.

Nagahata, Takashi, Yumi Saita, Toshitaka Sekine, and Towa Tachibana. 2004. "Equilibrium Land Prices of Japanese Prefectures: A Panel Cointegration Analysis." *Bank of Japan Working Paper Series*.

Nyblom, Jukka. 1989. "Testing for the Constancy of Parameters Over Time." *Journal of the American Statistical Association* 84 (405): 223-230.

OECD. 2006. "Economic Survey of Ireland." Paris.

———. 2004. "Economic Survey of the United Kingdom." Paris.

Otrok, Christoph and Marco E. Terrones. 2005. "House Prices, Interest Rates and Macroeconomic Fluctuations: International Evidence." *Unpublished Manuscript*.

Pesaran, H. Hashem and Yongcheol Shin. 1998. "Generalized Impulse Response Analysis in Linear Multivariate Models." *Economics Letters* 58 (1): 17-29.

Pesaran, M. Hashem, Til Schuermann, and Scott M. Weiner. 2004. "Modeling Regional Interdependencies using a Global Error-Correcting Macroeconometric Model." *Journal of Business & Economic Statistics* 22 (2): 129-162.

Ploberger, Werner and Walter Krämer. 1992. "The CUSUM Test with OLS Residuals." *Econometrica: Journal of the Econometric Society*: 271-285.

Poterba, James M., David N. Weil, and Robert Shiller. 1991. "House Price Dynamics: The Role of Tax Policy and Demography." *Brookings Papers on Economic Activity*: 143-203.

Quandt, Richard E. 1960. "Tests of the Hypothesis that a Linear Regression System Obeys Two Separate Regimes." *Journal of the American Statistical Association* 55 (290): 324-330.

Schnure, Calvin. 2005. *Boom-Bust Cycles in Housing: The Changing Role of Financial Structure* International Monetary Fund.

Taylor, DI, SW Nixon, SL Granger, BA Buckley, JP McMahon, and H-J Lin. 1995. "Responses of Coastal Lagoon Plant Communities to Different Forms of Nutrient Enrichment—a Mesocosm Experiment." *Aquatic Botany* 52 (1): 19-34.

Terrones, Marco E. 2004. "The Global House Price Boom." *International Monetary Fund, World Economic Outlook*: 71-89.

Terrones, Marcos and Christopher Otrok. 2004. "The Global House Price Boom." *IMF World Economic Outlook*: 71-136.

Tsatsaronis, K. and H. Zhu. 2004. "What Drives Housing Price Price Dynamics: Cross Country Evidence." *BIS Quarterly Review* Bank for international Settlements (March).

Vansteenkiste, Isabel. 2007. "Regional Housing Market Spillovers in the US: Lessons from Regional Divergences in a Common Monetary Policy Setting.".

Vansteenkiste, Isabel and Paul Hiebert. 2011. "Do House Price Developments Spillover Across Euro Area Countries? Evidence from a Global VAR." *Journal of Housing Economics* 20 (4): 299-314.

Wu, Jing, Yongheng Deng, and Hongyu Liu. 2014. "House Price Index Construction in the Nascent Housing Market: The Case of China." *The Journal of Real Estate Finance and Economics* 48 (3): 522-545.

Wu, Jing, Joseph Gyourko, and Yongheng Deng. 2012. "Evaluating Conditions in Major Chinese Housing Markets." *Regional Science and Urban Economics* 42 (3): 531-543.

Yu, Huayi. 2010. "China's House Price: Affected by Economic Fundamentals Or Real Estate Policy?" *Frontiers of Economics in China* 5 (1): 25-51.

Appendix A

INFORMATION ABOUT SHANGHAI METRO NETWORK

Figure 28 Shanghai Metro Network Map as of Dec. 2014

Table 23 Shanghai Metro Network Development

Line	Terminals (District)		Opened	Newest Extension	Length (km)	Stations
Line 1	Fujin Road (*Baoshan*)	Xinzhuang (*Minhang*)	1993	2007	36.4	28
Line 2	East Xujing (*Qingpu*)	Pudong International Airport (*Pudong*)	1999	2010	63.8	30
Line 3	North Jiangyang Road (*Baoshan*)	Shanghai South Railway Station (*Xuhui*)	2000	2006	40.3	29
Line 4 (loop)	Yishan Road (*Xuhui*)	Yishan Road (*Xuhui*)	2005	2007	33.7	26
Line 5	Xinzhuang (*Minhang*)	Minhang Development Zone (*Minhang*)	2003	—	17.2	11
Line 6	Gangcheng Road (*Pudong*)	Oriental Sports Center (*Pudong*)	2007	2011	32.3	28
Line 7	Meilan Lake (*Baoshan*)	Huamu Road (*Pudong*)	2009	2010	44.2	33
Line 8	Shiguang Road (*Yangpu*)	Shendu Highway (*Minhang*)	2007	2011	37.4	30
Line 9	Songjiang South Railway Station (*Songjiang*)	Middle Yanggao Road (*Pudong*)	2007	2012	52.1	26
Line 10	Xinjiangwancheng (*Yangpu*)	Hongqiao Railway Station (*Minhang*) Hangzhong Road (*Minhang)*	2010	2010	35.4	31
Line 11	North Jiading (*Jiading*) Huaqiao (*Kunshan, Jiangsu*)	Luoshan Road (*Pudong*)	2009	2013	72	34
Line 12	Qufu Road (*Zhabei*)	Jinhai Road (*Pudong*)	2013	2014	—	16
Line 13	Jinyun Road (*Changning*)	Jinshajiang Road (*Putuo*)	2012	—	8.3	6

Line	Terminals (District)		Opened	Newest Extension	Length (km)	Stations
Line 16	Luoshan Road (*Pudong*)	Dishui Lake (*Pudong*)	2013	—	51.9	11
Total					538	330

Appendix B

0/1 FIXED-WEIGHT MATRIX

	Changning	Luwan	Qingpu	Jingan	Huangpu	Putuo	Fengxian	Nanhui	Songjiang	Hongkou	Xuhui	Pudong	Minhang	Jinshan	Yangpu	Zhabei	Baoshan	Jiading
Changning	0	0	0	0.166667	0	0.2	0	0	0	0	0.2	0	0.142857	0	0	0	0	0.2
Luwan	0	0	0	0.166667	0.2	0	0	0	0	0	0.2	0.111111	0	0	0	0	0	0
Qingpu	0	0	0	0	0	0	0	0	0.25	0	0	0	0	0.333333	0	0	0	0.2
Jingan	0.2	0.25	0	0	0.2	0.2	0	0	0	0	0.2	0	0	0	0	0.2	0	0
Huangpu	0	0.25	0	0.166667	0	0	0	0	0	0.2	0	0.111111	0	0	0	0.2	0	0
Putuo	0.2	0	0	0.166667	0	0	0	0	0	0	0	0	0	0	0	0.2	0.166667	0.2
Fengxian	0	0	0	0	0	0	0	0.333333	0.25	0	0	0	0.142857	0.333333	0	0	0	0
Nanhui	0	0	0	0	0	0	0.25	0	0	0	0	0.111111	0.142857	0	0	0	0	0
Songjiang	0	0	0.333333	0	0	0	0.25	0	0	0	0	0	0.142857	0.333333	0	0	0	0
Hongkou	0	0	0	0	0.2	0	0	0	0	0	0	0.111111	0	0	0.333333	0.2	0.166667	0
Xuhui	0.2	0.25	0	0.166667	0	0	0	0	0	0	0	0.111111	0.142857	0	0	0	0	0
Pudong	0	0.25	0	0	0.2	0	0	0.333333	0	0.2	0.2	0	0.142857	0	0.333333	0	0.166667	0
Minhang	0.2	0	0	0	0	0	0.25	0.333333	0.25	0	0.2	0.111111	0	0	0	0	0	0.2
Jinshan	0	0	0.333333	0	0	0	0.25	0	0.25	0	0	0	0	0	0	0	0	0
Yangpu	0	0	0	0	0	0	0	0	0	0.2	0	0.111111	0	0	0	0	0.166667	0
Zhabei	0	0	0	0.166667	0.2	0.2	0	0	0	0.2	0	0	0	0	0	0	0.166667	0
Baoshan	0	0	0	0	0	0.2	0	0	0	0.2	0	0.111111	0	0	0.333333	0.2	0	0.2
Jiading	0.2	0	0.333333	0	0	0.2	0	0	0	0	0	0	0.142857	0	0	0	0.166667	0

Appendix C

STATISTICAL RESULTS OF MODEL #1

Table 24 MODEL #1: Unit Root Tests for the Domestic Variables

Variables	*5% Crit. Val.*	*CHANGNING*	*LUWAN*	*QINGPU*	*JING'AN*	*HUANGPU*	*PUTUO*	*FENGXIAN*
hp (with trend)	-3.45	−3.81*	−4.69*	-3.32	−6.10*	-1.98	-2.82	-2.48
Dhp	-2.89	-9.43	-7.26	-6.62	-9.72	-10.02	-8.42	-11.54

Variables	*5% Crit. Val*	*HONGKOU*	*XUHUI*	*PUDONG*	*MINHANG*	*JINSHAN*	*YANGPU*	*NANHUI*
hp (with trend)	-3.45	−4.06*	-2.76	-2.26	-1.47	-1.34	-1.56	-1.88
Dhp	-2.89	-8.12	-8.38	-9.18	-8.92	-10.34	-9.97	-7.44

Variables	*5% Crit. Val*	*ZHABEI*	*BAOSHAN*	*JIADING*	*SONGJIANG*
hp (with trend)	-3.45	-2.13	-1.04	-1.73	-1.52
Dhp	-2.89	-6.46	-10.42	-10.62	-10.32

*: Statistically significant at the 5% level

Table 25 MODEL #1: Unit Root Tests for the Foreign Variables

Variables	5% *Crit. Val.*	*CHANGNING*	*LUWAN*	*QINGPU*	*JING'AN*	*HUANGPU*	*PUTUO*	*FENGXIAN*	*NANHUI*	*SONGJIANG*
hps (with trend)	-3.45	-2.45	-2.95	-1.27	-2.54	-1.81	-2.35	-1.25	-1.84	-2.22
Dhps	-2.89	-7.40	-10.08	-9.02	-8.65	-8.91	-8.37	-9.27	-10.80	-8.13

(*continued*)

Variables	*5% Crit. Val.*	*HONGKOU*	*XUHUI*	*PUDONG*	*MINHANG*	*JINSHAN*	*YANGPU*	*ZHABEI*	*BAOSHAN*	*JIADING*
hps (with trend)	3.45	-1.41	-3.12	-1.32	-1.80	-2.56	-1.26	-1.83	-1.71	-1.87
Dhps	2.89	-9.69	-8.36	-8.79	-6.63	-9.16	-10.02	-11.60	-7.89	-6.53

*: Statistically significant at the 5% level

Table 26 MODEL #1: Unit Root Tests for the Global Variables

Variables	*5% Crit. Val.*	ADF *t-Statistic*
m (with trend)	-3.45	-1.00
Dm	-2.89	-5.13
cpi (with trend)	-3.45	-2.60
Dcpi	-2.89	-5.49
ibor (no trend)	-2.89	-3.16
Dibor	-2.89	-9.92
lrh (no trend)	-2.89	-2.35
Dlrh	-2.89	-4.76
tst (no trend)	-3.45	-3.19
Dtst	-2.89	-5.22

Table 27 MODEL #1: The Order of Integration Concluded by ADF Tests at the 5% Significance Level

Domestic and Foreign Variables

Variables	CHANGNING	LUWAN	QINGPU	JING'AN	HUANGPU	PUTUO	FENGXIAN	NANHUI	SONGJIANG
Domestic Var.	*TS*	*TS*	*I(1)*	*TS*	*I(1)*	*I(1)*	*I(1)*	*I(1)*	*I(1)*
Foreign Var.	*I(1)*	*I(1)*	*I(1)*	*I(1)*	*I(1)*	*I(1)*	*I(1)*	*I(1)*	*I(1)*

(*continued*)

Variables	HONGKOU	XUHUI	PUDONG	MINHANG	JINSHAN	YANGPU	ZHABEI	BAOSHAN	JIADING
Domestic Var.	*TS*	*I(1)*	*I(1)*	*I(1)*	*I(1)*	*I(1)*	*I(1)*	*I(1)*	*I(1)*
Foreign Var.	*I(1)*	*I(1)*	*I(1)*	*I(1)*	*I(1)*	*I(1)*	*I(1)*	*I(1)*	*I(1)*

Global Variables

Variables	M	CPI	IBOR	lrh	tst
integration	*I(1)*	*I(1)*	*I(0)*	*I(1)*	*I(1)*

Table 28 MODEL #1: Lag Order Selection - Individual District VARX Models

District	*p*	*q*	*AIC*	*District*	*p*	*q*	*AIC*
CHANGNING	1	1	35.10	*HONGKOU*	1	1	31.90
CHANGNING	1	2	34.68	*HONGKOU*	1	2	30.02
CHANGNING	2	1	34.24	*HONGKOU*	2	1	31.18
CHANGNING	2	2	33.71	*HONGKOU*	2	2	29.57
LUWAN	1	1	-3.05	*XUHUI*	1	1	53.03
LUWAN	1	2	-2.15	*XUHUI*	1	2	49.08
LUWAN	2	1	-4.02	*XUHUI*	2	1	52.21
LUWAN	2	2	-3.15	*XUHUI*	2	2	48.26
QINGPU	1	1	71.57	*PUDONG*	1	1	62.50
QINGPU	1	2	67.21	*PUDONG*	1	2	60.63
QINGPU	2	1	71.14	*PUDONG*	2	1	66.46
QINGPU	2	2	66.65	*PUDONG*	2	2	63.00
JING'AN	1	1	33.34	*MINHANG*	1	1	65.49
JING'AN	1	2	31.24	*MINHANG*	1	2	61.43
JING'AN	2	1	32.41	*MINHANG*	2	1	64.51
JING'AN	2	2	30.31	*MINHANG*	*2*	*2*	60.70
HUANGPU	1	1	-10.39	*JINSHAN*	*1*	*1*	114.38
HUANGPU	1	2	-15.01	*JINSHAN*	*1*	*2*	119.37
HUANGPU	2	1	-10.18	*JINSHAN*	*2*	*1*	113.38
HUANGPU	2	2	-14.68	*JINSHAN*	*2*	*2*	119.15
PUTUO	1	1	91.23	*YANGPU*	*1*	*1*	72.86
PUTUO	1	2	87.32	*YANGPU*	*1*	*2*	70.59
PUTUO	2	1	90.39	*YANGPU*	*2*	*1*	73.12
PUTUO	2	2	86.55	*YANGPU*	*2*	*2*	70.63
FENGXIAN	1	1	36.22	*ZHABEI*	*1*	*1*	98.10
FENGXIAN	1	2	34.85	*ZHABEI*	*1*	*2*	93.18
FENGXIAN	2	1	37.43	*ZHABEI*	*2*	*1*	97.47
FENGXIAN	2	2	36.75	*ZHABEI*	*2*	*2*	92.30
NANHUI	1	1	67.03	*BAOSHAN*	*1*	*1*	126.35
NANHUI	1	2	71.03	*BAOSHAN*	*1*	*2*	123.81
NANHUI	2	1	66.44	*BAOSHAN*	*2*	*1*	126.67
NANHUI	2	2	70.06	*BAOSHAN*	*2*	*2*	123.83
SONGJIANG	1	1	72.57	*JIADING*	*1*	*1*	108.67
SONGJIANG	1	2	69.33	*JIADING*	*1*	*2*	105.41
SONGJIANG	2	1	72.44	*JIADING*	*2*	*1*	107.91

SONGJIANG	2	2	69.71	*JIADING*	*2*	*2*	104.60

Table 29 MODEL #1: Lag Orders of Individual District VARX Models and Corresponding Residual Serial Correlation F-Statistics

District	*p*	*q*		*5% Crit. Val.*	*hp*
CHANGNING	1	1	*F(4,83)*	*2.48*	0.76
LUWAN	1	2	*F(4,77)*	*2.49*	0.61
QINGPU	1	1	*F(4,83)*	*2.48*	1.08
JING'AN	1	1	*F(4,83)*	*2.48*	0.37
HUANGPU	2	1	*F(4,82)*	*2.48*	2.36
PUTUO	1	1	*F(4,83)*	*2.48*	0.30
FENGXIAN	2	1	*F(4,82)*	*2.48*	2.04
NANHUI	1	1	*F(4,83)*	*2.48*	0.80
SONGJIANG	1	1	*F(4,83)*	*2.48*	2.39
HONGKOU	1	1	*F(4,83)*	*2.48*	1.39
XUHUI	1	1	*F(4,83)*	*2.48*	1.11
PUDONG	2	1	*F(4,82)*	*2.48*	0.41
MINHANG	1	1	*F(4,83)*	*2.48*	0.26
JINSHAN	1	2	*F(4,77)*	*2.49*	3.98*
YANGPU	2	1	*F(4,82)*	*2.48*	1.28
ZHABEI	1	1	*F(4,83)*	*2.48*	1.04
BAOSHAN	1	1	*F(4,83)*	*2.48*	2.16
JIADING	1	1	*F(4,83)*	*2.48*	1.97

(*p*: lag order of domestic variables, *q*: lag order of foreign variables)

*: Statistically significant at the 5% level

Table 30 MODEL #1: *F*-Tests for Weak Exogeneity

District	*F test*	*5% Crit. Val.*	*hps*	*m*	*cpi*	*ibor*	*lrh*	*tst*
CHANGNING	F(1,93)	3.94	4.45*	1.61	0.03	0.46	0.00	0.74
LUWAN	F(1,93)	3.94	0.62	0.16	0.52	1.05	0.30	1.07
QINGPU	F(1,93)	3.94	0.89	0.06	0.01	1.27	0.04	2.64
JING'AN	F(1,93)	3.94	3.29	0.69	0.00	0.76	0.03	0.48
HUANGPU	F(1,93)	3.94	0.78	1.51	0.22	0.76	2.28	0.54
PUTUO	F(1,93)	3.94	2.57	0.73	0.01	0.40	0.11	0.08
FENGXIAN	F(1,93)	3.94	1.53	0.09	3.77	4.29*	5.53*	1.11
NANHUI	F(1,93)	3.94	1.55	1.73	1.73	0.46	0.02	0.43
SONGJIANG	F(1,93)	3.94	6.97	1.91	1.08	0.51	0.08	0.02
HONGKOU	F(1,93)	3.94	0.07	1.44	0.92	0.10	0.80	0.02
XUHUI	F(1,93)	3.94	6.50	0.97	0.35	0.13	0.66	1.59
PUDONG	F(1,93)	3.94	0.55	0.65	1.87	1.24	0.07	0.13
MINHANG	F(1,93)	3.94	0.53	0.09	0.01	0.22	0.01	2.87
JINSHAN	F(1,93)	3.94	1.78	0.60	0.51	0.00	0.00	0.00
YANGPU	F(1,93)	3.94	0.77	0.01	0.18	1.00	1.32	0.19
ZHABEI	F(1,93)	3.94	1.70	0.41	10.23*	0.02	0.24	0.10
BAOSHAN	F(1,93)	3.94	1.05	1.20	0.00	1.74	1.90	1.26
JIADING	F(1,93)	3.94	0.45	0.10	1.20	2.81	0.02	2.67

*: Statistically significant at the 5% level

Table 31 MODEL #1: Johansen's Trace Statistics

District	*5% Crit. Val.*	*CHANGNING*	*LUWAN*	*QINGPU*	*JING'AN*	*HUANGPU*	*PUTUO*	*FENGXIAN*	*NANHUI*	*HONGKOU*	*SONGJIANG*
r=0	28.81	47.17	54.53	53.52	57.94	44.76	40.21	38.03	55.08	60.39	69.49

(*continued*)

District	*5% Critical Val.*	*XUHUI*	*PUDONG*	*MINHANG*	*JINSHAN*	*YANGPU*	*ZHABEI*	*BAOSHAN*	*JIADING*
r=0	28.81	40.08	30.11	57.07	58.23	17.83*	33.29	40.23	43.63

Table 32 MODEL #1: Average Pairwise Cross-Section Correlations - Variable and Residuals

Variable *hp*

District	$Cor(hp, hp^{*})$	$Cor(d.hp, d.hp^{*})$	*VECMX* Residuals*
CHANGNING	0.876	0.016	-0.021
LUWAN	0.721	0.002	-0.042
QINGPU	0.877	0.044	0.001
JING'AN	0.841	0.088	-0.023
HUANGPU	0.863	0.007	-0.012
PUTUO	0.917	0.044	0.011
FENGXIAN	0.850	0.036	-0.001
NANHUI	0.908	0.030	0.026
SONGJIANG	0.903	-0.004	-0.002
HONGKOU	0.884	0.000	-0.033
XUHUI	0.903	0.006	0.004
PUDONG	0.900	0.097	-0.008
MINHANG	0.915	0.063	-0.012
JINSHAN	0.922	0.063	0.050
YANGPU	0.922	0.087	0.059
ZHABEI	0.914	0.069	0.024
BAOSHAN	0.920	0.014	-0.020
JIADING	0.913	0.032	-0.035

Table 33 MODEL #1: Structural Stability Tests

PK_{sub}

District	CHANGNING	LUWAN	QINGPU	JING'AN	HUANGPU	PUTUO	FENGXIAN	NANHUI	SONGJIANG
5% Crit. Val.	0.61	0.67	0.64	0.61	0.67	0.66	0.68	0.70	0.63
hp	0.76*	0.53	0.48	0.77*	0.43	0.40	0.66	0.37	0.40

District	HONGKOU	XUHUI	PUDONG	MINHANG	JINSHAN	YANGPU	ZHABEI	BAOSHAN	JIADING
5% Crit. Val.	0.63	0.67	0.64	0.66	0.64	0.60	0.68	0.66	0.67
hp	0.48	0.46	0.48	0.58	0.37	0.62*	0.43	0.37	0.53

*Statistically Significant at the 5 percent level

PK_{msq}

District	CHANGNING	LUWAN	QINGPU	JING'AN	HUANGPU	PUTUO	FENGXIAN	NANHUI	SONGJIANG
5% Crit. Val.	0.06	0.07	0.06	0.07	0.09	0.07	0.09	0.07	0.07
hp	0.03	0.02	0.04	0.04	0.04	0.02	0.06	0.02	0.02

District	HONGKOU	XUHUI	PUDONG	MINHANG	JINSHAN	YANGPU	ZHABEI	BAOSHAN	JIADING
5% Crit. Val.	0.07	0.08	0.07	0.07	0.08	0.08	0.07	0.08	0.07
hp	0.03	0.06	0.03	0.04	0.01	0.04	0.03	0.03	0.04

*Statistically Significant at the 5 percent level

Nyblom Test $\mathfrak{H}$

District	CHANGNING	LUWAN	QINGPU	JING'AN	HUANGPU	PUTUO	FENGXIAN	NANHUI	SONGJIANG
5% Crit. Val.	1.83	2.64	1.71	1.77	1.68	1.74	1.70	2.60	1.92
hp	0.87	1.01	0.50	0.99	1.12	1.08	0.63	1.63	0.58

District	HONGKOU	XUHUI	PUDONG	MINHANG	JINSHAN	YANGPU	ZHABEI	BAOSHAN	JIADING
5% Crit. Val.	1.81	1.82	1.77	1.62	2.76	2.01	1.79	1.71	1.73
hp	0.74	0.75	0.84	0.72	2.03	1.11	1.03	1.35	0.87

*Statistically Significant at the 5 percent level

Robust *QLR*

District	CHANGNING	LUWAN	QINGPU	JING'AN	HUANGPU	PUTUO	FENGXIAN	NANHUI	SONGJIANG
5% Crit. Val.	17.73	26.67	17.60	18.00	18.58	17.72	18.29	25.64	17.43
hp	12.63	46.38*	7.56	17.17	13.57	16.11	11.08	21.47	17.04

District	HONGKOU	XUHUI	PUDONG	MINHANG	JINSHAN	YANGPU	ZHABEI	BAOSHAN	JIADING
5% Crit. Val.	17.50	17.57	19.84	16.81	27.77	19.84	17.16	17.50	17.98
hp	12.62	14.13	15.32	9.92	24.28	16.04	15.98	16.67	12.02

*Statistically Significant at the 5 percent level

Table 35 MODEL #1: Contemporaneous Effects of Foreign Housing Price on Domestic Housing Price

High Elasticity Group	
District	*hp*
None	

Medium Elasticity Group	
District	*hp*
CHANGNING	0.64
	(0.23)
JING'AN	0.62
	(0.18)
QINGPU	0.57
	(0.18)
PUDONG	0.56
	(0.17)
MINHANG	0.49
	(0.19)
LUWAN	0.45
	(0.20)
HUANGPU	0.37
	(0.23)
JIADING	0.36
	(0.12)
XUHUI	0.35
	(0.12)
ZHABEI	0.33
	(0.09)
PUTUO	0.31
	(0.13)

Low Elasticity Group	
District	*hp*
SONGJIANG	0.26
	(0.14)
YANGPU	0.25
	(0.13)
FENGXIAN	0.23
	(0.21)
NANHUI	0.22
	(0.11)
JINSHAN	0.21
	(0.08)
BAOSHAN	0.06
	(0.11)
HONGKOU	0.00
	(0.20)

Figure 29 MODEL #1: GIRFs of a One Percent Positive Shock to the *Huangpu* Housing Price

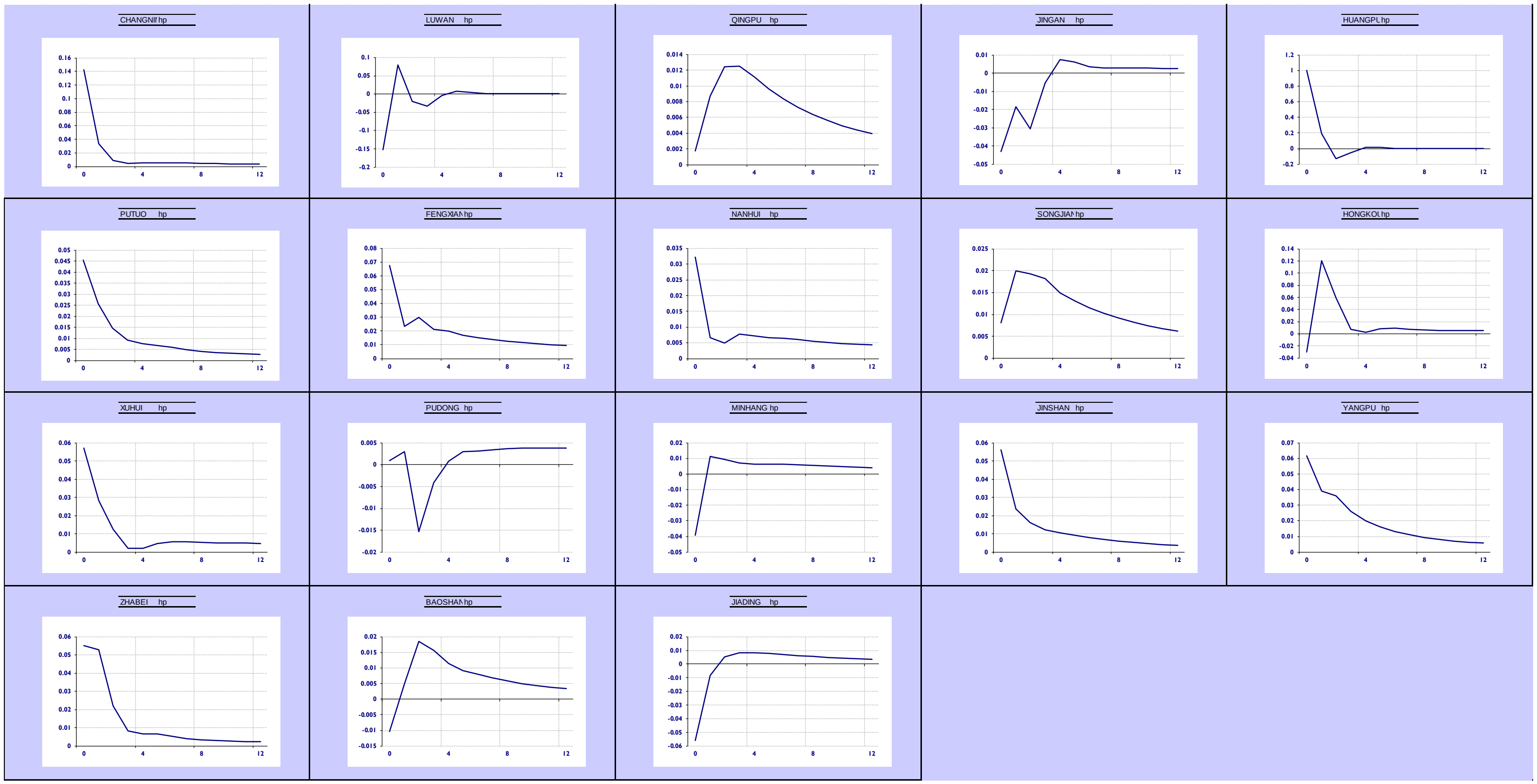


Figure 30 MODEL #1: GIRFs of a One Percent Positive Shock to the *Pudong* Housing Price

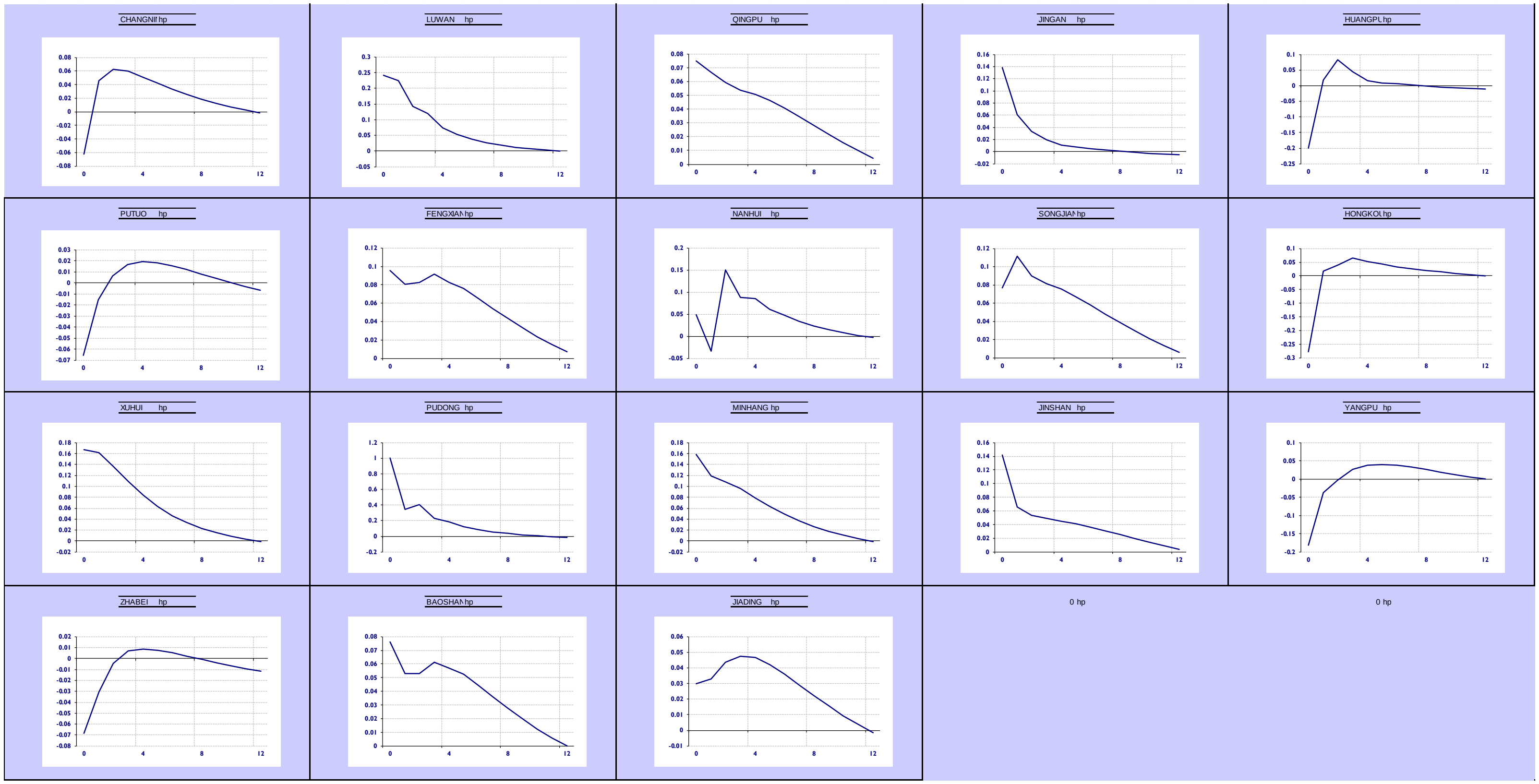
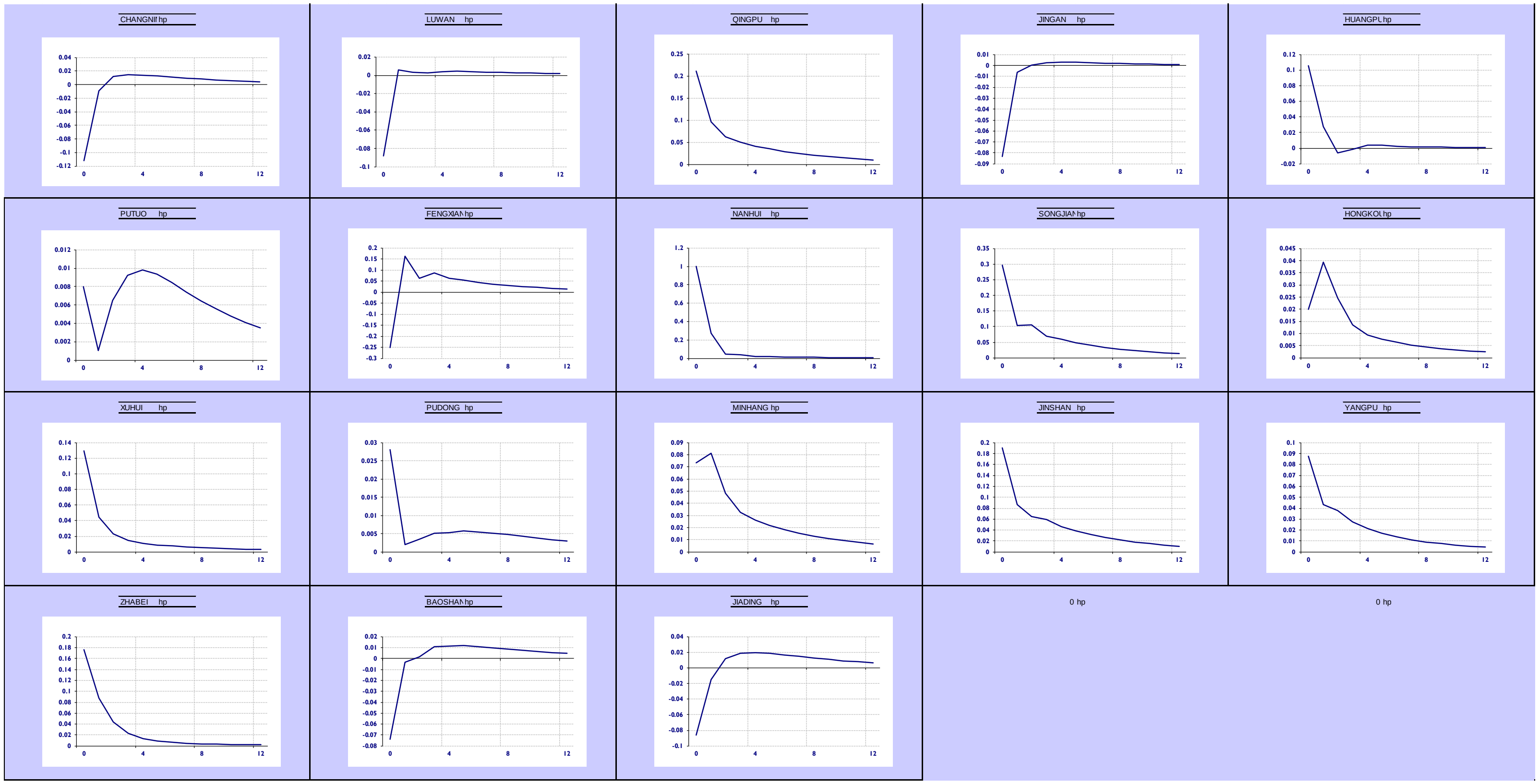


Figure 31 MODEL #1: GIRFs of a One Percent Positive Shock to the *Nanhui* Housing Price



Appendix D

STATISTICAL RESULTS OF MODEL #2

Table 36 MODEL #2: Unit Root Tests for the Domestic Variables

Variables	*5% Crit. Val.*	*CHANGNING*	*LUWAN*	*QINGPU*	*JING'AN*	*HUANGPU*	*PUTUO*
hp (with trend)	-3.45	-3.81^{*}	-4.69^{*}	-3.32	-6.10^{*}	-1.98	-2.82
Dhp	-2.89	-9.43	-7.26	-6.62	-9.72	-10.02	-8.42

Variables	*5% Crit. Val*	*HONGKOU*	*XUHUI*	*PUDONG*	*MINHANG*	*JINSHAN*	*YANGPU*	*NANHUI*
hp (with trend)	-3.45	-4.06^{*}	-2.76	-2.26	-1.47	-1.34	-1.56	-1.88
Dhp	-2.89	-8.12	-8.38	-9.18	-8.92	-10.34	-9.97	-7.44

Variables	*5% Crit. Val.*	*BAOSHAN*	*JIADING*	*SONGJIANG*	*ZHABEI*	*FENGXIAN*
hp (with trend)	-3.45	-1.04	-1.73	-1.52	-2.13	-2.48
Dhp	-2.89	-10.42	-10.62	-10.32	-6.46	-11.54

*: Statistically significant at the 5% level

Table 37 MODEL #2: Unit Root Tests for the Foreign Variables

Variables	*5%Crit. Val.*	*CHANGNING*	*LUWAN*	*QINGPU*	*JING'AN*	*HUANGPU*	*PUTUO*	*FENGXIAN*	*NANHUI*	*SONGJIANG*
hps (with trend)	-3.45	-2.14	-1.09	-2.06	-2.08	-2.63	-1.76	-1.67	-1.97	-1.80
Dhps	-2.89	-9.20	-5.08	-8.39	-8.05	-6.29	-8.78	-7.46	-8.24	-7.87

(*continued*)

Variables	*5%Crit. Val.*	*HONGKOU*	*XUHUI*	*PUDONG*	*MINHANG*	*JINSHAN*	*YANGPU*	*ZHABEI*	*BAOSHAN*	*JIADING*
hps (with trend)	3.45	-1.89	-2.30	-1.79	-2.01	-2.09	-1.40	-2.17	-1.36	-1.73
Dhps	2.89	-7.92	-9.02	-9.11	-7.96	-7.76	-10.42	-8.83	-9.05	-7.91

Table 38 MODEL #2: Unit Root Tests for the Global Variables

Variables	*5% Crit. Val.*	ADF *t-Statistic*
m (with trend)	-3.45	-1.00
Dm	-2.89	-5.13
cpi (with trend)	-3.45	-2.60
Dcpi	-2.89	-5.49
ibor (no trend)	-2.89	-3.16
Dibor	-2.89	-9.92
lrh (no trend)	-2.89	-2.35
Dlrh	-2.89	-4.76
tst (no trend)	-3.45	-3.19
Dtst	-2.89	-5.22

Table 39 MODEL #2: The Order of Integration Concluded by ADF Tests at the 5% Significance Level

Domestic and Foreign Variables

Variables	CHANGNING	LUWAN	QINGPU	JING'AN	HUANGPU	PUTUO	FENGXIAN	NANHUI	SONGJIANG
Domestic Var.	*TS*	*TS*	*I(1)*	*TS*	*I(1)*	*I(1)*	*I(1)*	*I(1)*	*I(1)*
Foreign Var.	*I(1)*	*I(1)*	*I(1)*	*I(1)*	*I(1)*	*I(1)*	*I(1)*	*I(1)*	*I(1)*

Variables	HONGKOU	XUHUI	PUDONG	MINHANG	JINSHAN	YANGPU	ZHABEI	BAOSHAN	JIADING
Domestic Var.	*TS*	*I(1)*	*I(1)*	*I(1)*	*I(1)*	*I(1)*	*I(1)*	*I(1)*	*I(1)*
Foreign Var.	*I(1)*	*I(1)*	*I(1)*	*I(1)*	*I(1)*	*I(1)*	*I(1)*	*I(1)*	*I(1)*

Global Variables

Variables	M	CPI	IBOR	lrh	tst
integration	*I(1)*	*I(1)*	*I(0)*	*I(1)*	*I(1)*

Table 40 MODEL #2: Lag Order Selection - Individual District VARX Models

District	*p*	*q*	*AIC*	*District*	*p*	*q*	*AIC*
CHANGNING	1	1	37.39	*HONGKOU*	1	1	30.55
CHANGNING	1	2	39.13	*HONGKOU*	1	2	27.55
CHANGNING	2	1	36.90	*HONGKOU*	2	1	29.74
CHANGNING	2	2	38.20	*HONGKOU*	2	2	26.85
LUWAN	1	1	-4.26	*XUHUI*	1	1	55.08
LUWAN	1	2	-2.99	*XUHUI*	1	2	51.52
LUWAN	2	1	-5.26	*XUHUI*	2	1	54.23
LUWAN	2	2	-3.97	*XUHUI*	2	2	50.81
QINGPU	1	1	65.99	*PUDONG*	1	1	61.99
QINGPU	1	2	63.03	*PUDONG*	1	2	59.20
QINGPU	2	1	65.07	*PUDONG*	2	1	65.34
QINGPU	2	2	62.20	*PUDONG*	2	2	61.18
JING'AN	1	1	31.37	*MINHANG*	1	1	65.70
JING'AN	1	2	30.00	*MINHANG*	1	2	62.40
JING'AN	2	1	30.44	*MINHANG*	2	1	64.70
JING'AN	2	2	29.00	*MINHANG*	*2*	*2*	*61.69*
HUANGPU	1	1	-10.07	*JINSHAN*	*1*	*1*	*113.30*
HUANGPU	1	2	-14.75	*JINSHAN*	*1*	*2*	*116.78*
HUANGPU	2	1	-9.25	*JINSHAN*	*2*	*1*	*112.30*
HUANGPU	2	2	-13.74	*JINSHAN*	*2*	*2*	*116.34*
PUTUO	1	1	87.87	*YANGPU*	*1*	*1*	*80.97*
PUTUO	1	2	85.28	*YANGPU*	*1*	*2*	*78.56*
PUTUO	2	1	87.42	*YANGPU*	*2*	*1*	*82.05*
PUTUO	2	2	84.69	*YANGPU*	*2*	*2*	*78.63*

(*continued*)

District	*p*	*q*	*AIC*
FENGXIAN	1	1	35.54
FENGXIAN	1	2	37.78
FENGXIAN	2	1	37.50
NANHUI	2	2	39.70
NANHUI	1	1	71.99
NANHUI	1	2	72.19
NANHUI	2	1	71.01
SONGJIANG	2	2	71.79
SONGJIANG	1	1	65.73
SONGJIANG	1	2	64.87
SONGJIANG	2	1	64.75

District	*p*	*q*	*AIC*
ZHABEI	*1*	*1*	*96.60*
ZHABEI	*1*	*2*	*90.88*
ZHABEI	*2*	*1*	*95.88*
BAOSHAN	*2*	*2*	*90.28*
BAOSHAN	*1*	*1*	*122.38*
BAOSHAN	*1*	*2*	*120.65*
BAOSHAN	*2*	*1*	*124.06*
JIADING	*2*	*2*	*122.03*
JIADING	*1*	*1*	*105.00*
JIADING	*1*	*2*	*103.01*
JIADING	*2*	*1*	*104.19*

Table 41 MODEL #2: Lag Orders of Individual District VARX Models and Corresponding Residual Serial Correlation F-Statistics

District	*p*	*q*		*5% Crit. Val.*	*hp*
CHANGNING	1	2	*F(4,77)*	*2.49*	*1.60*
LUWAN	1	2	*F(4,77)*	*2.49*	*0.51*
QINGPU	1	1	*F(4,83)*	*2.48*	*0.86*
JING'AN	1	1	*F(4,83)*	*2.48*	*0.23*
HUANGPU	2	1	*F(4,82)*	*2.48*	*2.32*
PUTUO	1	1	*F(4,83)*	*2.48*	*1.53*
FENGXIAN	2	2	*F(4,76)*	*2.49*	*1.32*
NANHUI	1	1	*F(4,77)*	*2.49*	*1.10*
SONGJIANG	1	1	*F(4,83)*	*2.48*	*1.32*
HONGKOU	1	1	*F(4,83)*	*2.48*	*1.18*
XUHUI	1	1	*F(4,83)*	*2.48*	*0.60*
PUDONG	2	1	*F(4,82)*	*2.48*	*0.69*
MINHANG	1	1	*F(4,83)*	*2.48*	*0.92*
JINSHAN	1	1	*F(4,77)*	*2.49*	*2.23*
YANGPU	2	1	*F(4,82)*	*2.48*	*0.60*
ZHABEI	1	1	*F(4,83)*	*2.48*	*1.23*
BAOSHAN	2	1	*F(4,82)*	*2.48*	*1.57*
JIADING	1	1	*F(4,83)*	*2.48*	*1.94*

(*p*: lag order of domestic variables, *q*: lag order of foreign variables)

*: Statistically significant at the 5% level

Table 42 MODEL #2: Cointegrating Relationships for the Individual VARX Models

DISTRICT	*RANK*	DISTRICT	*RANK*
CHANGNING	1	*HONGKOU*	1
LUWAN	1	*XUHUI*	1
QINGPU	1	*PUDONG*	1
JING'AN	1	*MINHANG*	1
HUANGPU	1	*JINSHAN*	1
PUTUO	1	*YANGPU*	0
FENGXIAN	0	*ZHABEI*	1
NANHUI	1	*BAOSHAN*	1
SONGJIANG	1	*JIADING*	1

Table 43 MODEL #2: Johansen's Trace Statistics

District	*5% Crit. Val.*	*CHANGNING*	*LUWAN*	*QINGPU*	*JING'AN*	*HUANGPU*	*PUTUO*	*FENGXIAN*	*NANHUI*	*SONGJIANG*
r=0	28.81	60.08	59.28	43.64	54.58	47.25	33.60	28.59*	63.57	57.78

(*continued*)

District	*5% Critical Val.*	*HONGKOU*	*XUHUI*	*PUDONG*	*MINHANG*	*JINSHAN*	*YANGPU*	*ZHABEI*	*BAOSHAN*	*JIADING*
r=0	28.81	59.22	44.27	31.79	59.51	51.86	21.67*	32.60	35.10	38.06

Table 44 MODEL #2: *F*-Tests for Weak Exogeneity

District	*F test*	*5% Crit. Val.*	*hps*	*m*	*cpi*	*ibor*	*lrh*	*tst*
CHANGNING	F(1,93)	3.94	0.76	6.09*	1.19	0.08	0.11	0.83
LUWAN	F(1,93)	3.94	0.03	0.11	0.72	0.47	0.18	1.33
QINGPU	F(1,93)	3.94	2.84	0.50	0.71	1.01	0.26	0.83
JING'AN	F(1,93)	3.94	5.41*	0.72	0.02	1.00	0.01	0.39
HUANGPU	F(1,93)	3.94	2.22	1.12	0.39	1.43	2.39	0.70
PUTUO	F(1,93)	3.94	2.74	1.06	0.32	0.16	0.41	0.26
FENGXIAN	F(1,93)	3.94	0.15	1.23	3.78	8.55*	2.42	1.36
NANHUI	F(1,93)	3.94	0.74	3.66	1.50	0.15	0.00	0.65
SONGJIANG	F(1,93)	3.94	6.27*	0.13	0.50	0.01	1.36	0.63
HONGKOU	F(1,93)	3.94	0.26	1.79	0.60	0.50	0.84	0.00
XUHUI	F(1,93)	3.94	2.39	0.25	0.23	0.16	1.77	0.43
PUDONG	F(1,93)	3.94	0.14	0.86	1.70	1.25	0.01	0.09
MINHANG	F(1,93)	3.94	0.34	0.26	0.17	0.54	0.00	3.12
JINSHAN	F(1,93)	3.94	1.69	0.50	0.06	0.05	2.16	0.08
YANGPU	F(1,93)	3.94	6.67*	0.33	0.15	0.35	0.47	0.05
ZHABEI	F(1,93)	3.94	0.40	0.10	9.90*	0.00	0.02	0.07
BAOSHAN	F(1,93)	3.94	3.33	2.63	0.78	1.30	0.12	1.11
JIADING	F(1,93)	3.94	1.25	2.00	1.36	3.20	0.11	3.78

*Statistically Significant at the 5 percent level

Table 45 MODEL #2: Average Pairwise Cross-Section Correlations - Variable and Residuals

Variable *hp*

District	$Cor(hp, hp^*)$	$Cor(\mathrm{d}.hp, \mathrm{d}.hp^*)$	*VECMX* Residuals*
CHANGNING	0.876	0.016	-0.038
LUWAN	0.721	0.002	-0.073
QINGPU	0.877	0.044	0.033
JING’AN	0.841	0.088	-0.051
HUANGPU	0.863	0.007	-0.030
PUTUO	0.917	0.044	0.005
FENGXIAN	0.850	0.036	-0.030
NANHUI	0.908	0.030	0.031
SONGJIANG	0.903	-0.004	0.017
HONGKOU	0.884	0.000	-0.051
XUHUI	0.903	0.006	-0.013
PUDONG	0.900	0.097	0.003
MINHANG	0.915	0.063	0.020
JINSHAN	0.922	0.063	0.035
YANGPU	0.922	0.087	0.027
ZHABEI	0.914	0.069	0.016
BAOSHAN	0.920	0.014	-0.004
JIADING	0.913	0.032	0.031

Table 46 MODEL #2: Structural Stability Tests

PK_{sub}

District	CHANGNING	LUWAN	QINGPU	JING'AN	HUANGPU	PUTUO	FENGXIAN	NANHUI	SONGJIANG
5% Crit. Val.	0.67	0.65	0.67	0.60	0.70	0.68	0.64	0.68	0.77
hp	0.71*	0.45	0.61	0.78 *	0.41	0.53	0.57	0.35	0.57

District	HONGKOU	XUHUI	PUDONG	MINHANG	JINSHAN	YANGPU	ZHABEI	BAOSHAN	JIADING
5% Crit. Val.	0.64	0.66	0.61	0.65	0.66	0.69	0.69	0.68	0.64
hp	0.43	0.55	0.45	0.56	0.34	0.58	0.41	0.39	0.49

*Statistically Significant at the 5 percent level

PK_{msq}

District	CHANGNING	LUWAN	QINGPU	JING'AN	HUANGPU	PUTUO	FENGXIAN	NANHUI	SONGJIANG
5% Crit. Val.	0.08	0.07	0.07	0.07	0.09	0.07	0.07	0.06	0.10
hp	0.02	0.02	0.04	0.04	0.03	0.02	0.05	0.02	0.04

District	HONGKOU	XUHUI	PUDONG	MINHANG	JINSHAN	YANGPU	ZHABEI	BAOSHAN	JIADING
5% Crit. Val.	0.07	0.08	0.07	0.07	0.08	0.08	0.07	0.08	0.07
hp	0.03	0.06	0.03	0.04	0.01	0.04	0.03	0.03	0.04

*Statistically Significant at the 5 percent level

Nyblom Test $\mathfrak{H}$

District	CHANGNING	LUWAN	QINGPU	JING'AN	HUANGPU	PUTUO	FENGXIAN	NANHUI	SONGJIANG
5% Crit. Val.	2.72	2.66	1.69	1.97	1.87	1.83	2.70	2.71	2.72
hp	1.36	0.86	0.46	0.82	1.07	0.92	1.88	1.36	1.36

District	HONGKOU	XUHUI	PUDONG	MINHANG	JINSHAN	YANGPU	ZHABEI	BAOSHAN	JIADING
5% Crit. Val.	1.85	1.70	1.79	1.98	1.57	2.77	1.88	1.65	2.00
hp	0.65	0.53	0.73	0.92	0.65	1.58	1.25	1.02	1.48

*Statistically Significant at the 5 percent level

Robust *QLR*

District	CHANGNING	LUWAN	QINGPU	JING'AN	HUANGPU	PUTUO	FENGXIAN	NANHUI	SONGJIANG
5% Crit. Val.	26.66	27.36	18.05	17.97	19.63	17.91	26.50	27.02	18.30
hp	27.78	34.31 *	9.05	11.67	12.75	14.36	20.63	17.66	12.40

District	HONGKOU	XUHUI	PUDONG	MINHANG	JINSHAN	YANGPU	ZHABEI	BAOSHAN	JIADING
5% Crit. Val.	17.67	18.10	20.54	18.17	28.33	19.73	18.27	18.45	18.01
hp	10.62	11.77	16.51	13.33	21.84	19.22	15.55	16.73	13.37

*Statistically Significant at the 5 percent level

Table 47 MODEL #2: Contemporaneous Effects of Foreign Housing Price on Domestic Housing Price

High Elasticity Group	
District	*hp*
YANGPU	0.80
	(0.15)
FENGXIAN	0.80
	(0.25)
CHANGNING	0.78
	(0.21)

Medium Elasticity Group	
District	*hp*
JING'AN	0.61
	(0.24)
JIADING	0.48
	(0.19)
JINSHAN	0.46
	(0.14)
QINGPU	0.44
	(0.20)
PUDONG	0.43
	(0.17)
MINHANG	0.42
	(0.20)
HUANGPU	0.41
	(0.18)
PUTUO	0.34
	(0.15)
ZHABEI	0.32
	(0.12)
NANHUI	0.31
	(0.20)

Low Elasticity Group	
District	*hp*
SONGJIANG	0.25
	(0.21)
JIADING	0.17
	(0.15)
BAOSHAN	0.03
	(0.11)
LUWAN	-0.05
	(0.21)

Figure 32 MODEL #2: GIRFs of a One Percent Positive Shock to the *Pudong* Housing Price

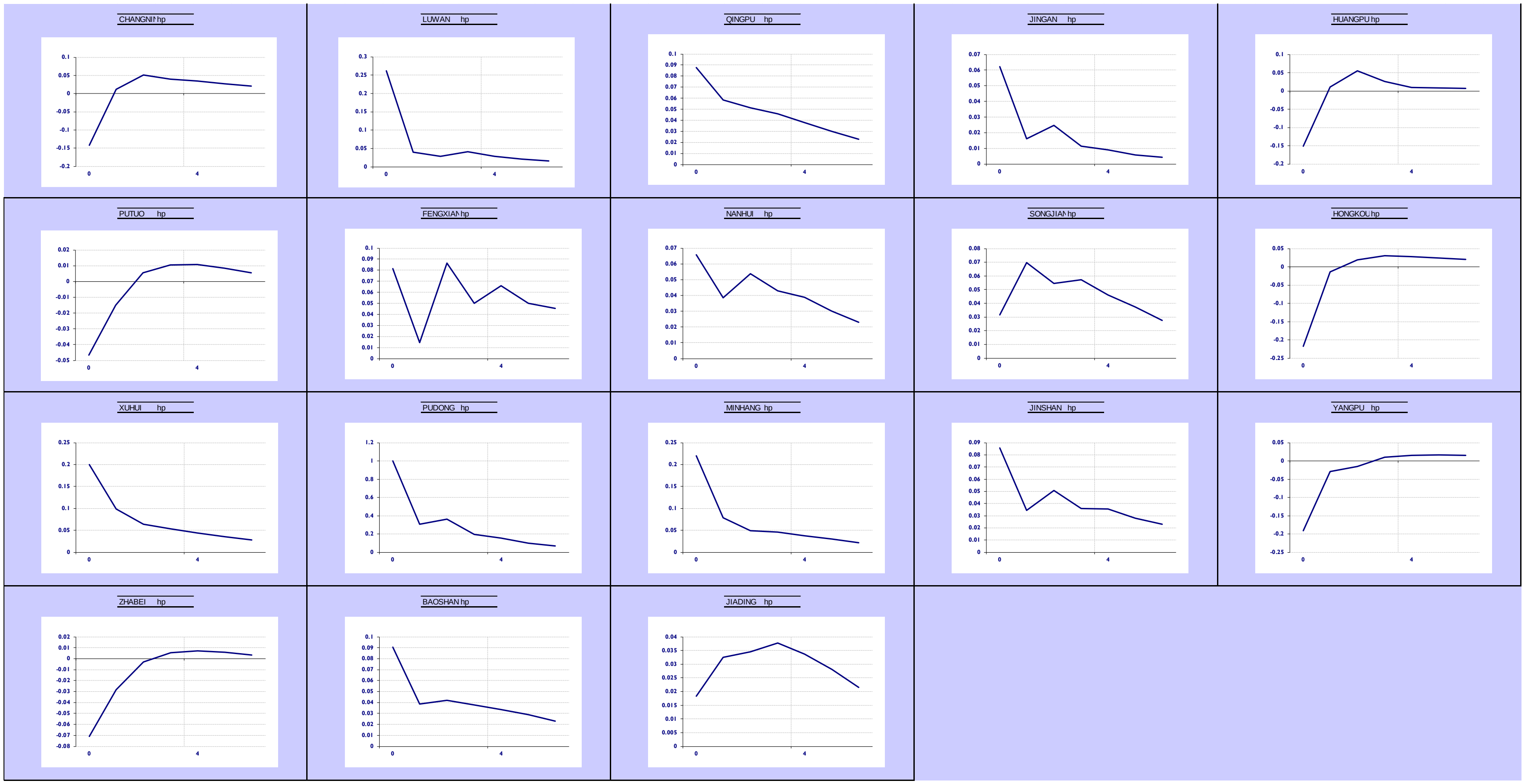


Figure 33 MODEL #2: GIRFs of a One Percent Positive Shock to the *Huangpu* Housing Price

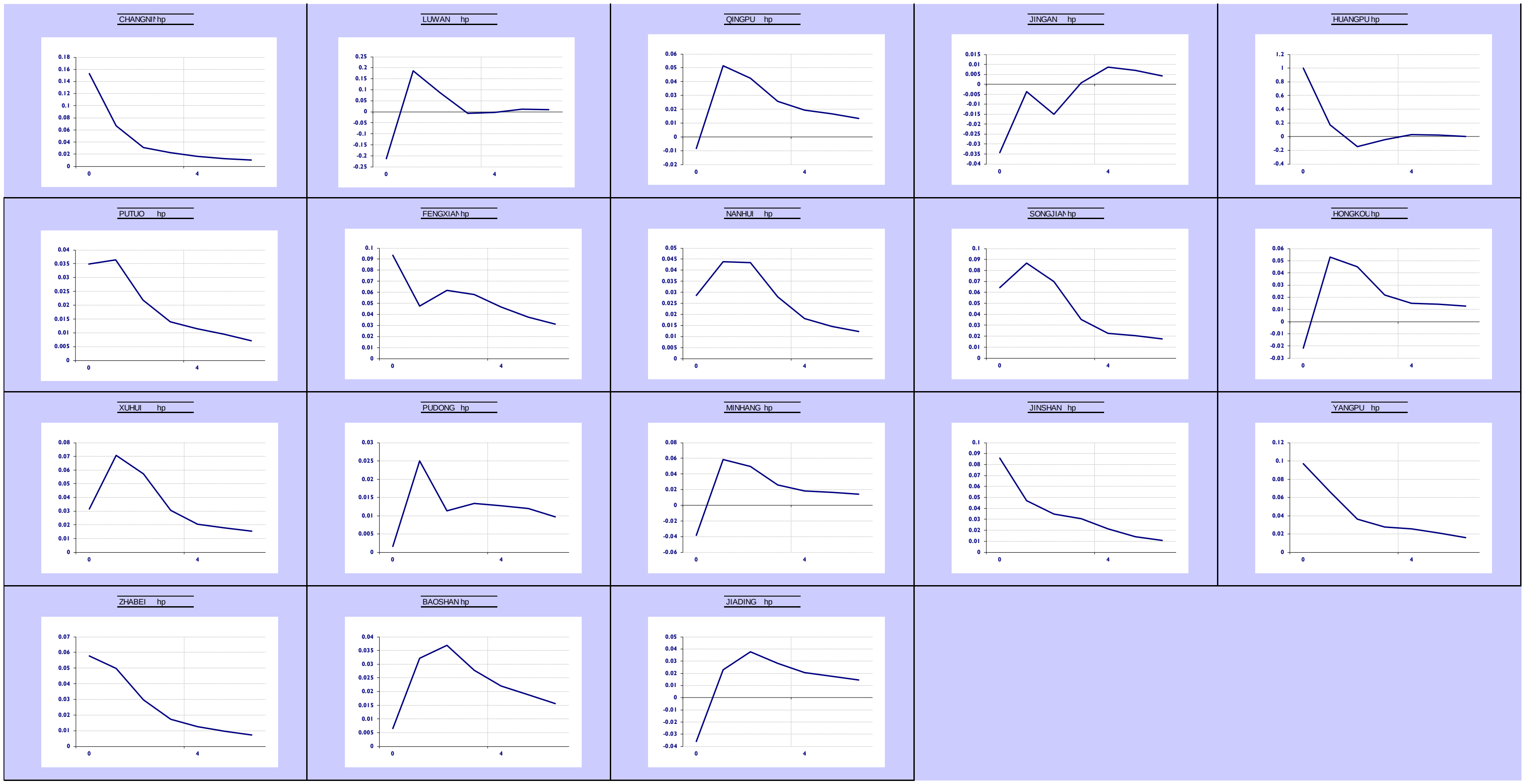


Figure 34 MODEL #2: GIRFs of a One Percent Positive Shock to the *Nanhui* Housing Price

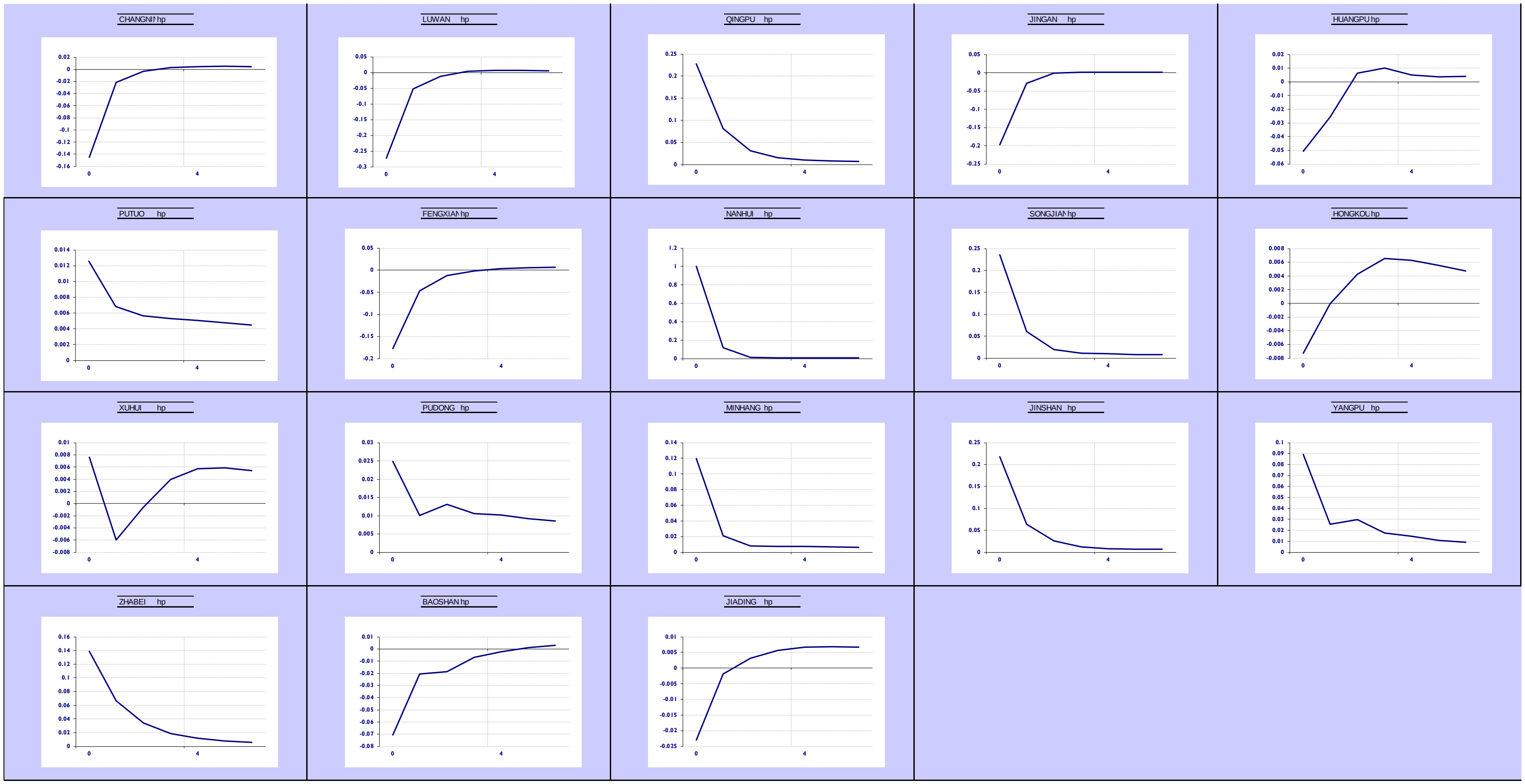
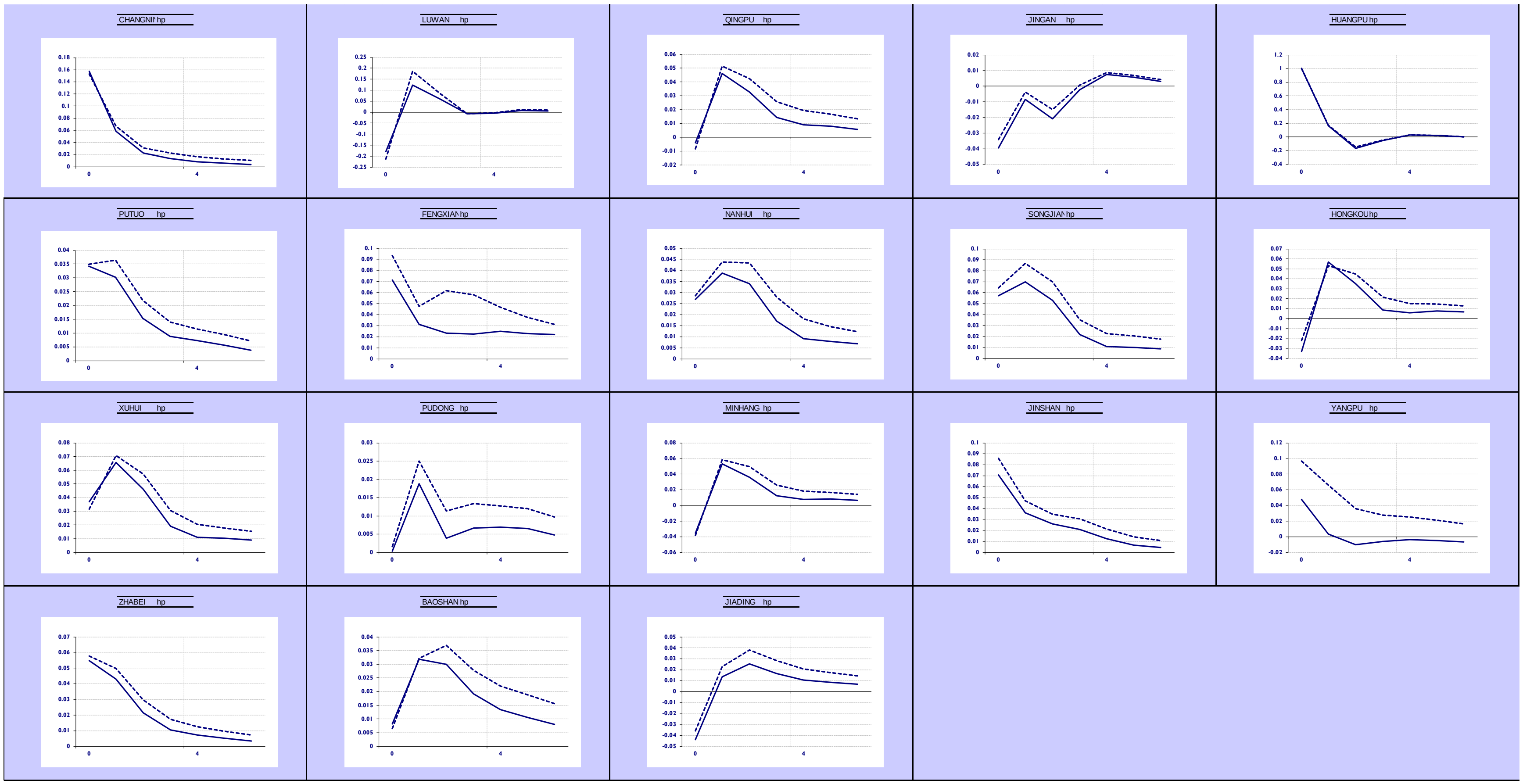
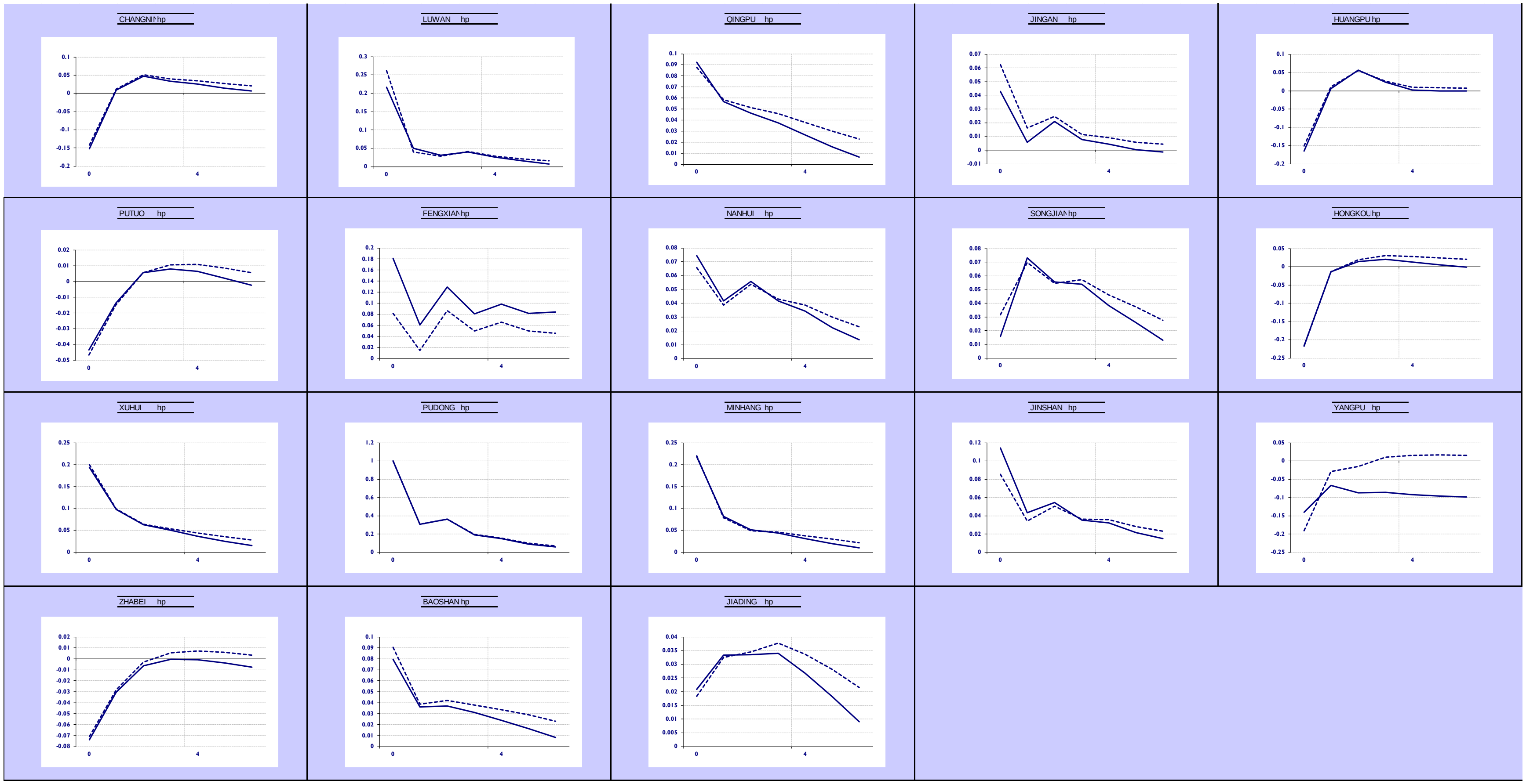


Figure 35 MODEL #2 Counterfactual Analysis: GIRFs of a One Percent Positive Shock to the *Huangpu* Housing Price



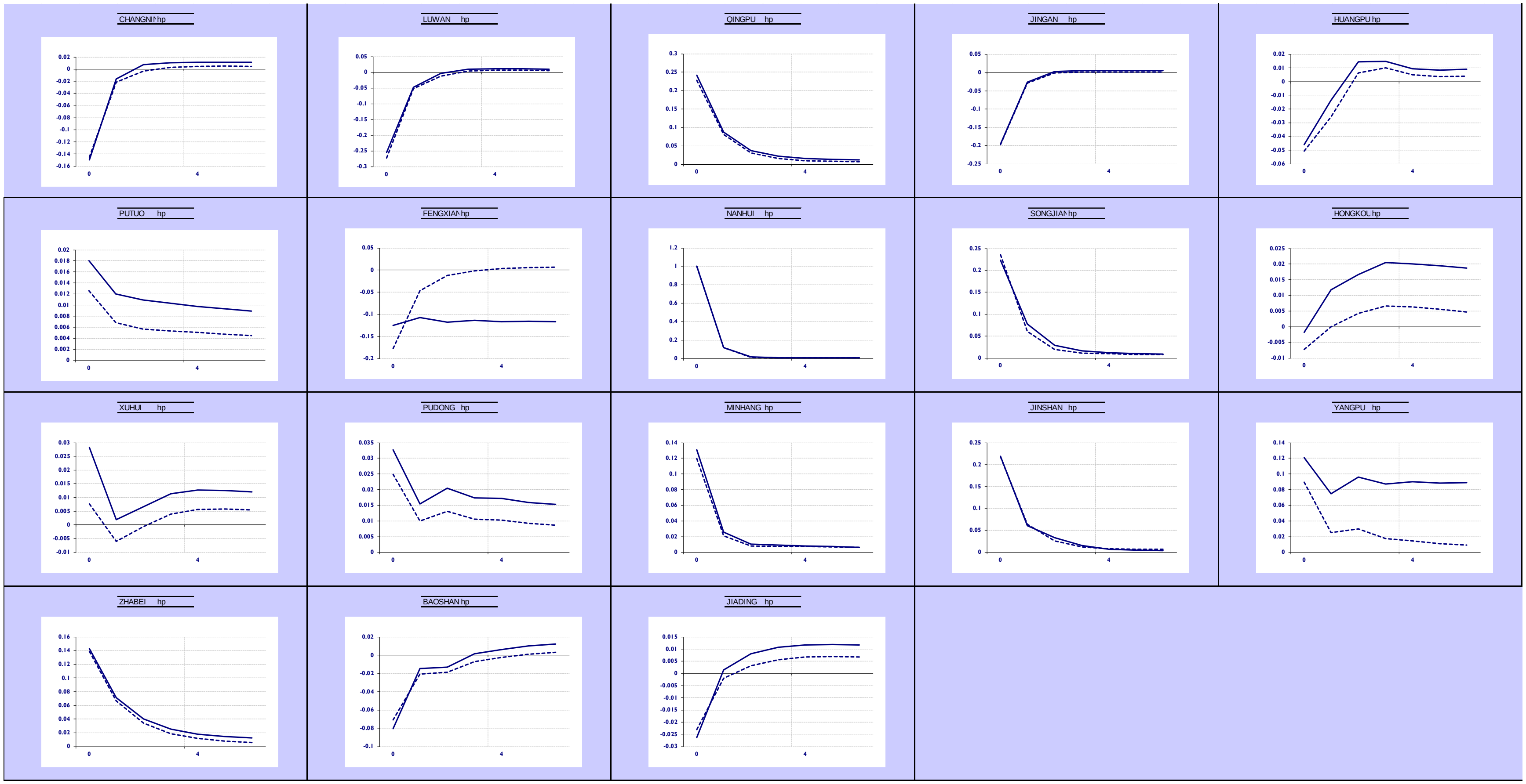
(--- Dec. 2014, — Jan. 2006)

Figure 36 MODEL #2 Counterfactual Analysis: GIRFs of a One Percent Positive Shock to the *Pudong* Housing Price



(--- Dec. 2014, — Jan. 2006)

Figure 37 MODEL #2 Counterfactual Analysis: GIRFs of a One Percent Positive Shock to the *Nanhui* Housing Price



(--- Dec. 2014, — Jan. 2006)

Appendix E

STATISTICAL RESULTS OF MODEL #3

Table 48 MODEL #3: Structural Stability Tests at the 5% Significance Level

PK_{sub}

District	CHANGNING	LUWAN	QINGPU	JING'AN	HUANGPU	PUTUO	FENGXIAN	NANHUI	SONGJIANG
Crit. Val.	0.73	0.84	0.66	0.79	0.74	0.58	0.90	0.60	0.63
hp	0.78*	0.58	0.62	0.56	0.42	0.51	0.52	0.46	0.63

District	HONGKOU	XUHUI	PUDONG	MINHANG	JINSHAN	YANGPU	ZHABEI	BAOSHAN	JIADING	CHONGMING
Crit. Val.	0.62	0.66	1.03	0.59	0.60	1.01	1.15	0.89	0.58	1.22
hp	0.39	0.57	0.63	0.47	0.37	0.61	0.41	0.49	0.44	0.45

*Statistically Significant at the 5 percent level

PK_{msq}

District	HONGKOU	XUHUI	PUDONG	MINHANG	JINSHAN	YANGPU	ZHABEI	BAOSHAN	JIADING	CHONGMING
Crit. Val.	0.07	0.07	0.23	0.06	0.05	0.25	0.36	0.18	0.04	0.38
hp	0.02	0.05	0.05	0.04	0.02	0.07	0.04	0.04	0.03	0.03

District	HONGKOU	XUHUI	PUDONG	MINHANG	JINSHAN	YANGPU	ZHABEI	BAOSHAN	JIADING	CHONGMING
Crit. Val.	0.07	0.07	0.23	0.06	0.05	0.25	0.36	0.18	0.04	0.38
hp	0.02	0.05	0.05	0.04	0.02	0.07	0.04	0.04	0.03	0.03

*Statistically Significant at the 5 percent level

Nyblom Test $\mathfrak{H}$

District	CHANGNING	LUWAN	QINGPU	JING'AN	HUANGPU	PUTUO	FENGXIAN	NANHUI	SONGJIANG
Crit. Val.	2.28	3.11	2.08	2.45	1.99	1.85	2.27	2.11	2.06
hp	1.40	1.17	0.64	1.04	1.18	1.02	0.89	0.85	0.72

District	HONGKOU	XUHUI	PUDONG	MINHANG	JINSHAN	YANGPU	ZHABEI	BAOSHAN	JIADING	CHONGMING
Crit. Val.	2.12	2.03	2.30	2.23	3.03	2.15	2.31	2.08	3.09	2.59
hp	0.66	0.67	0.96	0.76	2.07	1.39	1.58	1.09	2.36	0.73

*Statistically Significant at the 5 percent level

Robust QLR

District	CHANGNING	LUWAN	QINGPU	JING'AN	HUANGPU	PUTUO	FENGXIAN	NANHUI	SONGJIANG
Crit. Val.	20.58	224.69	21.09	22.42	21.75	20.75	22.56	22.04	21.03
hp	21.34*	51.03	9.93	14.75	15.11	12.70	13.63	10.64	19.89

District	HONGKOU	XUHUI	PUDONG	MINHANG	JINSHAN	YANGPU	ZHABEI	BAOSHAN	JIADING	CHONGMING
Crit. Val.	21.71	21.25	22.47	20.80	234.01	23.33	23.61	21.09	192.55	23.69
hp	12.96	13.66	18.09	13.87	28.98	23.81*	18.00	14.01	37.94	12.09

*Statistically Significant at the 5 percent level

Table 49 MODEL #3: Unit Root Tests for the Domestic Variables

Variables	*5% Crit. Val.*	*CHANGNING*	*LUWAN*	*QINGPU*	*JING'AN*	*HUANGPU*	*PUTUO*	*JIADING*
hp (with trend)	-3.45	−3.81*	−4.69*	-3.32	−6.10*	-1.98	-2.82	-1.73
Dhp	-2.89	-9.43	-7.26	-6.62	-9.72	-10.02	-8.42	-10.62

Variables	*5% Crit. Val*	*HONGKOU*	*XUHUI*	*PUDONG*	*MINHANG*	*JINSHAN*	*YANGPU*	*ZHABEI*
hp (with trend)	-3.45	−4.06*	-2.76	-2.26	-1.47	-1.34	-1.56	-2.13
Dhp	-2.89	-8.12	-8.38	-9.18	-8.92	-10.34	-9.97	-6.46

Variables	*5% Crit. Val*	*CHONGMING*	*FENGXIAN*	*NANHUI*	*SONGJIANG*	*BAOSHAN*
hp (with trend)	-3.45	-2.66	-2.48	-1.88	-1.52	-1.04
Dhp	-2.89	-11.07	-11.54	-7.44	-10.32	-10.42

*: Statistically significant at the 5% level

Table 50 MODEL #3: Unit Root Tests for the Foreign Variables

Variables	*5%Crit. Val.*	*CHANGNING*	*LUWAN*	*QINGPU*	*JING'AN*	*HUANGPU*	*PUTUO*
hps (with trend)	-3.45	-2.36	-1.05	-2.07	-2.19	-2.01	-1.73
Dhps	-2.89	-9.17	-5.01	-8.46	-8.09	-6.50	-8.72

Variables	*5% Crit. Val*	*CHONGMING*	*FENGXIAN*	*NANHUI*	*SONGJIANG*	*BAOSHAN*	*JIADING*
hp (with trend)	-3.45	-1.61	-1.72	-2.16	-1.68	-1.43	-1.76
Dhp	-2.89	-7.56	-7.72	-8.49	-7.98	-9.13	-7.67

Variables	*5%Crit. Val.*	*HONGKOU*	*XUHUI*	*PUDONG*	*MINHANG*	*JINSHAN*	*YANGPU*	*ZHABEI*
hps (with trend)	-3.45	-1.83	-2.30	-1.71	-2.02	-2.16	-1.36	-1.68
Dhps	-2.89	-8.11	-9.08	-9.27	-8.13	-7.97	-10.43	-8.96

*: Statistically significant at the 5% level

Table 51 MODEL #3: Unit Root Tests for the Global Variables

Variables	*5% Crit. Val.*	ADF *t-Statistic*
m (with trend)	-3.45	-1.00
Dm	-2.89	-5.13
cpi (with trend)	-3.45	-2.60
Dcpi	-2.89	-5.49
ibor (no trend)	-2.89	-3.16
Dibor	-2.89	-9.92
lrh (no trend)	-2.89	-2.35
Dlrh	-2.89	-4.76
tst (no trend)	-3.45	-3.19
Dtst	-2.89	-5.22

Table 52 MODEL #3: The Order of Integration Concluded by ADF Tests at the 5% Significance Level

Domestic and Foreign Variables

Variables	CHANGNING	LUWAN	QINGPU	JING'AN	HUANGPU	PUTUO	FENGXIAN
Domestic Var.	*TS*	*TS*	*I(1)*	*TS*	*I(1)*	*I(1)*	*I(1)*
Foreign Var.	*I(1)*	*I(1)*	*I(1)*	*I(1)*	*I(1)*	*I(1)*	*I(1)*

Variables	HONGKOU	XUHUI	PUDONG	MINHANG	JINSHAN	YANGPU	ZHABEI
Domestic Var.	*TS*	*I(1)*	*I(1)*	*I(1)*	*I(1)*	*I(1)*	*I(1)*
Foreign Var.	*I(1)*	*I(1)*	*I(1)*	*I(1)*	*I(1)*	*I(1)*	*I(1)*

Variables	CHONGMING	NANHUI	SONGJIANG	BAOSHAN	JIADING
Domestic Var.	*I(1)*	*I(1)*	*I(1)*	*I(1)*	*I(1)*
Foreign Var.	*I(1)*	*I(1)*	*I(1)*	*I(1)*	*I(1)*

Global Variables

Variables	M	CPI	IBOR	lrh	tst
integration	*I(1)*	*I(1)*	*I(0)*	*I(1)*	*I(1)*

Table 53 MODEL #3: Lag Order Selection of the Individual District VARX Models

District	*p*	*q*	*AIC*	*District*	*p*	*q*	*AIC*
CHANGNING	1	1	36.25	*HONGKOU*	1	1	30.84
CHANGNING	1	2	37.76	*HONGKOU*	1	2	27.62
CHANGNING	2	1	35.79	*HONGKOU*	2	1	30.08
CHANGNING	2	2	36.88	*HONGKOU*	2	2	26.96
LUWAN	1	1	-4.58	*XUHUI*	1	1	55.64
LUWAN	1	2	-3.26	*XUHUI*	1	2	52.04
LUWAN	2	1	-5.58	*XUHUI*	2	1	54.77
LUWAN	2	2	-4.25	*XUHUI*	2	2	51.32
QINGPU	1	1	65.77	*PUDONG*	1	1	62.21
QINGPU	1	2	63.10	*PUDONG*	1	2	59.20
QINGPU	2	1	64.84	*PUDONG*	2	1	65.53
QINGPU	2	2	62.26	*PUDONG*	2	2	61.29
JING'AN	1	1	31.51	*MINHANG*	1	1	66.49
JING'AN	1	2	30.11	*MINHANG*	1	2	62.95
JING'AN	2	1	30.58	*MINHANG*	2	1	65.50
JING'AN	2	2	29.11	*MINHANG*	*2*	*2*	62.28
HUANGPU	1	1	-10.49	*JINSHAN*	*1*	*1*	112.59
HUANGPU	1	2	-14.93	*JINSHAN*	*1*	*2*	116.67
HUANGPU	2	1	-9.80	*JINSHAN*	*2*	*1*	111.63
HUANGPU	2	2	-14.13	*JINSHAN*	*2*	*2*	116.08
PUTUO	1	1	87.83	*YANGPU*	*1*	*1*	79.24
PUTUO	1	2	85.15	*YANGPU*	*1*	*2*	76.46
PUTUO	2	1	87.41	*YANGPU*	*2*	*1*	80.67
PUTUO	2	2	84.61	*YANGPU*	*2*	*2*	76.89

(*continued*)

District	*p*	*q*	*AIC*
FENGXIAN	1	1	35.82
FENGXIAN	1	2	38.01
FENGXIAN	2	1	37.81
FENGXIAN	2	2	39.91
NANHUI	1	1	72.02
NANHUI	1	2	72.03
NANHUI	2	1	71.03
NANHUI	2	2	71.61
SONGJIANG	1	1	66.48
SONGJIANG	1	2	65.18
SONGJIANG	2	1	65.53
SONGJIANG	2	2	64.55
CHONGMING	1	1	3.77
CHONGMING	1	2	0.08
CHONGMING	2	1	3.83
CHONGMING	2	2	-0.19

District	*p*	*q*	*AIC*
ZHABEI	*1*	*1*	96.93
ZHABEI	*1*	*2*	91.26
ZHABEI	*2*	*1*	96.21
ZHABEI	2	2	90.61
BAOSHAN	*2*	*2*	121.39
BAOSHAN	*1*	*1*	119.57
BAOSHAN	*1*	*2*	123.29
BAOSHAN	*2*	*1*	121.22
JIADING	*2*	*2*	104.96
JIADING	*1*	*1*	102.91
JIADING	*1*	*2*	104.15
JIADING	*2*	*1*	102.20

Table 54 MODEL #3: Lag Orders of Individual District VARX Models and Corresponding Residual Serial Correlation F-Statistics

District	*p*	*q*		*5% Crit. Val.*	*hp*
CHANGNING	1	2	*F(4,77)*	*2.49*	*1.60*
LUWAN	1	2	*F(4,77)*	*2.49*	*0.51*
QINGPU	1	1	*F(4,83)*	*2.48*	*0.86*
JING'AN	1	1	*F(4,83)*	*2.48*	*0.23*
HUANGPU	2	1	*F(4,82)*	*2.48*	*2.32*
PUTUO	1	1	*F(4,83)*	*2.48*	*1.53*
FENGXIAN	2	2	*F(4,76)*	*2.49*	*1.32*
NANHUI	1	1	*F(4,77)*	*2.49*	*1.10*
SONGJIANG	1	1	*F(4,83)*	*2.48*	*1.32*
HONGKOU	1	1	*F(4,83)*	*2.48*	*1.18*
XUHUI	1	1	*F(4,83)*	*2.48*	*0.60*
PUDONG	2	1	*F(4,82)*	*2.48*	*0.69*
MINHANG	1	1	*F(4,83)*	*2.48*	*0.92*
JINSHAN	1	1	*F(4,83)*	*2.48*	2.85*
YANGPU	2	1	*F(4,82)*	*2.48*	*0.60*
ZHABEI	1	1	*F(4,83)*	*2.48*	*1.23*
BAOSHAN	2	1	*F(4,82)*	*2.48*	*1.57*
JIADING	1	1	*F(4,83)*	*2.48*	*1.94*
CHONGMING	2	1	*F(4,82)*	*2.48*	*1.61*

(*p*: lag order of domestic variables, *q*: lag order of foreign variables)

*: Statistically significant at the 5% level

Table 55 MODEL #3: Cointegrating Relationships for the Individual VARX Models

DISTRICT	*RANK*	DISTRICT	*RANK*
CHANGNING	1	*HONGKOU*	1
LUWAN	1	*XUHUI*	1
QINGPU	1	*PUDONG*	1
JING'AN	1	*MINHANG*	1
HUANGPU	1	*JINSHAN*	1
PUTUO	1	*YANGPU*	0
FENGXIAN	0	*ZHABEI*	1
NANHUI	1	*BAOSHAN*	1
SONGJIANG	1	*JIADING*	1
CHONGMING	1		

Table 56 MODEL #3: Johansen's Trace Statistics

District	*5% Critical Val.*	*CHANGNING*	*LUWAN*	*QINGPU*	*JING'AN*	*HUANGPU*	*PUTUO*	*FENGXIAN*
r=0	28.81	57.41	58.66	43.42	55.08	46.43	33.56	28.58*

(*continued*)

District	*5% Critical Val.*	*SONGJIANG*	*HONGKOU*	*XUHUI*	*PUDONG*	*MINHANG*	*JINSHAN*	*YANGPU*
r=0	28.81	59.24	59.87	45.46	31.83	60.56	51.53	19.03*

District	*5% Critical Val.*	*BAOSHAN*	*JIADING*	*CHONGMING*	*NANHUI*	*ZHABEI*
r=0	28.81	33.51	38.04	29.38	63.45	32.76

Table 57 MODEL #3: *F*-Tests for Weak Exogeneity

District	*F test*	*5% Crit. Val.*	*hps*	*m*	*cpi*	*ibor*	*lrh*	*tst*
CHANGNING	F(1,93)	3.94	1.33	6.75*	1.35	0.17	0.00	1.26
LUWAN	F(1,93)	3.94	0.03	0.11	0.67	0.49	0.19	1.26
QINGPU	F(1,93)	3.94	3.01	0.51	0.74	1.10	0.24	0.75
JING'AN	F(1,93)	3.94	5.23*	0.71	0.01	1.02	0.01	0.42
HUANGPU	F(1,93)	3.94	2.14	1.15	0.41	1.35	2.31	0.67
PUTUO	F(1,93)	3.94	2.71	1.01	0.32	0.19	0.32	0.29
FENGXIAN	F(1,93)	3.94	0.17	1.27	3.83	8.16*	2.55	1.36
NANHUI	F(1,93)	3.94	0.61	3.50	1.54	0.20	0.01	0.66
SONGJIANG	F(1,93)	3.94	5.97*	0.20	0.50	0.03	1.27	0.60
HONGKOU	F(1,93)	3.94	0.31	1.86	0.60	0.46	0.71	0.00
XUHUI	F(1,93)	3.94	2.33	0.26	0.23	0.18	1.74	0.45
PUDONG	F(1,93)	3.94	0.11	0.85	1.76	1.19	0.00	0.08
MINHANG	F(1,93)	3.94	0.31	0.25	0.20	0.45	0.01	3.15
JINSHAN	F(1,93)	3.94	1.74	0.45	0.06	0.08	2.30	0.07
YANGPU	F(1,94)	3.95	6.67*	0.33	0.15	0.35	0.47	0.05
ZHABEI	F(1,93)	3.94	0.45	0.09	9.91*	0.00	0.01	0.08
BAOSHAN	F(1,93)	3.94	3.53	2.68	0.84	1.31	0.27	0.79
JIADING	F(1,93)	3.94	1.33	1.82	1.44	3.00	0.10	3.90
CHONGMING	F(1,93)	3.94	0.10	0.48	0.08	0.27	3.64	1.28

*Statistically Significant at the 5 percent level

Table 58 MODEL #3 Average Pairwise Cross-Section Correlations: Variable and Residuals

Variable *hp*

District	$Cor(hp, hp^{*})$	$Cor(\mathrm{d}.hp, \mathrm{d}.hp^{*})$	*VECMX* Residuals*
CHANGNING	0.873	0.009	-0.036
LUWAN	0.719	0.003	-0.066
QINGPU	0.876	0.040	0.031
JING’AN	0.837	0.080	-0.053
HUANGPU	0.862	0.013	-0.026
PUTUO	0.914	0.042	0.002
FENGXIAN	0.847	0.036	-0.033
NANHUI	0.907	0.046	0.035
SONGJIANG	0.901	-0.010	0.008
HONGKOU	0.883	0.007	-0.045
XUHUI	0.903	0.019	-0.003
PUDONG	0.900	0.096	0.010
MINHANG	0.913	0.067	0.013
JINSHAN	0.921	0.060	0.030
YANGPU	0.920	0.087	0.023
ZHABEI	0.911	0.067	0.007
BAOSHAN	0.920	0.023	0.005
JIADING	0.911	0.025	0.029
CHONGMING	0.855	0.056	0.005

Figure 38 Model #3: The GIRFs of a One Percent Housing Price Shock to *Chongming*

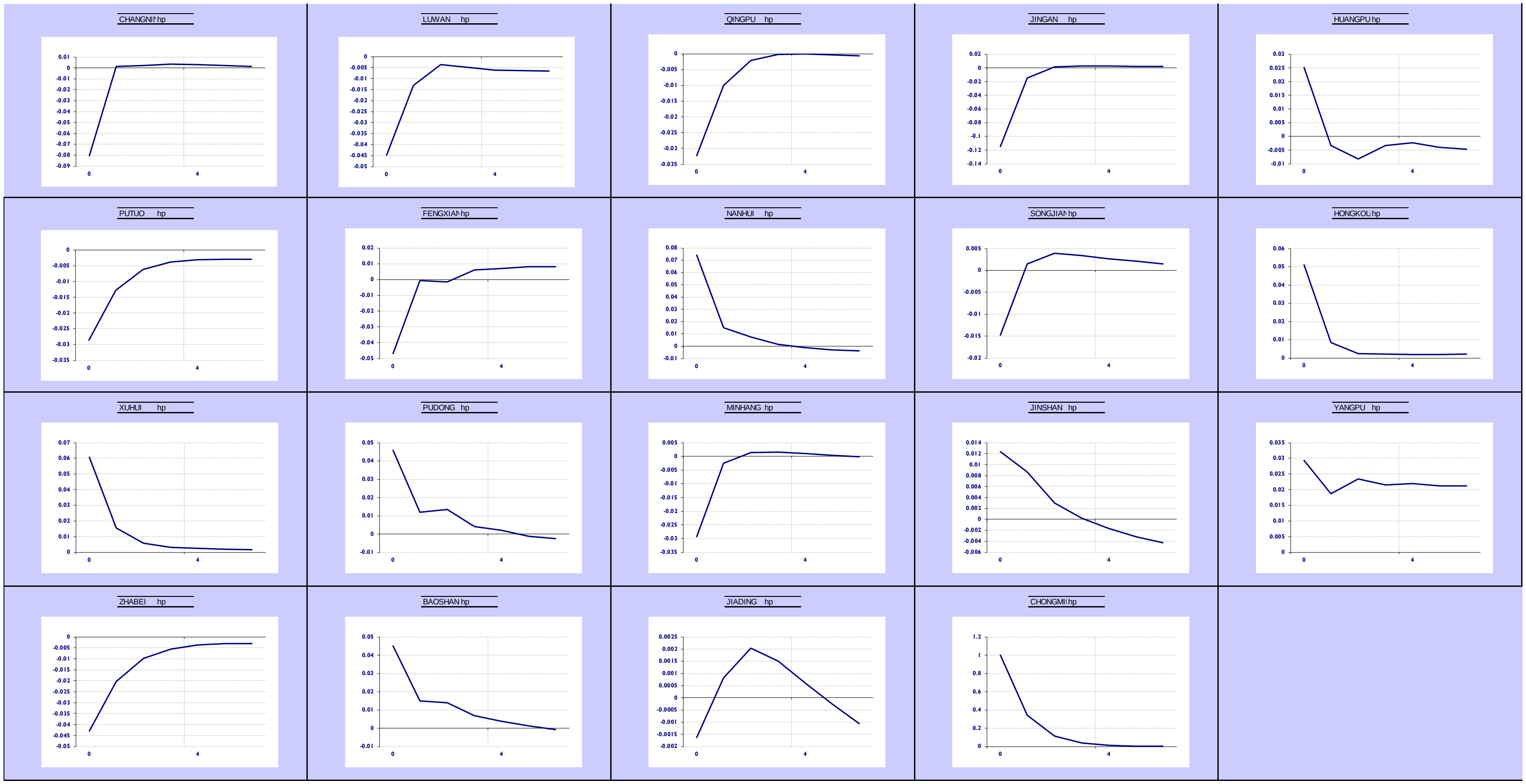
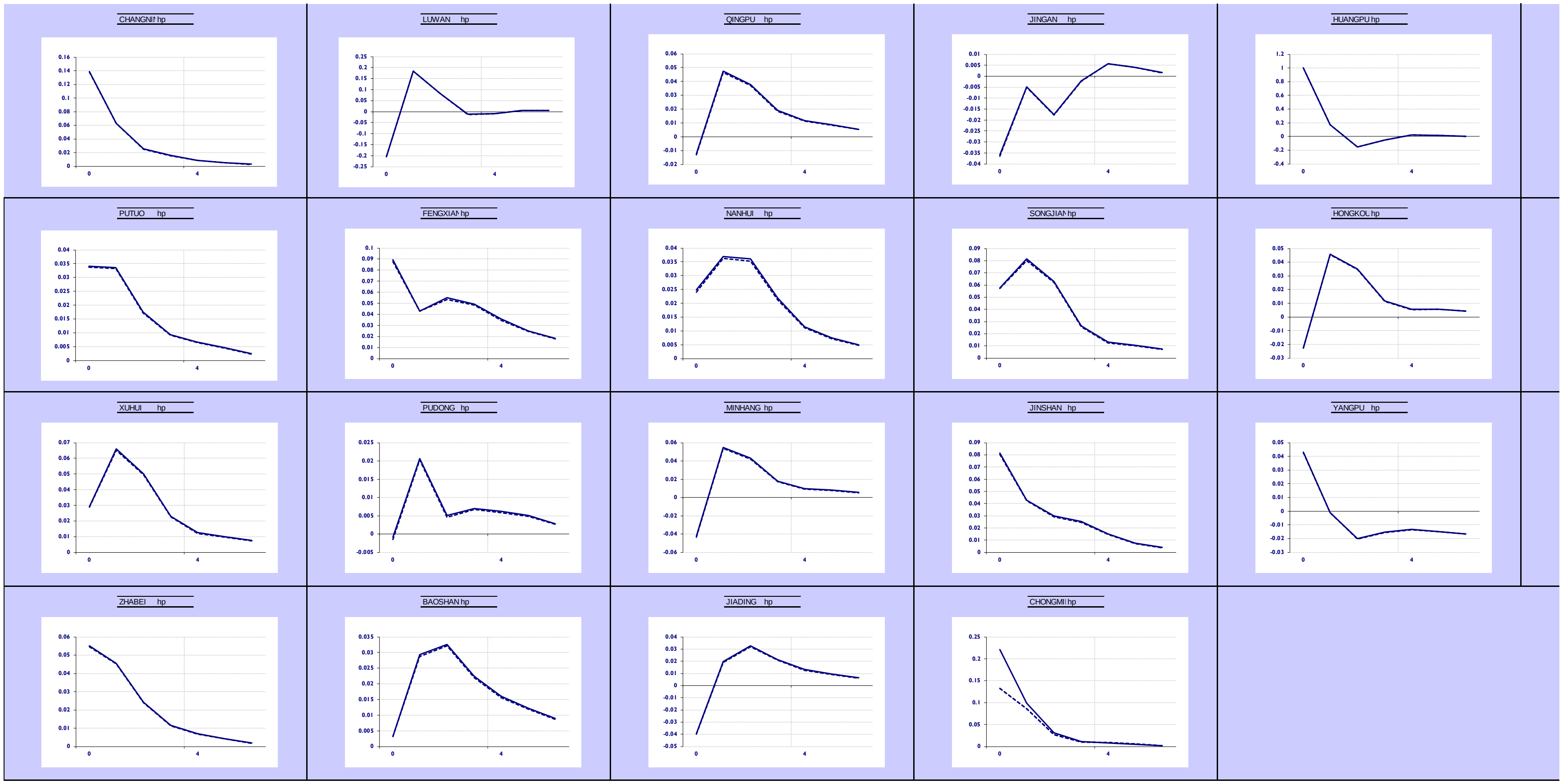
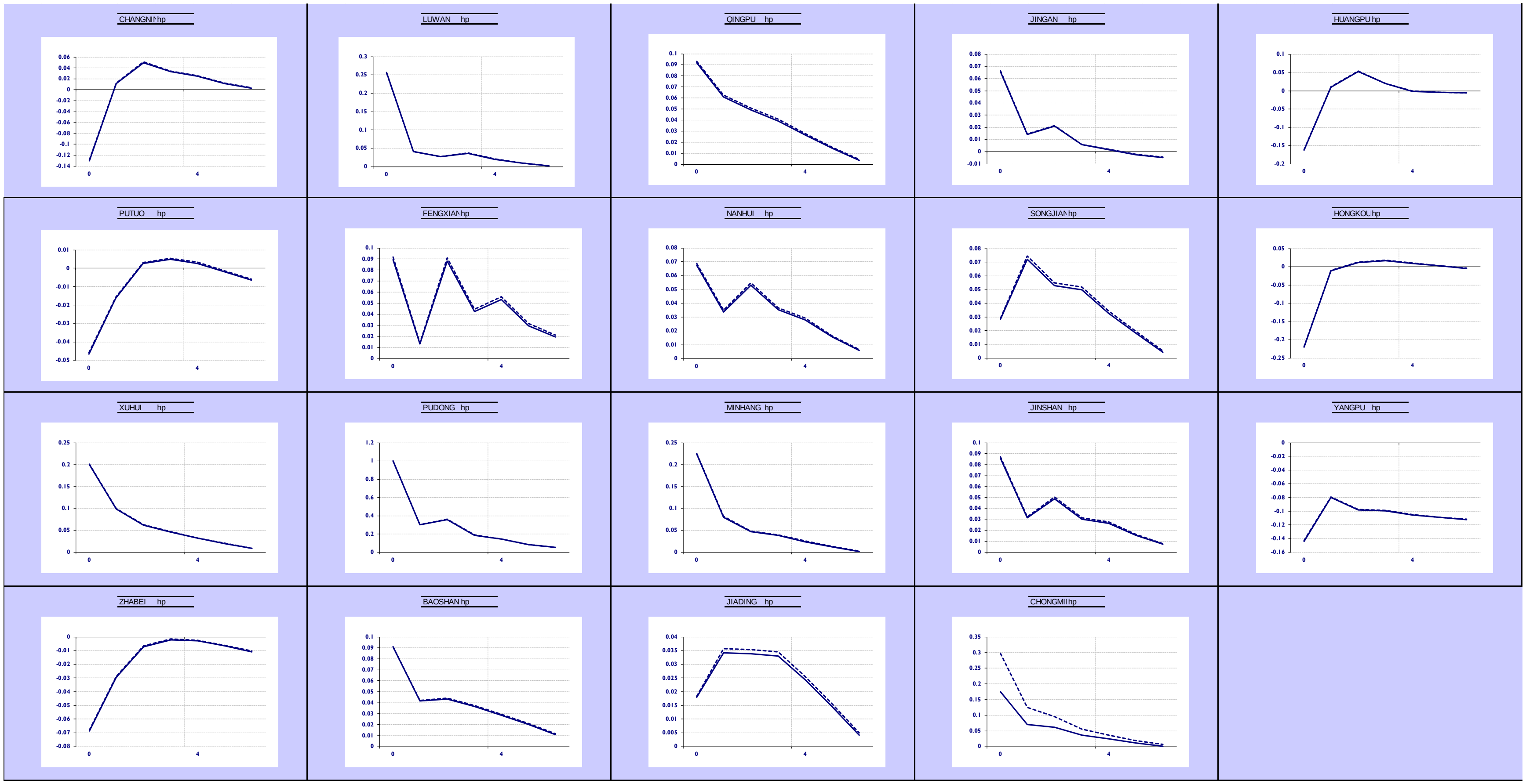


Figure 39 Model #3 Sensitivity Test: a One Percent Housing Price Shock to *Huangpu*



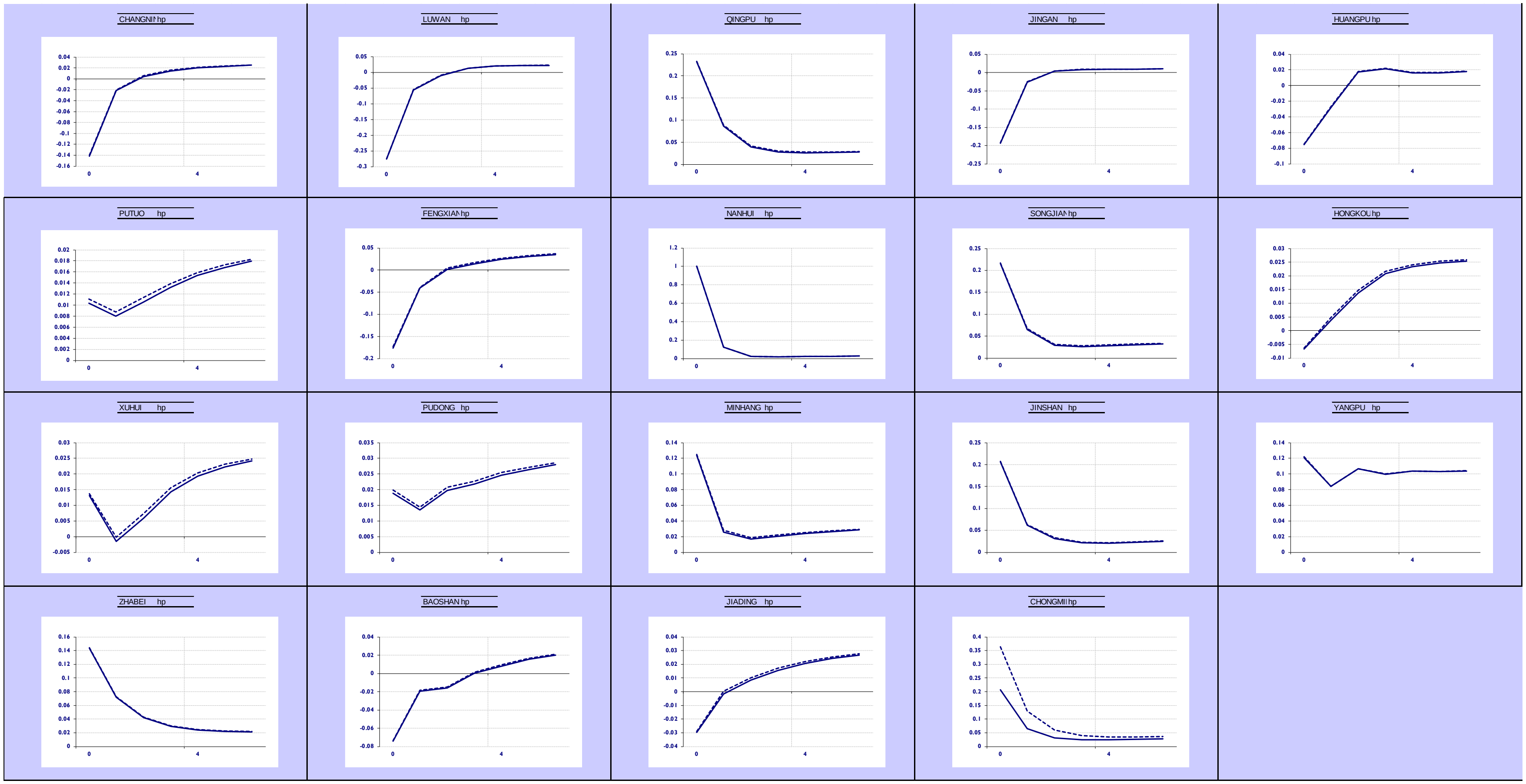
(--- Type I Weight Matrix, —Type II Weight Matrix)

Figure 40 Model #3 Sensitivity Test: a One Percent Housing Price Shock to *Pudong*



(--- Type I Weight Matrix, —Type II Weight Matrix)

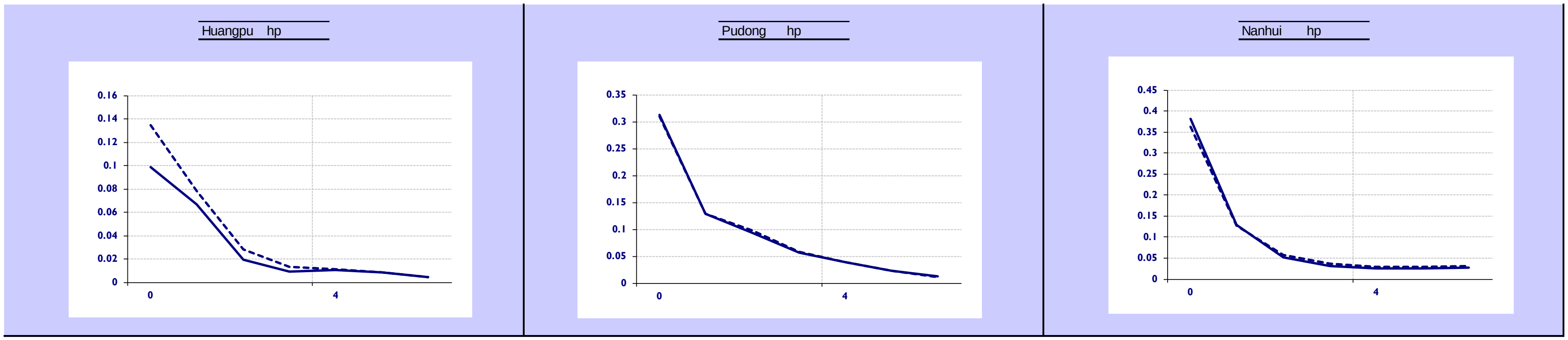
Figure 41 Model #3 Sensitivity Test: a One Percent Housing Price Shock to *Nanhui*



(--- Type I Weight Matrix, —Type II Weight Matrix)

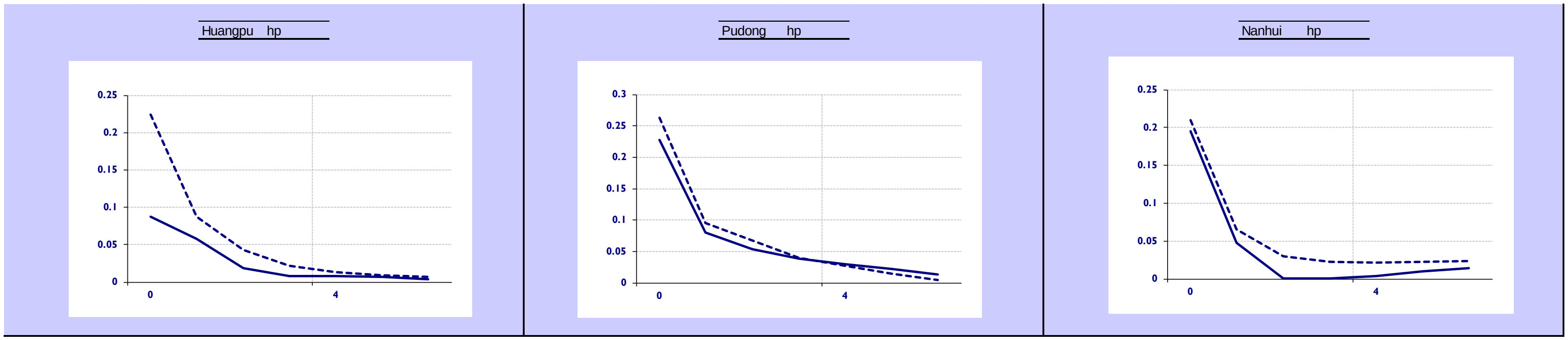
Figure 42 Model #3: Comparing the Impact of Housing Price Shocks Before and After the Bridge Opened

Type I Weight Matrix



(--- Weight of 2009m11, —Weight of 2009m10)

Type II Weight Matrix



(--- Weight of 2009m11, —Weight of 2009m10)

Appendix F

FIXED-WEIGHT FOR THE GVAR MODEL WITH LAND PRICE

DISTRICT	*CENTER*	*QINGPU*	*FENGXIAN*	*NANHUI*	*SONGJIANG*	*PUDONG*	*MINHANG*	*JINSHAN*	*BAOSHAN*	*JIADING*
CENTER	0	0.333333	0	0	0	0.333333	0.2	0	0.5	0.333333
QINGPU	0.2	0	0	0	0.25	0	0	0	0	0.333333
FENGXIAN	0	0	0	0.333333	0.25	0	0.2	0.5	0	0
NANHUI	0	0	0.25	0	0	0.333333	0.2	0	0	0
SONGJIANG	0	0.333333	0.25	0	0	0	0.2	0.5	0	0
PUDONG	0.2	0	0	0.333333	0	0	0.2	0	0	0
MINHANG	0.2	0	0.25	0.333333	0.25	0.333333	0	0	0	0
JINSHAN	0	0	0.25	0	0.25	0	0	0	0	0
BAOSHAN	0.2	0	0	0	0	0	0	0	0	0.333333
JIADING	0.2	0.333333	0	0	0	0	0	0	0.5	0

Appendix G

STATISTICAL RESULTS OF MODEL #4

Table 59 MODEL #4 Unit Root Tests for the Domestic Variables

Variables	*5% Crit. Val.*	*CENTER*	*QINGPU*	*FENGXIAN*	*NANHUI*	*SONGJIANG*
hp (with trend)	-3.45	-2.27	-3.32	-2.48	-1.88	-1.52
Dhp	-2.89	-8.36	-6.62	-11.54	-7.44	-10.32

(continued)

Variables	*5% Crit. Val*	*PUDONG*	*MINHANG*	*JINSHAN*	*BAOSHAN*	*JIADING*
hp (with trend)	3.45	-2.26	-1.47	-1.34	-1.04	-1.73
Dhp	2.89	-9.18	-8.92	-10.34	-10.42	-10.62

(continued)

Variables	*5% Crit. Val.*	*CENTER*	*QINGPU*	*FENGXIAN*	*NANHUI*	*SONGJIANG*
lp (with trend)	-3.45	−4.67	-6.06	-5.64	-5.92	-2.72
lp (no trend)	-2.89	-4.32	-5.56	-5.67	-5.30	-2.05
Dlp	-2.89	-8.31	-9.93	-8.00	-9.27	-9.88

(continued)

Variables	*5% Crit. Val*	*PUDONG*	*MINHANG*	*JINSHAN*	*BAOSHAN*	*JIADING*
lp (with trend)	3.45	-4.10	-5.46	-5.83	-5.43	-3.38
lp (no trend)	-2.89	-3.53	-4.58	-5.75	-5.39	-3.04
Dlp	-2.89	-9.90	-8.79	-9.17	-8.99	-5.48

Table 60 MODEL #4: Unit Root Tests for the Foreign Variables

Variables	*5% Crit. Val.*	*CENTER*	*QINGPU*	*FENGXIAN*	*NANHUI*	*SONGJIANG*
hp (with trend)	-3.45	-1.82	-1.49	-1.25	-1.84	-2.22
Dhp	-2.89	-8.90	-7.01	-9.27	-10.80	-9.40

(continued)

Variables	*5% Crit. Val*	*PUDONG*	*MINHANG*	*JINSHAN*	*BAOSHAN*	*JIADING*
hp (with trend)	-3.45	-1.78	-1.74	-2.05	-1.82	-1.90
Dhp	-2.89	-8.88	-8.28	-10.48	-8.03	-7.67

(continued)

Variables	*5% Crit. Val.*	*CENTER*	*QINGPU*	*FENGXIAN*	*NANHUI*	*SONGJIANG*
lp (with trend)	-3.45	-3.31	-3.62	-4.87	-4.35	-4.95
lp (no trend)	-2.89	-2.50	-2.95	-1.57	-1.65	-2.23
Dlp	-2.89	-8.56	-8.17	-8.81	-8.46	-8.30

(continued)

Variables	*5% Crit. Val*	*PUDONG*	*MINHANG*	*JINSHAN*	*BAOSHAN*	*JIADING*
lp (with trend)	-3.45	-5.27	-4.35	-5.91	-3.37	-4.83
lp (no trend)	-2.89	-3.00	-2.99	-5.61	-2.91	-3.84
Dlp	-2.89	-8.24	-10.71	-9.02	-13.21	-8.21

Table 61 MODEL #4: Unit Root Tests for the Global Variables

Variables	*5% Crit. Val.*	ADF *t-Statistic*
m (with trend)	-3.45	-1.00
Dm	-2.89	-5.13
cpi (with trend)	-3.45	-2.60
Dcpi	-2.89	-5.49
ibor (no trend)	-2.89	-3.16
Dibor	-2.89	-9.92
lrh (no trend)	-2.89	-2.35
Dlrh	-2.89	-4.76
tst (no trend)	-3.45	-3.19
Dtst	-2.89	-5.22

Table 62 MODEL #4: The Order of Integration Concluded by ADF Tests at The 5% Significance Level

Housing Price

Variables	CENTER	QINGPU	FENGXIAN	NANHUI	SONGJIANG
Domestic Var.	*I(1)*	*I(1)*	*I(1)*	*I(1)*	*I(1)*
Foreign Var.	*I(1)*	*I(1)*	*I(1)*	*I(1)*	*I(1)*

Variables	PUDONG	MINHANG	JINSHAN	BAOSHAN	JIADING
Domestic Var.	*I(1)*	*I(1)*	*I(1)*	*I(1)*	*I(1)*
Foreign Var.	*I(1)*	*I(1)*	*I(1)*	*I(1)*	*I(1)*

Land Price

Variables	CENTER	QINGPU	FENGXIAN	NANHUI	SONGJIANG
Domestic Var.	*TS*	*TS*	*TS*	*TS*	*I(1)*
Foreign Var.	*I(1)*	*I(0)*	*I(0)*	*I(0)*	*I(0)*

Variables	PUDONG	MINHANG	JINSHAN	BAOSHAN	JIADING
Domestic Var.	*TS*	*TS*	*TS*	*TS*	*I(1)*
Foreign Var.	*I(0)*	*I(0)*	*I(0)*	*I(1)*	*I(0)*

Global Variables

Variables	M	CPI	IBOR	lrh	tst
integration	*I(1)*	*I(1)*	*I(0)*	*I(1)*	*I(1)*

Table 63 MODEL #4: Lag Order Selection of the Individual District VARX Models – Housing Price Variable

District	*p*	*q*	*AIC*	*District*	*p*	*q*	*AIC*
CENTER	1	1	26.76	*PUDONG*	1	1	-62.66
CENTER	1	2	18.90	*PUDONG*	1	2	-71.36
CENTER	2	1	24.44	*PUDONG*	2	1	-62.47
CENTER	2	2	16.30	*PUDONG*	2	2	-70.22
QINGPU	1	1	-96.73	*MINHANG*	1	1	-72.74
QINGPU	1	2	-99.61	*MINHANG*	1	2	-81.76
QINGPU	2	1	-98.02	*MINHANG*	2	1	-74.85
QINGPU	2	2	-101.01	*MINHANG*	2	2	-83.83
FENGXIAN	1	1	-80.32	*JINSHAN*	1	1	2.28
FENGXIAN	1	2	-81.06	*JINSHAN*	1	2	11.58
FENGXIAN	2	1	-80.72	*JINSHAN*	2	1	1.45
FENGXIAN	2	2	-80.62	*JINSHAN*	2	2	10.41
NANHUI	1	1	-68.72	*BAOSHAN*	1	1	-18.07
NANHUI	1	2	-69.83	*BAOSHAN*	1	2	-17.93
NANHUI	2	1	-70.35	*BAOSHAN*	2	1	-19.82
NANHUI	2	2	-68.81	*BAOSHAN*	*2*	*2*	-20.08
SONGJIANG	1	1	-71.50	*JIADING*	*1*	*1*	-33.48
SONGJIANG	1	2	-76.18	*JIADING*	*1*	*2*	-39.10
SONGJIANG	2	1	-72.55	*JIADING*	*2*	*1*	-36.71
SONGJIANG	2	2	-75.36	*JIADING*	*2*	*2*	-42.80

Table 64 MODEL #4: Lag Orders of Individual District $VARX^*$ Models and Corresponding Residual Serial Correlation F-Statistics

District	*p*	*q*		*5% Crit. Val.*	*hp*	*lp*
CENTER	1	2	*F(4,73)*	*2.50*	*0.51*	*1.95*
QINGPU	1	2	*F(4,73)*	*2.50*	*0.53*	*1.18*
FENGXIAN	1	1	*F(4,80)*	*2.49*	*0.74*	*1.61*
NANHUI	1	1	*F(4,80)*	*2.49*	*0.69*	*0.10*
SONGJIANG	2	1	*F(4,78)*	*2.49*	*1.52*	*0.34*
PUDONG	1	1	*F(4,80)*	*2.49*	2.83^*	*0.41*
MINHANG	2	2	*F(4,71)*	*2.50*	*0.89*	*0.59*
JINSHAN	1	1	*F(4,80)*	*2.49*	*2.07*	*1.51*
BAOSHAN	1	1	*F(4,80)*	*2.49*	*2.25*	*1.00*
JIADING	1	1	*F(4,80)*	*2.49*	4.03^*	*0.58*

(*p*: lag order of domestic variables, *q*: lag order of foreign variables)

*: Statistically significant at the 5% level

Table 65 MODEL #4: Cointegrating Relationships for the Individual VARX Models

DISTRICT	*RANK*
CENTER	2
QINGPU	2
FENGXIAN	2
NANHUI	2
SONGJIANG	2
PUDONG	1
MINHANG	2
JINSHAN	2
BAOSHAN	2
JIADING	2

Table 66 MODEL #4: Johansen's Trace Statistics

District	*5% Critical Val.*	*CENTER*	*QINGPU*	*FENGXIAN*	*NANHUI*	*SONGJIANG*
r=0	60.22	130.32	126.06	118.16	127.93	133.87
r=1	31.35	53.10	50.02	54.97	54.01	61.84

(*continued*)

District	*5% Critical Val.*	*PUDONG*	*MINHANG*	*JINSHAN*	*BAOSHAN*	*JIADING*
r=0	60.22	66.26	111.34	113.83	106.80	111.97
r=1	31.35	26.24*	44.26	44.09	33.89	39.97

Table 67 MODEL #4: *F*-Tests for Weak Exogeneity

District	*F test*	*5% Crit. Val.*	*hps*	*lps*	*m*	*cpi*	*ibor*	*lrh*	*tst*
CENTER	F(2,90)	3.10	2.39	0.22	0.11	2.31	2.12	2.05	0.27
QINGPU	F(2,90)	3.10	0.14	2.03	0.14	0.17	0.20	1.78	1.08
FENGXIAN	F(2,90)	3.10	0.95	0.08	0.34	1.64	5.86*	0.30	2.54
NANHUI	F(2,90)	3.10	1.59	0.85	0.55	0.14	0.10	1.30	0.78
SONGJIANG	F(2,90)	3.10	4.25*	0.16	1.21	1.68	1.16	0.15	0.81
PUDONG	F(1,88)	3.95	0.29	0.03	0.07	0.01	1.62	1.05	1.69
MINHANG	F(2,90)	3.10	0.14	2.42	0.06	0.10	1.55	1.58	0.87
JINSHAN	F(2,82)	3.11	0.20	0.20	0.24	1.03	0.89	1.16	1.05
BAOSHAN	F(2,82)	3.11	1.64	1.35	3.48*	0.26	1.00	0.56	0.26
JIADING	F(2,90)	3.10	0.55	0.19	0.52	1.28	0.01	5.22*	1.48

*Statistically Significant at the 5 percent level

Table 68 MODEL #4: Average Pairwise Cross-Section Correlations - Variable and Residuals

Variable *hp*

District	$Cor(hp, hp^*)$	$Cor(\text{d}.hp, \text{d}.hp^*)$	*VECMX* Residuals*
CENTER	0.948	0.035	-0.061
QINGPU	0.910	0.102	0.024
FENGXIAN	0.870	0.016	-0.072
NANHUI	0.930	0.033	-0.004
SONGJIANG	0.932	-0.007	-0.024
PUDONG	0.926	0.122	-0.003
MINHANG	0.937	0.115	-0.011
JINSHAN	0.945	0.059	0.056
BAOSHAN	0.947	0.028	-0.003
JIADING	0.943	0.058	-0.043

Variable *lp*

District	$Cor(lp, lp^*)$	$Cor(\mathrm{d}.lp, \mathrm{d}.lp^*)$	*VECMX* Residuals*
CENTER	0.151	0.080	-0.015
QINGPU	0.178	0.034	-0.027
FENGXIAN	0.127	0.096	-0.039
NANHUI	0.249	0.093	0.017
SONGJIANG	0.272	0.116	-0.009
PUDONG	0.272	0.078	-0.019
MINHANG	0.146	0.041	-0.061
JINSHAN	0.210	0.122	0.034
BAOSHAN	0.200	0.075	0.036
JIADING	0.231	-0.015	-0.028

Table 69 MODEL #4: Structural Stability Tests (Housing Price)

PK_{sub}

District	CENTER	QINGPU	FENGXIAN	NANHUI	SONGJIANG
5% Crit. Val.	0.63	0.62	0.62	0.67	0.64
hp	0.47	0.59	0.76*	0.43	0.43

District	PUDONG	MINHANG	JINSHAN	BAOSHAN	JIADING
5% Crit. Val.	0.82	0.60	0.62	0.63	0.65
hp	0.47	0.60*	0.36	0.36	0.52

*Statistically Significant at the 5 percent level

PK_{msq}

District	CENTER	QINGPU	FENGXIAN	NANHUI	SONGJIANG
5% Crit. Val.	0.07	0.07	0.07	0.07	0.07
hp	0.04	0.05	0.09*	0.04	0.02

District	PUDONG	MINHANG	JINSHAN	BAOSHAN	JIADING
5% Crit. Val.	0.15	0.06	0.07	0.05	0.08
hp	0.04	0.05	0.02	0.02	0.04

*Statistically Significant at the 5 percent level

Nyblom Test $\mathfrak{H}$

District	CENTER	QINGPU	FENGXIAN	NANHUI	SONGJIANG
5% Crit. Val.	1.95	1.97	1.95	2.02	2.12
hp	0.69	0.73	0.84	0.88	0.67

District	PUDONG	MINHANG	JINSHAN	BAOSHAN	JIADING
5% Crit. Val.	2.02	2.11	3.13	3.15	2.02
hp	1.43	0.82	2.01	1.89	1.22

*Statistically Significant at the 5 percent level

Robust QLR

District	CENTER	QINGPU	FENGXIAN	NANHUI	SONGJIANG
5% Crit. Val.	20.62	19.69	19.63	21.00	20.64
hp	12.85	12.27	14.93	13.55	18.13

District	PUDONG	MINHANG	JINSHAN	BAOSHAN	JIADING
5% Crit. Val.	22.64	20.15	231.22	241.86	21.33
hp	21.30	12.04	26.65	48.30	15.13

*Statistically Significant at the 5 percent level

Table 70 MODEL #4: Structural Stability Tests (Land Price)

PK_{sub}

District	CENTER	QINGPU	FENGXIAN	NANHUI	SONGJIANG
5% Crit. Val.	0.60	0.69	0.63	0.68	0.64
hp	0.57	0.44	0.39	0.42	0.54

District	PUDONG	MINHANG	JINSHAN	BAOSHAN	JIADING
5% Crit. Val.	1.05	0.61	0.58	0.65	0.67
hp	0.42	0.57	0.42	0.46	0.57

*Statistically Significant at the 5 percent level

PK_{msq}

District	CENTER	QINGPU	FENGXIAN	NANHUI	SONGJIANG
5% Crit. Val.	0.06	0.09	0.07	0.07	0.06
hp	0.06*	0.03	0.02	0.03	0.05

District	PUDONG	MINHANG	JINSHAN	BAOSHAN	JIADING
5% Crit. Val.	0.27	0.07	0.05	0.07	0.06
hp	0.02	0.02	0.02	0.03	0.04

*Statistically Significant at the 5 percent level

Nyblom Test $\mathfrak{H}$

District	CENTER	QINGPU	FENGXIAN	NANHUI	SONGJIANG
5% Crit. Val.	2.00	2.04	2.09	1.83	2.18
hp	1.26	0.73	1.48	1.05	1.38

District	PUDONG	MINHANG	JINSHAN	BAOSHAN	JIADING
5% Crit. Val.	2.16	2.09	3.06	3.14	1.95
hp	1.23	0.77	1.96	1.68	2.53*

*Statistically Significant at the 5 percent level

Robust *QLR*

District	CENTER	QINGPU	FENGXIAN	NANHUI	SONGJIANG
5% Crit. Val.	21.72	21.23	21.05	20.49	22.18
hp	17.25	13.83	18.37	22.18*	15.53

District	PUDONG	MINHANG	JINSHAN	BAOSHAN	JIADING
5% Crit. Val.	21.81	21.87	205.30	107.58	20.53
hp	15.89	14.49	54.76	57.82	26.25*

*Statistically Significant at the 5 percent level

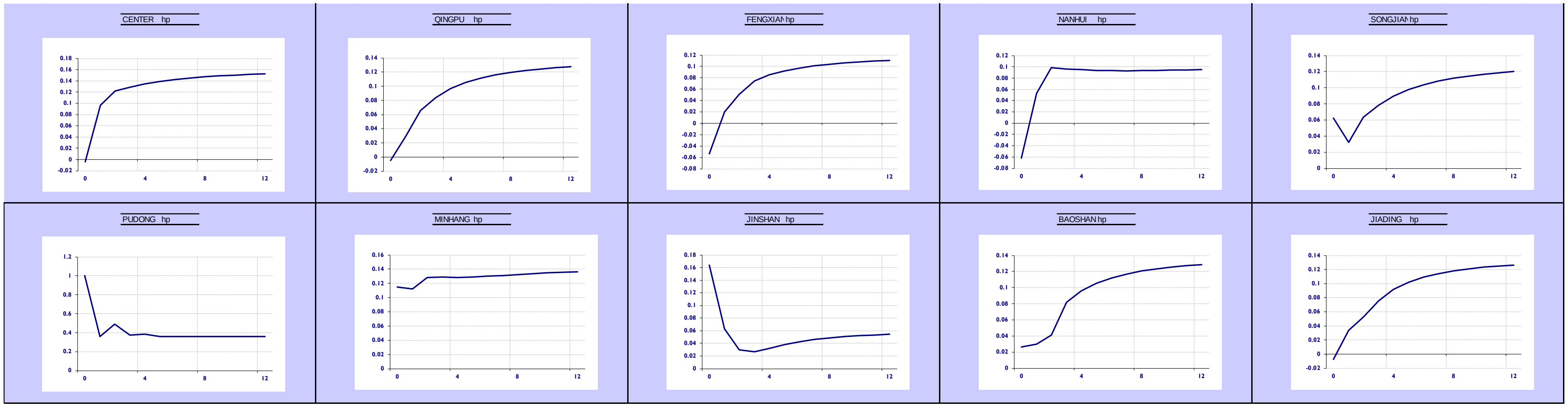
Table 71 MODEL #4: Contemporaneous Effects of Foreign Variables on Domestic Counterparts

District	*hp*	*lp*
CENTER	0.313	-0.013
	(0.103)	(0.101)
QINGPU	0.605	0.156
	(0.184)	(0.181)
FENGXIAN	0.292	0.173
	(0.212)	(0.111)
NANHUI	0.345	0.442
	(0.113)	(0.139)
SONGJIANG	0.256	0.588
	(0.140)	(0.146)
PUDONG	0.501	0.271
	(0.142)	(0.141)
MINHANG	0.615	0.294
	(0.174)	(0.154)
JINSHAN	0.193	0.368
	(0.072)	(0.081)
BAOSHAN	0.361	0.347
	(0.103)	(0.157)
JIADING	0.362	0.245
	(0.127)	(0.124)

*( ) Standard error

Figure 43 MODEL #4: GIRFs of a One Percent Positive Shock to the *Pudong* Housing Price

Effect on Housing Price



Effect on Land Price

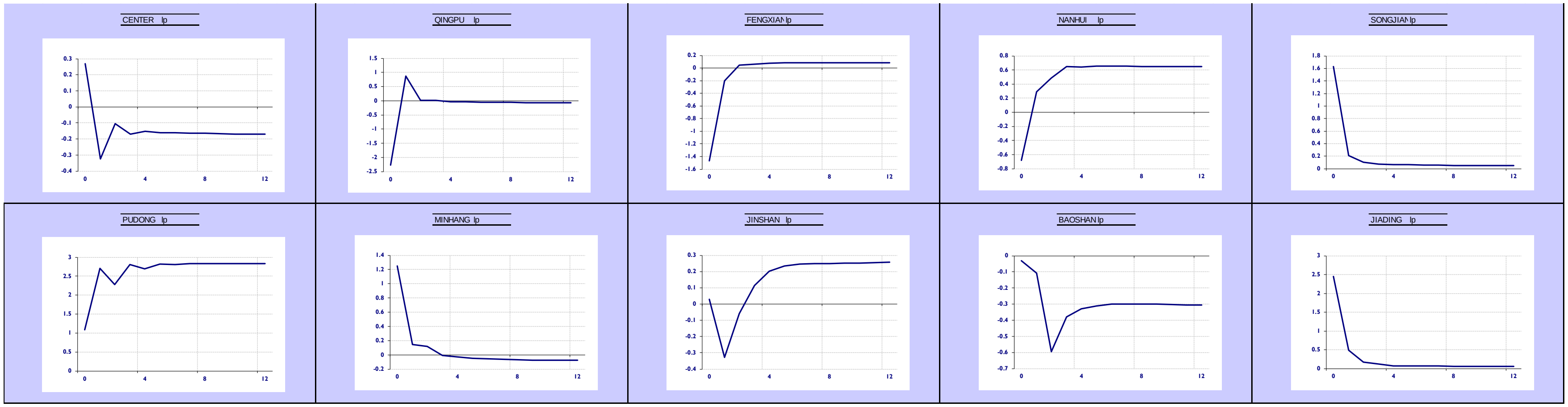
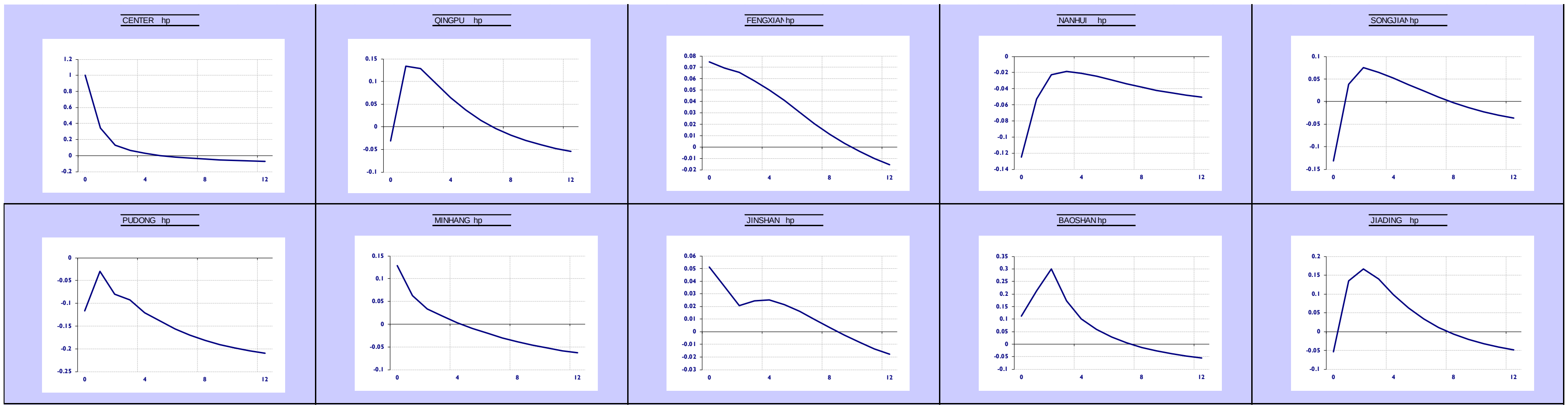


Figure 44 MODEL #4: GIRFs of a One Percent Positive Shock to the *Center* Housing Price

Effect on Housing Price



Effect on Land Price

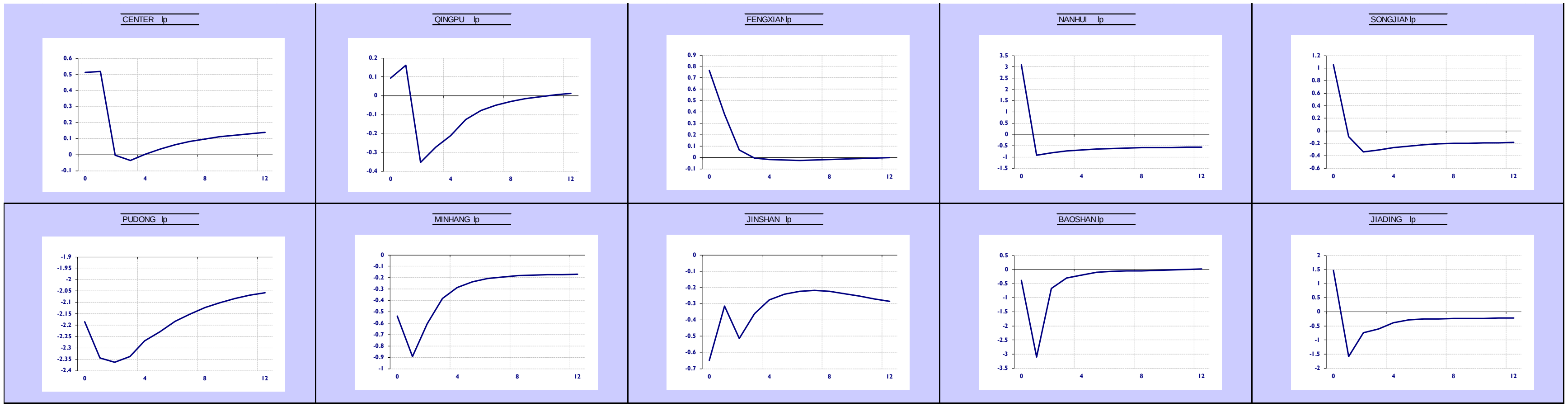
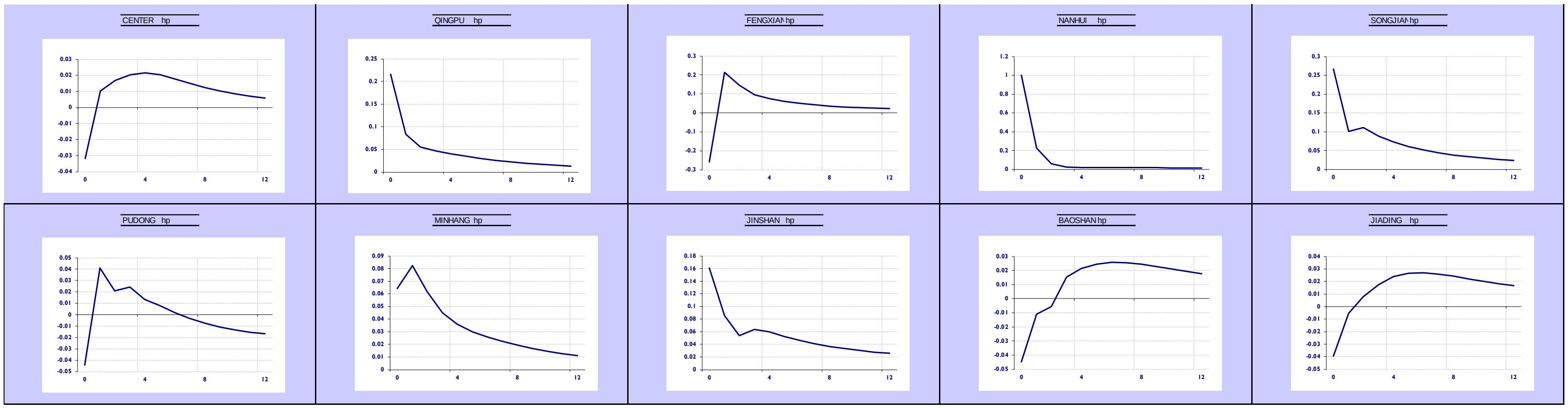


Figure 45 MODEL #4: GIRFs of a One Percent Positive Shock to the *Nanhui* Housing Price

Effect on Housing Price



Effect on Land Price

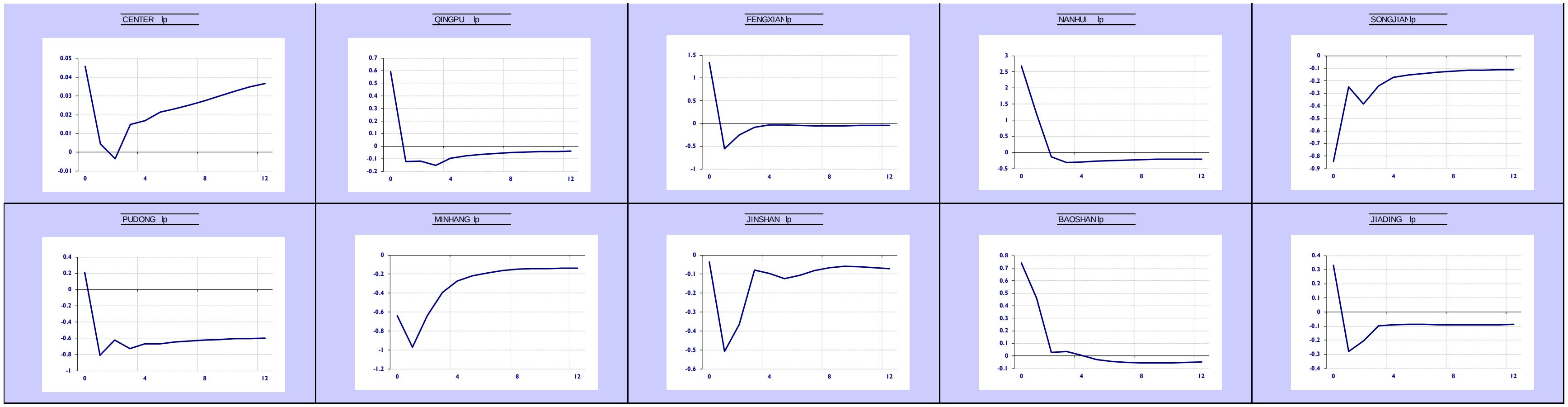
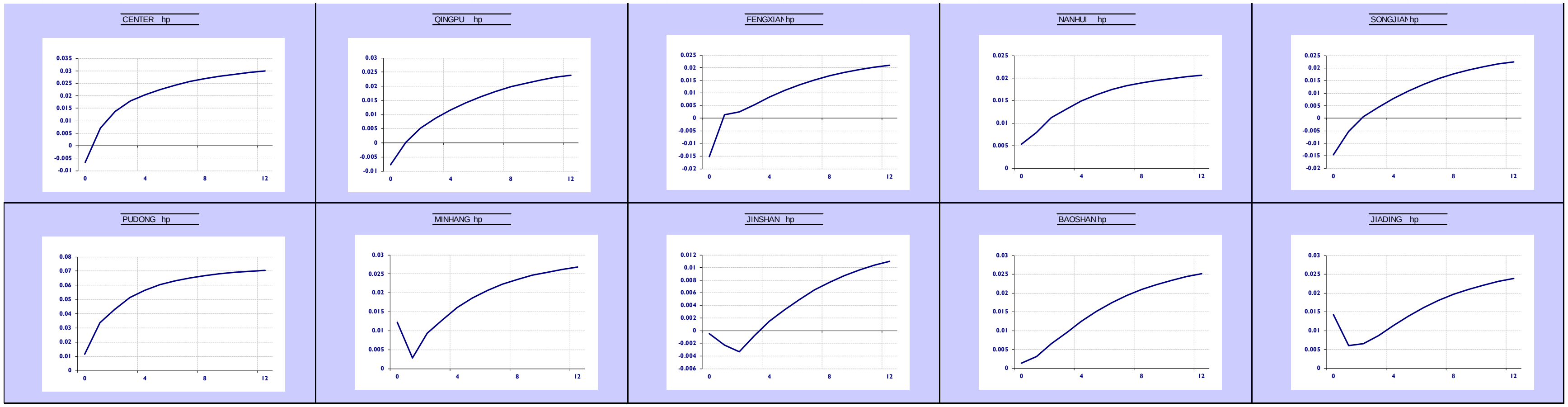


Figure 46 MODEL #4: GIRFs of a One Percent Positive Shock to the *Pudong* Land Price

Effect on Housing Price



Effect on Land Price

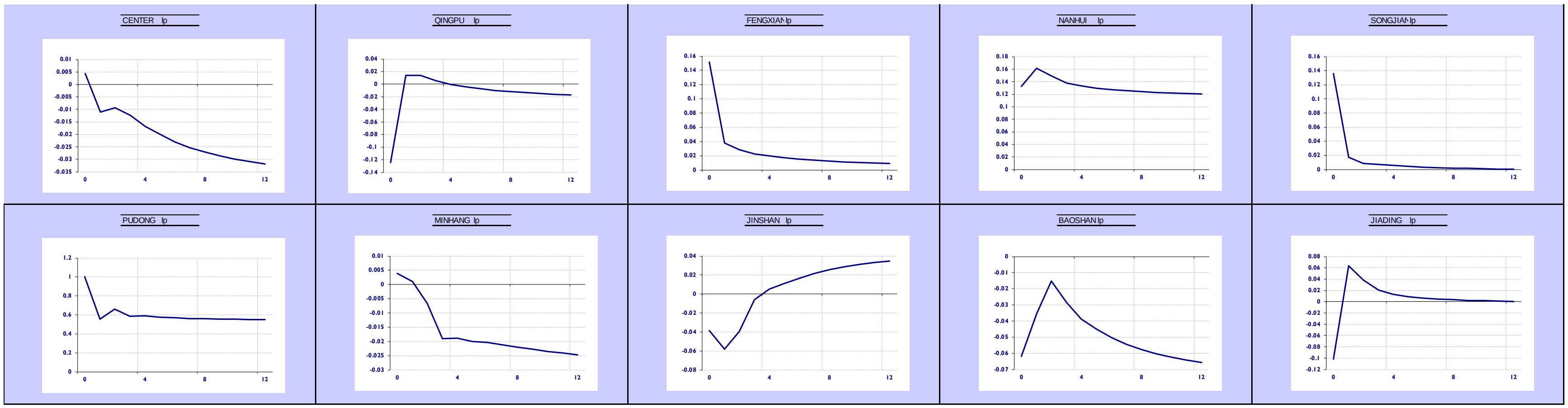
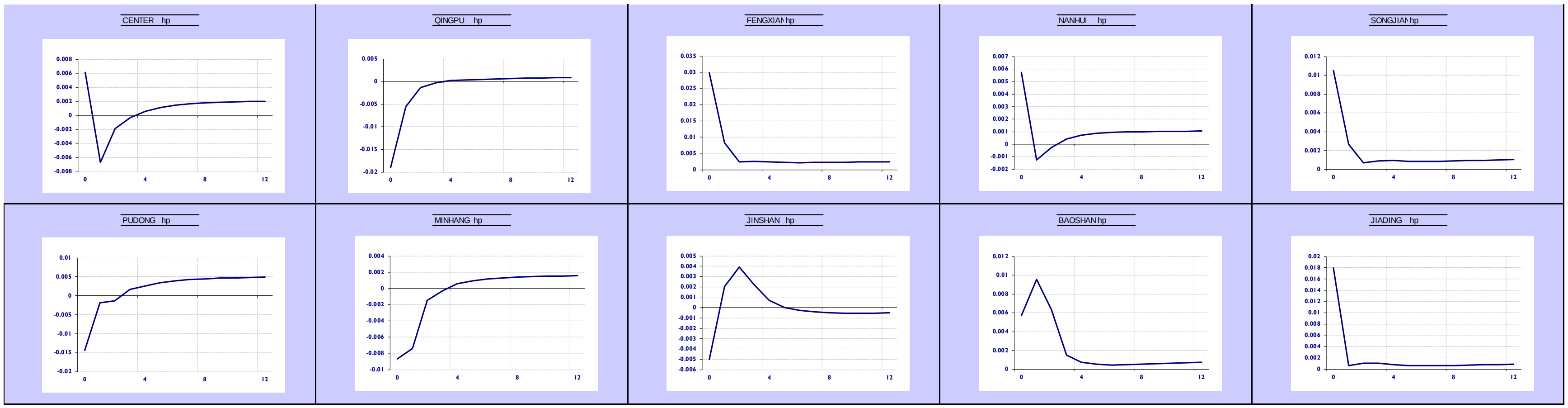


Figure 47 MODEL #4: GIRFs of a One Percent Positive Shock to the *Center* Land Price

Effect on Housing Price



Effect on Land Price

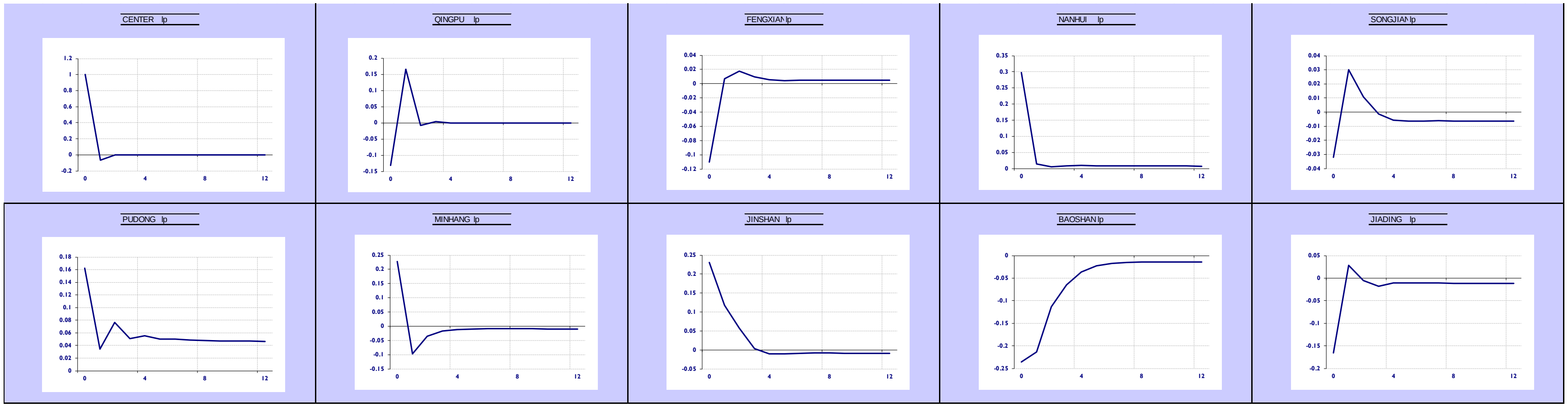
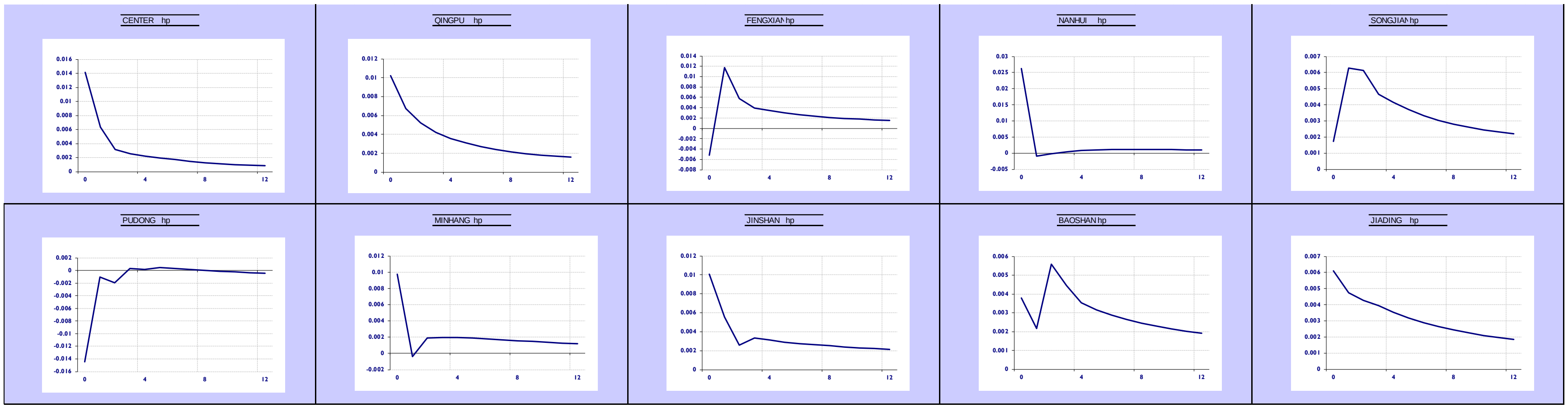
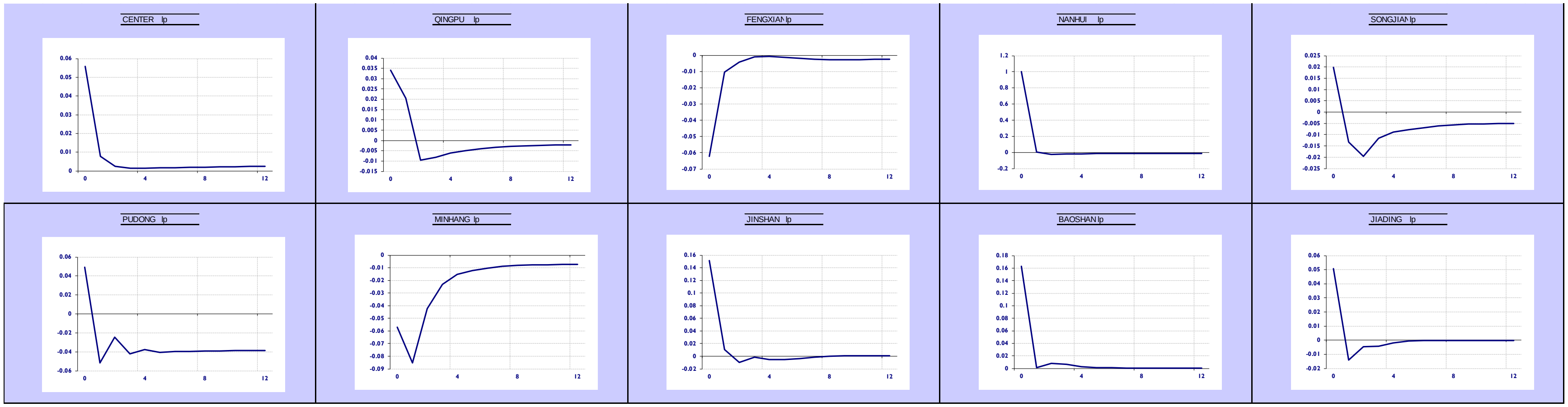


Figure 48 MODEL #4: GIRFs of a One Percent Positive Shock to the *Nanhui* Land Price

Effect on Housing Price



Effect on Land Price



Appendix H

STATISTICAL RESULTS OF MODEL #5

Table 72 MODEL #5: Unit Root Tests for the Domestic Variables

Variables	*5% Crit. Val.*	*CENTER*	*QINGPU*	*FENGXIAN*	*NANHUI*	*SONGJIANG*
hp (with trend)	-3.45	-2.27	-3.32	-2.48	-1.88	-1.52
Dhp	-2.89	-8.36	-6.62	-11.54	-7.44	-10.32

(continued)

Variables	*5% Crit. Val*	*PUDONG*	*MINHANG*	*JINSHAN*	*BAOSHAN*	*JIADING*
hp (with trend)	3.45	-2.26	-1.47	-1.34	-1.04	-1.73
Dhp	2.89	-9.18	-8.92	-10.34	-10.42	-10.62

(continued)

Variables	*5% Crit. Val.*	*CENTER*	*QINGPU*	*FENGXIAN*	*NANHUI*	*SONGJIANG*
lp (with trend)	-3.45	-4.67	-6.06	-5.64	-5.92	-2.72
lp (no trend)	-2.89	-4.32	-5.56	-5.67	-5.30	-2.05
Dlp	-2.89	-8.31	-9.93	-8.00	-9.27	-9.88

(continued)

Variables	*5% Crit. Val*	*PUDONG*	*MINHANG*	*JINSHAN*	*BAOSHAN*	*JIADING*
lp (with trend)	-3.45	-4.10	-5.46	-5.83	-5.43	-3.38
lp (no trend)	-2.89	-3.53	-4.58	-5.75	-5.39	-3.04
Dlp	-2.89	-9.90	-8.79	-9.17	-8.99	-5.48

Table 73 MODEL #5: Unit Root Tests for the Foreign Variables

Variables	*5% Crit. Val.*	*CENTER*	*QINGPU*	*FENGXIAN*	*NANHUI*	*SONGJIANG*
hp (with trend)	-3.45	-1.55	-1.27	-1.39	-1.81	-1.55
Dhp	-2.89	-8.28	-6.89	-7.78	-8.32	-8.03

(continued)

Variables	*5% Crit. Val*	*PUDONG*	*MINHANG*	*JINSHAN*	*BAOSHAN*	*JIADING*
hp (with trend)	3.45	-1.46	-1.56	-1.79	-1.63	-1.43
Dhp	2.89	-6.82	-7.59	-8.14	-7.18	-7.36

(continued)

Variables	*5% Crit. Val.*	*CENTER*	*QINGPU*	*FENGXIAN*	*NANHUI*	*SONGJIANG*
lp (with trend)	-3.45	-3.57	-3.30	-4.06	-3.39	-3.86
lp (no trend)	-2.89	-2.88	-1.37	-1.14	-2.09	-2.68
Dlp	-2.89	-4.58	-8.21	-8.30	-10.61	-8.80

(continued)

Variables	*5% Crit. Val*	*PUDONG*	*MINHANG*	*JINSHAN*	*BAOSHAN*	*JIADING*
lp (with trend)	-3.45	-2.01	-3.95	-3.61	-3.52	-3.94
lp (no trend)	-2.89	-1.38	-2.77	-0.88	-2.03	-3.03
Dlp	-2.89	-8.49	-4.95	-8.14	-10.23	-8.21

Table 74 MODEL #5: Unit Root Tests for the Global Variables

Variables	*5% Crit. Val.*	ADF *t-Statistic*
m (with trend)	-3.45	-1.00
Dm	-2.89	-5.13
cpi (with trend)	-3.45	-2.60
Dcpi	-2.89	-5.49
ibor (no trend)	-2.89	-3.16
Dibor	-2.89	-9.92
lrh (no trend)	-2.89	-2.35
Dlrh	-2.89	-4.76
tst (no trend)	-3.45	-3.19
Dtst	-2.89	-5.22

Table 75 MODEL #5: The Order of Integration Concluded by ADF Tests at the 5% Significance Level

Housing Price

Variables	CENTER	QINGPU	FENGXIAN	NANHUI	SONGJIANG
Domestic Var.	*I(1)*	*I(1)*	*I(1)*	*I(1)*	*I(1)*
Foreign Var.	*I(1)*	*I(1)*	*I(1)*	*I(1)*	*I(1)*

Variables	PUDONG	MINHANG	JINSHAN	BAOSHAN	JIADING
Domestic Var.	*I(1)*	*I(1)*	*I(1)*	*I(1)*	*I(1)*
Foreign Var.	*I(1)*	*I(1)*	*I(1)*	*I(1)*	*I(1)*

Land Price

Variables	CENTER	QINGPU	FENGXIAN	NANHUI	SONGJIANG
Domestic Var.	*TS*	*TS*	*TS*	*TS*	*I(1)*
Foreign Var.	*I(0)*	*I(1)*	*I(0)*	*I(1)*	*I(0)*

Variables	PUDONG	MINHANG	JINSHAN	BAOSHAN	JIADING
Domestic Var.	*TS*	*TS*	*TS*	*TS*	*I(1)*
Foreign Var.	*I(1)*	*I(0)*	*I(0)*	*I(1)*	*I(0)*

Global Variables

Variables	M	CPI	IBOR	lrh	tst
integration	*I(1)*	*I(1)*	*I(0)*	*I(1)*	*I(1)*

Table 76 MODEL #5: Lag Order Selection of the Individual District VARX Models

District	*p*	*q*	*AIC*	*District*	*p*	*q*	*AIC*
CENTER	1	1	30.84	*PUDONG*	1	1	-64.73
CENTER	1	2	24.24	*PUDONG*	1	2	-70.96
CENTER	2	1	28.52	*PUDONG*	2	1	-65.17
CENTER	2	2	22.02	*PUDONG*	2	2	-69.12
QINGPU	1	1	-94.47	*MINHANG*	1	1	-72.74
QINGPU	1	2	-97.26	*MINHANG*	1	2	-81.00
QINGPU	2	1	-96.24	*MINHANG*	2	1	-75.46
QINGPU	2	2	-99.76	*MINHANG*	2	2	-83.56
FENGXIAN	1	1	-80.26	*JINSHAN*	1	1	9.60
FENGXIAN	1	2	-82.56	*JINSHAN*	1	2	12.23
FENGXIAN	2	1	-80.39	*JINSHAN*	2	1	7.68
FENGXIAN	2	2	-82.50	*JINSHAN*	2	2	11.11
NANHUI	1	1	-58.19	*BAOSHAN*	1	1	-21.96
NANHUI	1	2	-65.01	*BAOSHAN*	1	2	-24.75
NANHUI	2	1	-61.44	*BAOSHAN*	2	1	-22.97
NANHUI	2	2	-66.88	*BAOSHAN*	*2*	*2*	-25.93
SONGJIANG	1	1	-69.33	*JIADING*	*1*	*1*	-22.07
SONGJIANG	1	2	-70.81	*JIADING*	*1*	*2*	-26.10
SONGJIANG	2	1	-70.27	*JIADING*	*2*	*1*	-25.71
SONGJIANG	2	2	-68.38	*JIADING*	*2*	*2*	-28.68

Table 77 MODEL #5: Lag Orders of Individual District VARX Models and Corresponding Residual Serial Correlation F-Statistics

District	*p*	*q*		*5% Crit. Val.*	*hp*	*lp*
CENTER	1	1	*F(4,80)*	*2.49*	*0.48*	*0.57*
QINGPU	1	1	*F(4,80)*	*2.49*	*0.74*	*1.00*
FENGXIAN	1	1	*F(4,80)*	*2.49*	*0.58*	*2.18*
NANHUI	1	1	*F(4,80)*	*2.49*	*0.80*	*0.40*
SONGJIANG	2	2	*F(4,71)*	*2.50*	*0.83*	*0.20*
PUDONG	1	1	*F(4,80)*	*2.49*	*1.97*	*0.34*
MINHANG	1	1	*F(4,80)*	*2.49*	*0.10*	*1.20*
JINSHAN	1	1	*F(4,80)*	*2.49*	*2.00*	*1.17*
BAOSHAN	1	1	*F(4,80)*	*2.49*	*1.02*	*1.03*
JIADING	1	1	*F(4,80)*	*2.49*	*1.64*	*0.94*

(*p*: lag order of domestic variables, *q*: lag order of foreign variables)

*: Statistically significant at the 5% level

Table 78 MODEL #5: Cointegrating Relationships for the Individual VARX Models

DISTRICT	*RANK*
CENTER	2
QINGPU	2
FENGXIAN	2
NANHUI	2
SONGJIANG	2
PUDONG	2
MINHANG	2
JINSHAN	2
BAOSHAN	2
JIADING	2

Table 79 MODEL #5: Johansen's Trace Statistics

District	*5% Critical Val.*	*CENTER*	*QINGPU*	*FENGXIAN*	*NANHUI*	*SONGJIANG*
r=0	60.22	140.93	130.73	118.24	145.97	119.65
r=1	31.35	65.20	52.44	52.21	62.39	41.28

(*continued*)

District	*5% Critical Val.*	*PUDONG*	*MINHANG*	*JINSHAN*	*BAOSHAN*	*JIADING*
r=0	60.22	93.01	110.25	115.18	92.87	121.25
r=1	31.35	36.30	45.07	50.96	36.33	46.27

Table 80 MODEL #5: *F*-Tests for Weak Exogeneity

District	*F test*	*5% Crit. Val.*	*hps*	*lps*	*m*	*cpi*	*ibor*	*lrh*	*tst*
CENTER	F(2,90)	3.10	1.22	0.04	0.10	2.46	2.83	1.75	0.33
QINGPU	F(2,90)	3.10	0.09	1.81	0.01	0.35	0.00	1.10	1.32
FENGXIAN	F(2,90)	3.10	0.11	0.20	0.29	1.97	6.99*	0.47	1.97
NANHUI	F(2,90)	3.10	2.64	0.34	0.59	0.03	0.54	0.94	1.05
SONGJIANG	F(2,80)	3.11	0.13	3.68*	1.05	1.09	1.52	1.09	1.17
PUDONG	F(2,90)	3.10	0.39	0.96	0.25	0.90	0.63	0.40	0.40
MINHANG	F(2,90)	3.10	0.62	1.45	0.07	0.13	1.44	1.09	0.92
JINSHAN	F(2,82)	3.11	0.10	0.27	0.12	1.21	1.60	0.45	0.17
BAOSHAN	F(2,90)	3.10	2.57	0.08	2.92	0.11	3.61*	1.00	0.80
JIADING	F(2,90)	3.10	0.33	1.26	0.28	1.69	0.01	4.90*	1.82

*Statistically Significant at the 5 percent level

Table 81 MODEL #5: Average Pairwise Cross-Section Correlations - Variable and Residuals

Variable *hp*

District	$Cor(hp, hp^*)$	$Cor(\mathrm{d}.hp, \mathrm{d}.hp^*)$	*VECMX Residuals*
CENTER	0.942	0.031	-0.044
QINGPU	0.904	0.089	-0.041
FENGXIAN	0.863	0.018	-0.090
NANHUI	0.927	0.062	-0.013
SONGJIANG	0.925	-0.016	-0.050
PUDONG	0.923	0.118	-0.047
MINHANG	0.932	0.116	-0.033
JINSHAN	0.941	0.054	0.001
BAOSHAN	0.944	0.043	-0.058
JIADING	0.937	0.044	-0.025

Variable *lp*

District	$Cor(hp, hp^*)$	$Cor(\mathrm{d}.hp, \mathrm{d}.hp^*)$	*VECMX Residuals*
CENTER	0.161	0.069	-0.035
QINGPU	0.181	0.031	-0.067
FENGXIAN	0.137	0.091	-0.032
NANHUI	0.262	0.096	-0.002
SONGJIANG	0.269	0.097	-0.042
PUDONG	0.285	0.082	-0.037
MINHANG	0.155	0.036	-0.068
JINSHAN	0.199	0.128	-0.016
BAOSHAN	0.197	0.086	-0.024
JIADING	0.232	-0.014	-0.036

Table 82 MODEL #5: Structural Stability Tests (Housing Price)

PK_{sub}

District	CENTER	QINGPU	FENGXIAN	NANHUI	SONGJIANG
5% Crit. Val.	0.65	0.69	0.62	0.70	0.77
hp	0.50	0.62	0.76*	0.46	0.54

District	PUDONG	MINHANG	JINSHAN	BAOSHAN	JIADING
5% Crit. Val.	0.63	0.65	0.60	0.63	0.62
hp	0.49	0.58	0.33	0.52	0.59

*Statistically Significant at the 5 percent level

PK_{msq}

District	CENTER	QINGPU	FENGXIAN	NANHUI	SONGJIANG
5% Crit. Val.	0.06	0.08	0.06	0.09	0.12
hp	0.05	0.06	0.09*	0.04	0.04

District	PUDONG	MINHANG	JINSHAN	BAOSHAN	JIADING
5% Crit. Val.	0.07	0.08	0.07	0.08	0.07
hp	0.05	0.05	0.02	0.04	0.04

*Statistically Significant at the 5 percent level

Nyblom Test $\mathfrak{H}$

District	CENTER	QINGPU	FENGXIAN	NANHUI	SONGJIANG
5% Crit. Val.	1.88	2.27	2.02	2.04	3.42
hp	0.62	0.53	0.85	0.89	1.39

District	PUDONG	MINHANG	JINSHAN	BAOSHAN	JIADING
5% Crit. Val.	1.95	1.94	2.99	2.18	1.97
hp	1.60	0.78	2.00	1.69	1.39

*Statistically Significant at the 5 percent level

Robust *QLR*

District	CENTER	QINGPU	FENGXIAN	NANHUI	SONGJIANG
5% Crit. Val.	20.85	22.80	21.36	20.84	378.68
hp	13.50	11.04	19.95	15.94	198.08

District	PUDONG	MINHANG	JINSHAN	BAOSHAN	JIADING
5% Crit. Val.	21.10	20.50	212.43	19.83	21.38
hp	18.17	11.65	59.46	19.37	17.22

*Statistically Significant at the 5 percent level

Table 83 MODEL #5: Structural Stability Tests (Land Price)

PK_{sub}

District	CENTER	QINGPU	FENGXIAN	NANHUI	SONGJIANG
5% Crit. Val.	0.59	0.64	0.68	0.66	0.57
hp	0.58	0.45	0.39	0.33	0.49

District	PUDONG	MINHANG	JINSHAN	BAOSHAN	JIADING
5% Crit. Val.	0.63	0.68	0.56	0.57	0.63
hp	0.63	0.59	0.37	0.53	0.48

*Statistically Significant at the 5 percent level

PK_{msq}

District	CENTER	QINGPU	FENGXIAN	NANHUI	SONGJIANG
5% Crit. Val.	0.06	0.08	0.07	0.07	0.05
hp	0.06	0.03	0.02	0.02	0.06*

District	PUDONG	MINHANG	JINSHAN	BAOSHAN	JIADING
5% Crit. Val.	0.06	0.07	0.05	0.05	0.06
hp	0.03	0.02	0.02	0.04	0.03

*Statistically Significant at the 5 percent level

Nyblom Test $\mathfrak{H}$

District	CENTER	QINGPU	FENGXIAN	NANHUI	SONGJIANG
5% Crit. Val.	2.10	2.11	2.10	2.05	3.53
hp	1.41	0.65	1.23	1.05	2.73

District	PUDONG	MINHANG	JINSHAN	BAOSHAN	JIADING
5% Crit. Val.	2.11	2.09	3.05	2.28	1.99
hp	0.81	0.70	1.25	0.68	2.45*

*Statistically Significant at the 5 percent level

Robust *QLR*

District	CENTER	QINGPU	FENGXIAN	NANHUI	SONGJIANG
5% Crit. Val.	21.33	20.39	20.60	21.51	200.28
hp	16.33	12.49	20.98*	16.32	44.26

District	PUDONG	MINHANG	JINSHAN	BAOSHAN	JIADING
5% Crit. Val.	21.77	20.79	220.04	22.30	21.15
hp	16.32	16.87	64.13	13.37	33.65*

*Statistically Significant at the 5 percent level

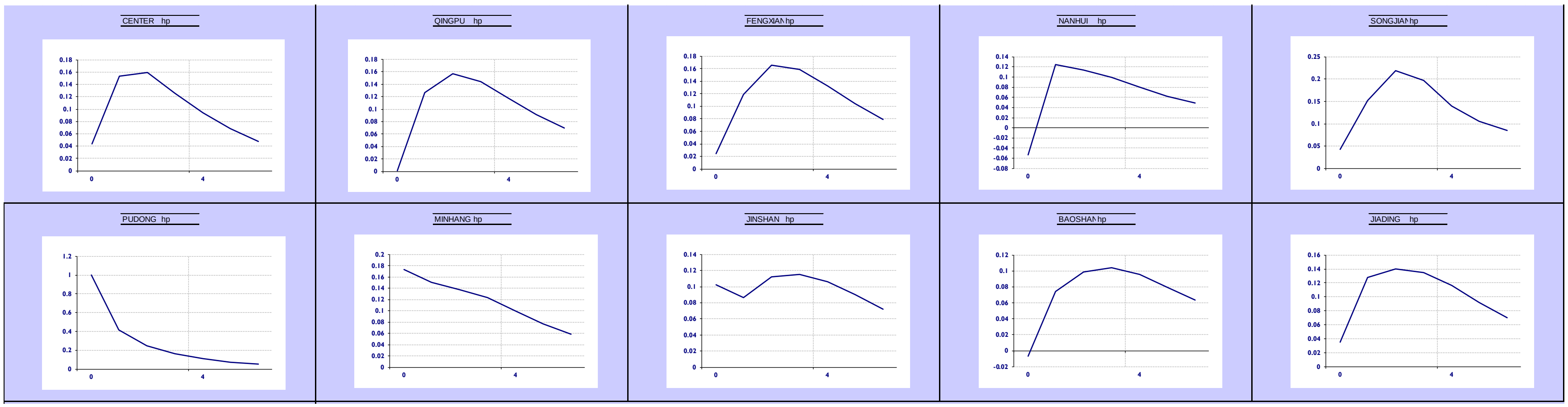
Table 84 MODEL #5: Contemporaneous Effects of Foreign Variables on Domestic Counterparts

District	*hp*	*lp*
CENTER	0.293	0.078
	(0.103)	(0.113)
QINGPU	0.771	0.385
	(0.225)	(0.256)
FENGXIAN	0.498	0.260
	(0.264)	(0.163)
NANHUI	0.645	0.837
	(0.196)	(0.194)
SONGJIANG	0.395	0.431
	(0.198)	(0.227)
PUDONG	0.749	0.580
	(0.254)	(0.187)
MINHANG	0.752	0.226
	(0.210)	(0.198)
JINSHAN	0.426	0.664
	(0.126)	(0.154)
BAOSHAN	0.303	0.584
	(0.098)	(0.231)
JIADING	0.342	0.258
	(0.141)	(0.179)

*( ) Standard error

Figure 49 MODEL #5: GIRFs of a One Percent Positive Shock to the *Pudong* Housing Price

Effects on Housing Price



Effects on Land Price

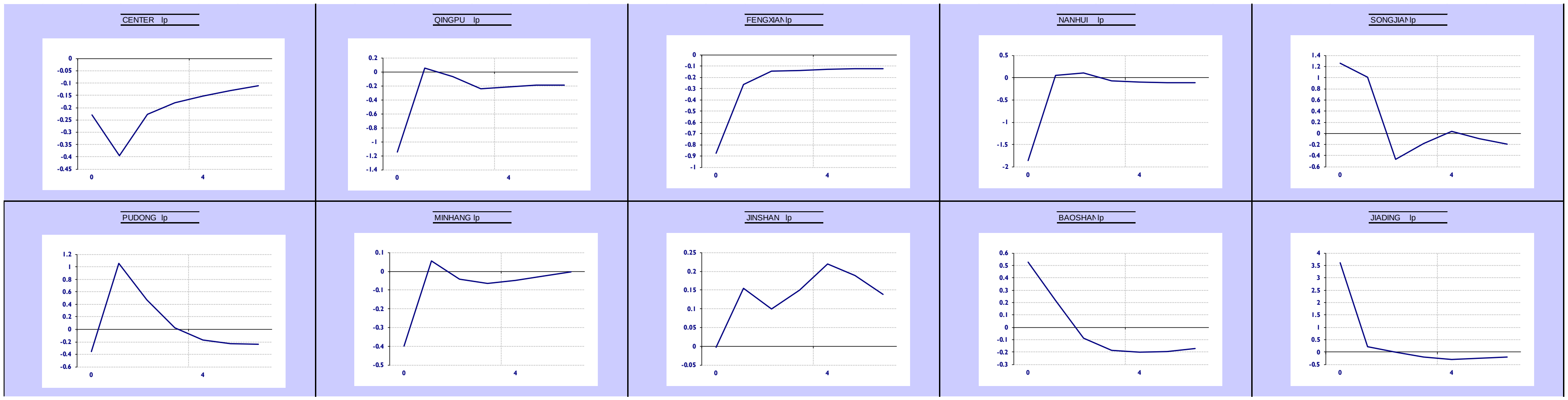
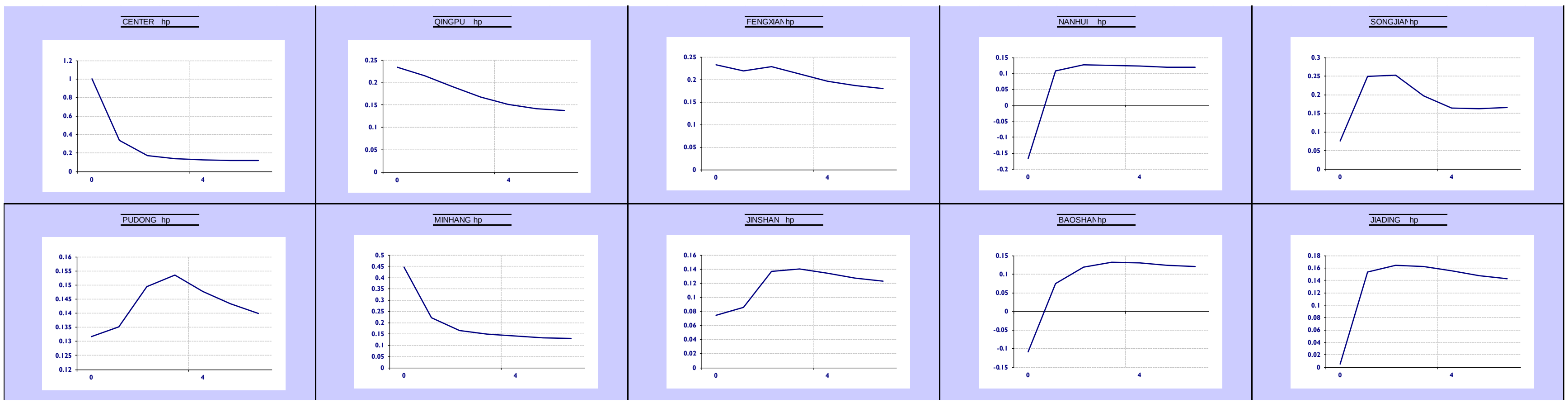


Figure 50 MODEL #5: GIRFs of a One Percent Positive Shock to the *Center* Housing Price

Effects on Housing Price



Effects on Land Price

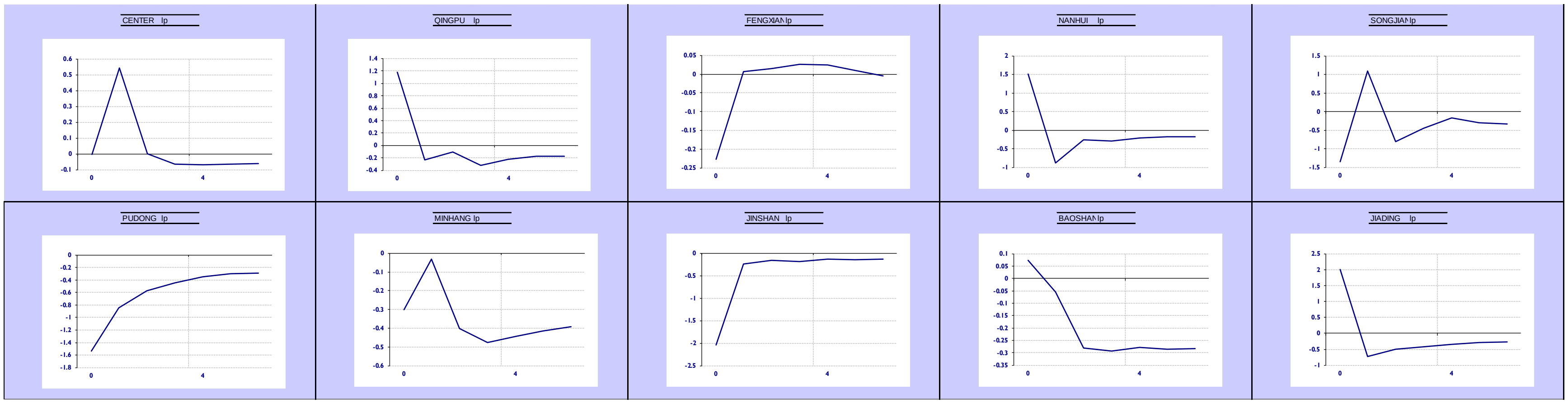
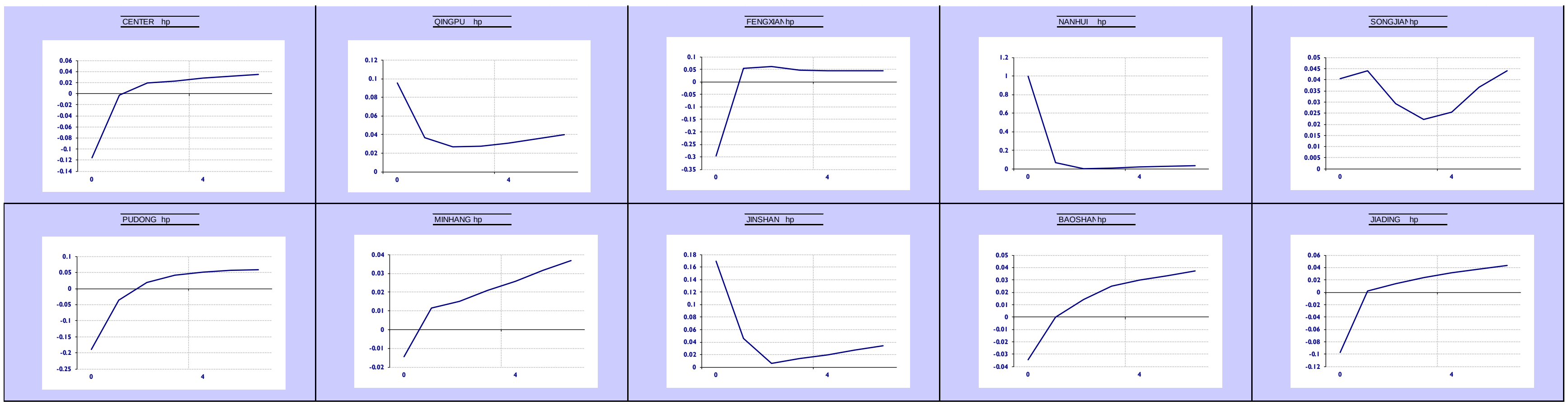


Figure 51 MODEL #5: GIRFs of a One Percent Positive Shock to the *Nanhui* Housing Price

Effects on Housing Price



Effects on Land Price

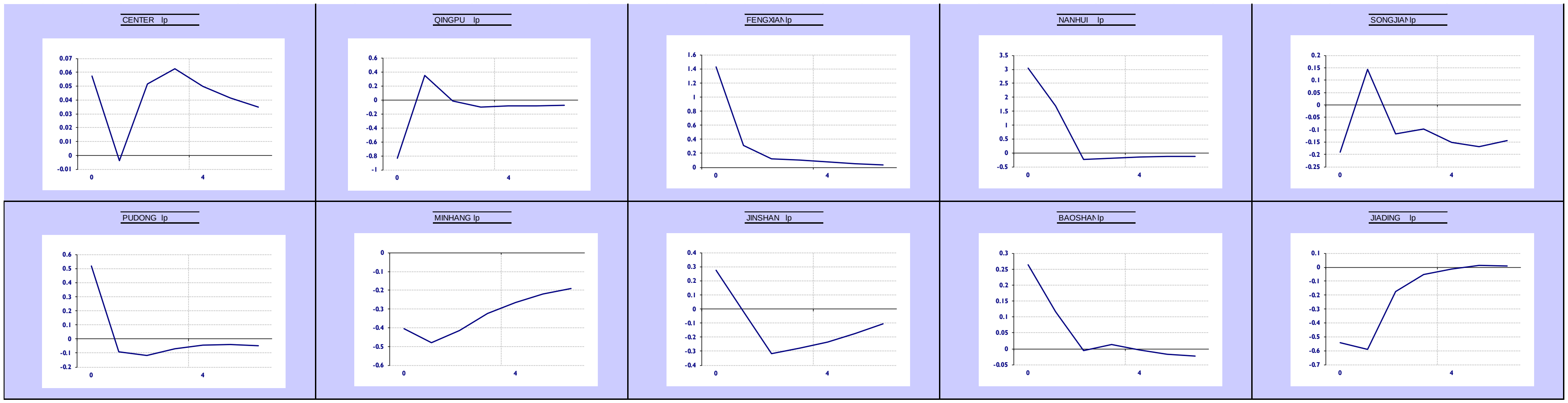
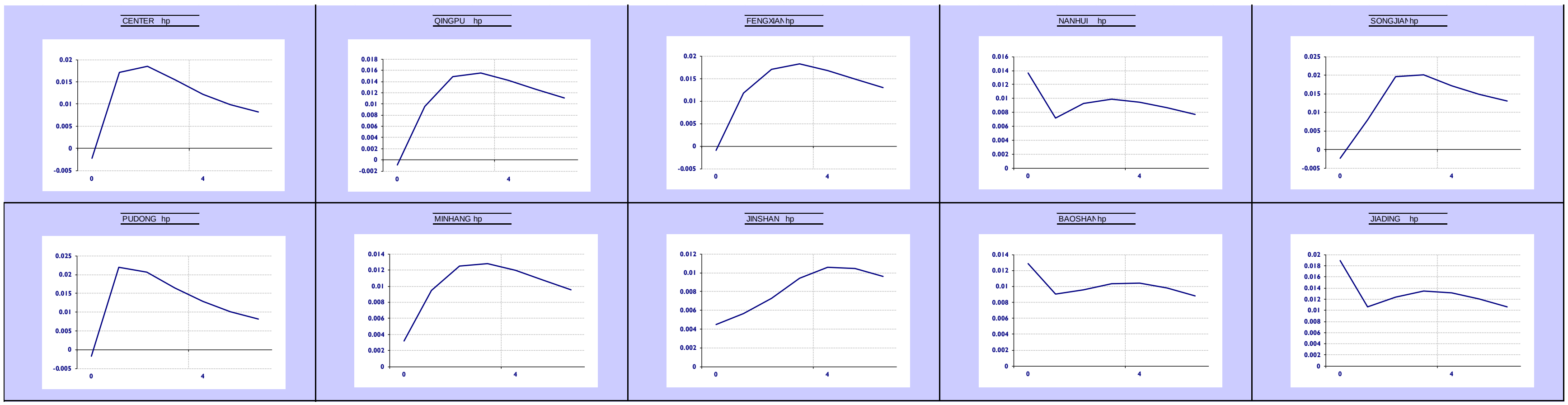


Figure 52 MODEL #5: GIRFs of One Percent Positive Shock to the *Pudong* Land Price

Effects on Housing Price



Effects on Land Price

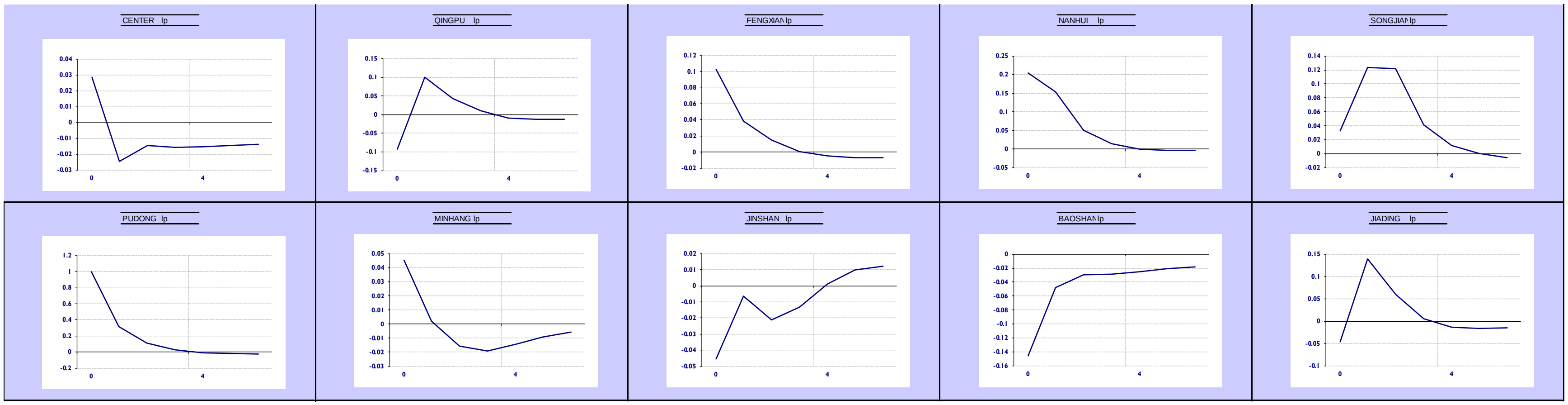
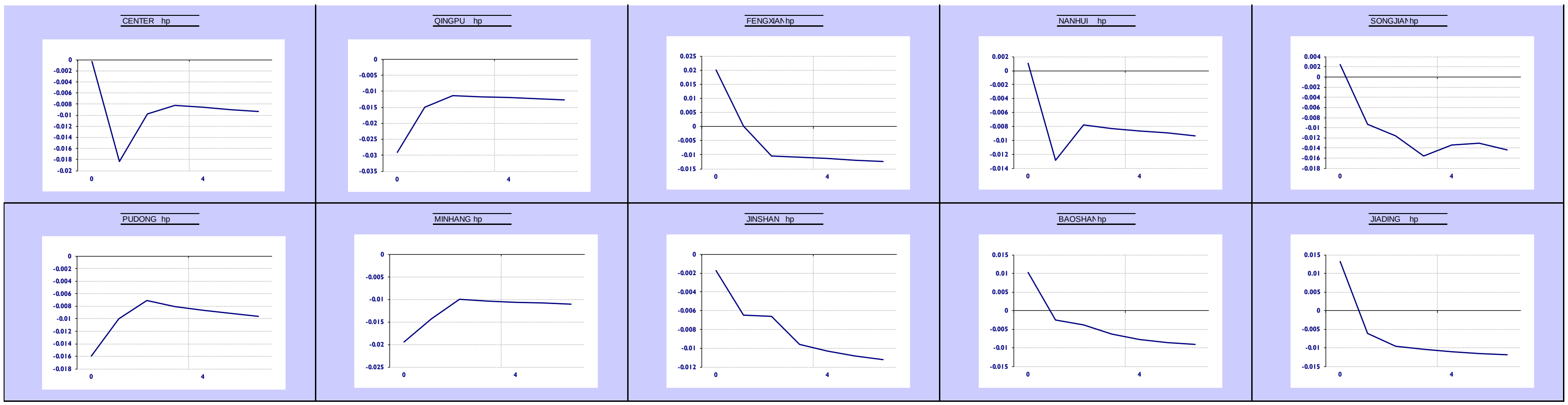


Figure 53 MODEL #5: GIRFs of a One Percent Positive Shock to the *Center* Land Price

Effects on Housing Price



Effects on Land Price

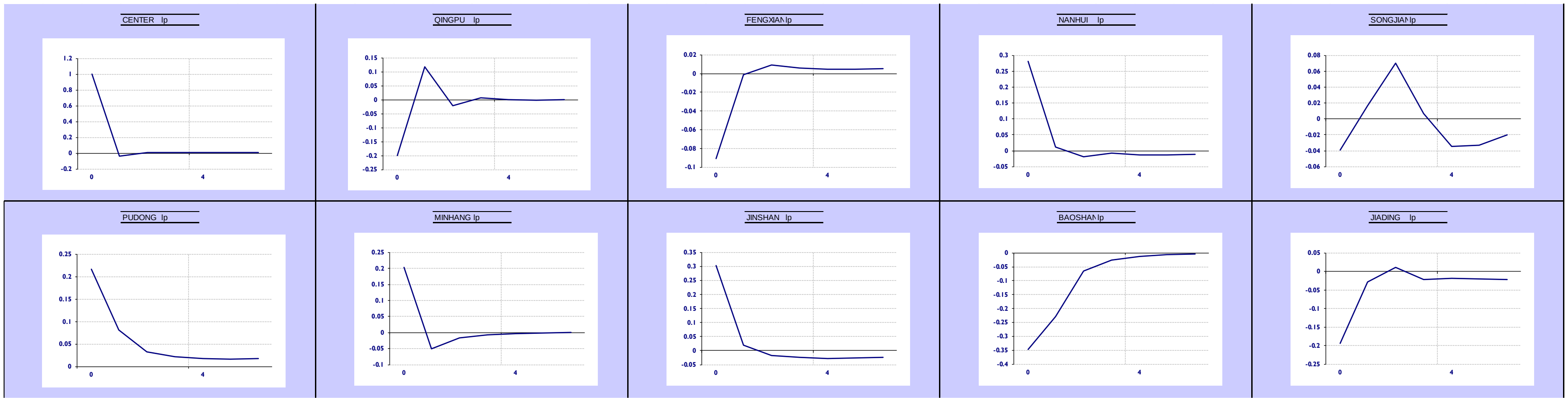
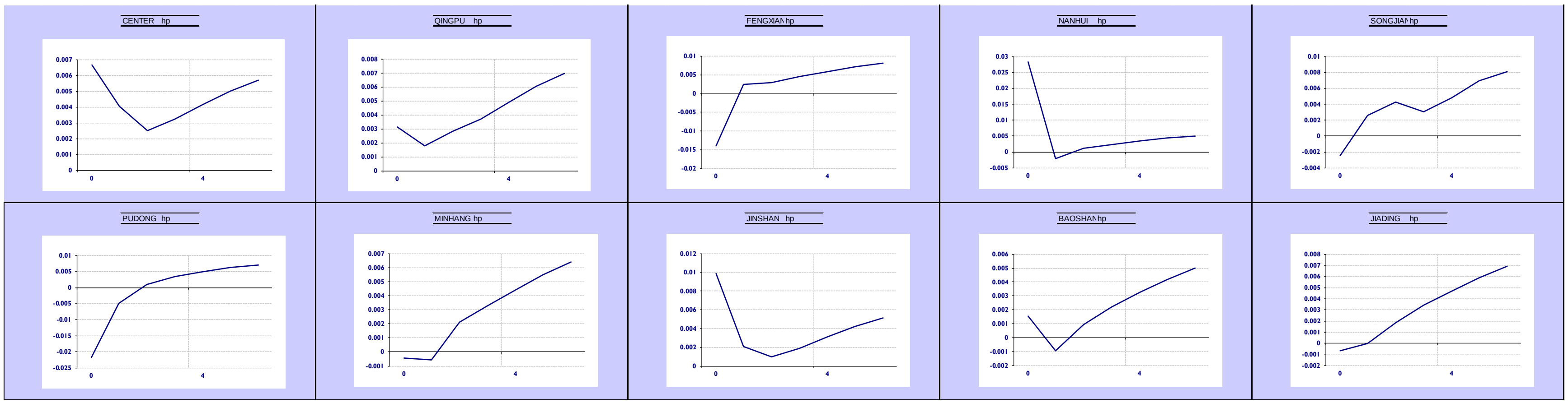


Figure 54 MODEL #5: GIRFs of a One Percent Positive Shock to the *Nanhui* Land Price

Effects on Housing Price



Effects on Land Price

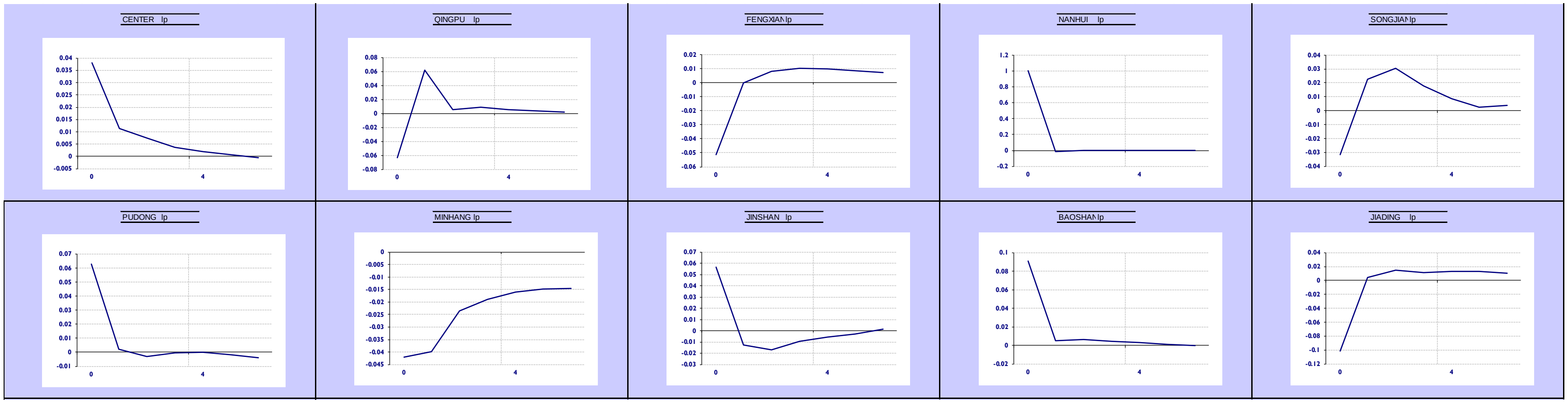
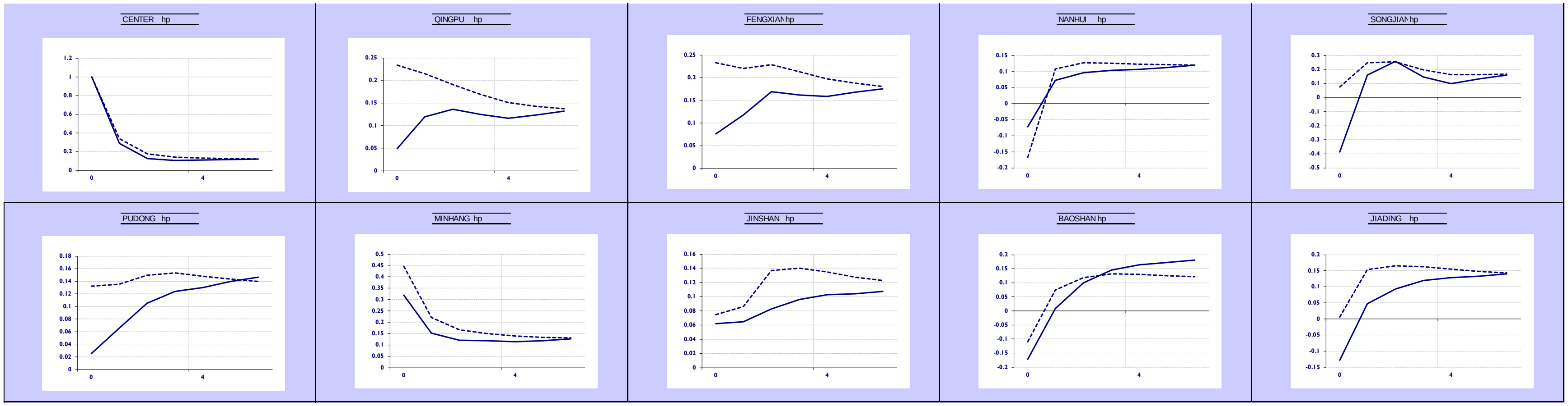
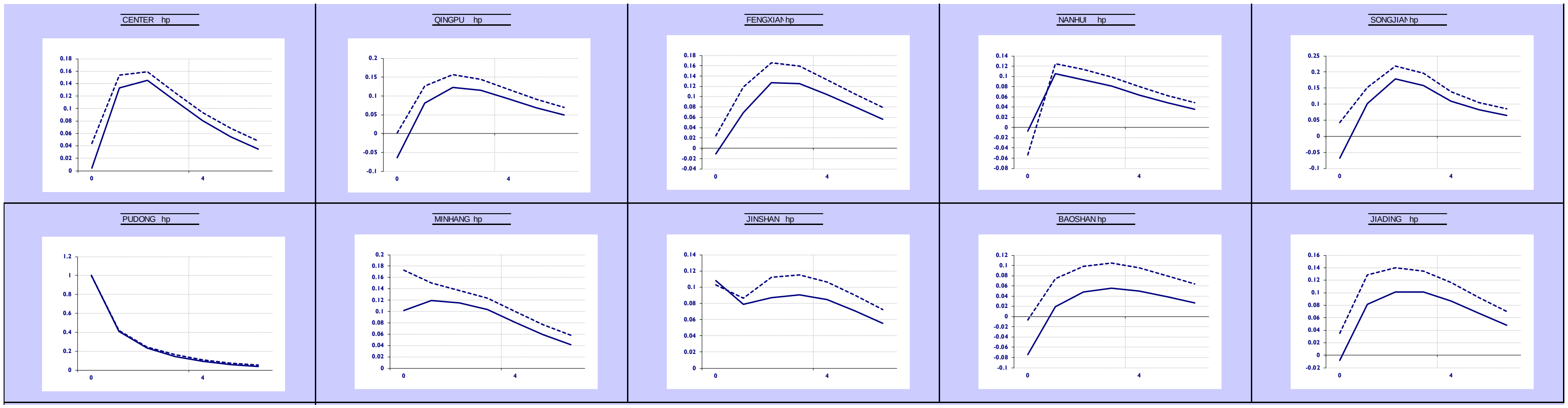


Figure 55 MODEL #5 Counterfactual Analysis: GIRFs of a One Percent Positive Shock to the *Center* Housing Price - Effects on Housing Price



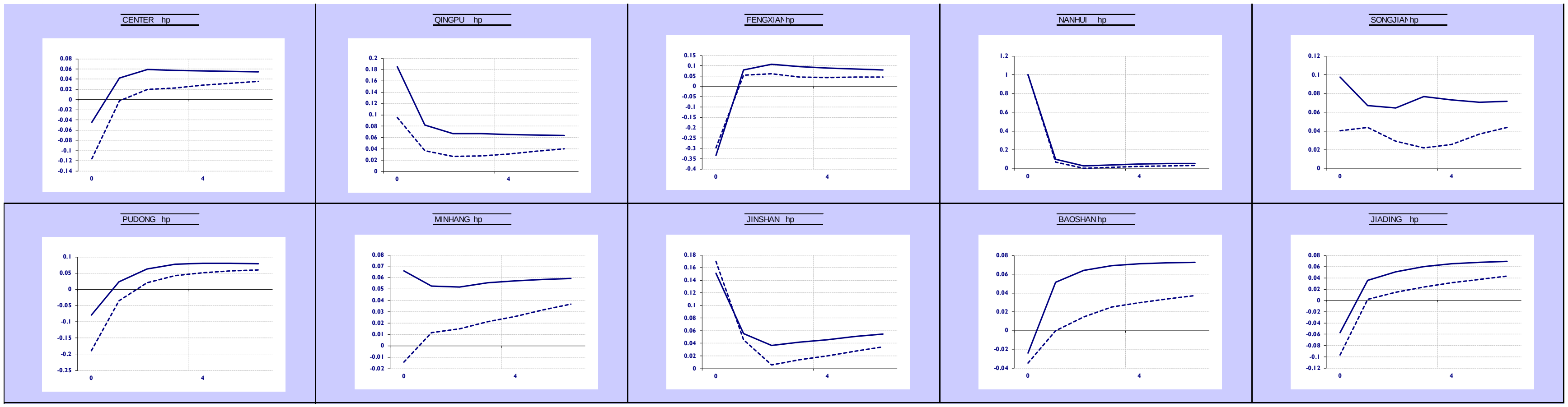
(--- Dec. 2014, — Jan. 2006)

Figure 56 MODEL #5 Counterfactual Analysis: GIRFs of a One Percent Positive Shock to the *Pudong* Housing Price - Effects on Housing Price



(--- Dec. 2014, — Jan. 2006)

Figure 57 MODEL #5 Counterfactual Analysis: GIRFs of a One Percent Positive Shock to the *Nanhui* Housing Price - Effects on Housing Price



(--- Dec. 2014, — Jan. 2006)